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Farmers' resilience index: A tool to metricize the resilience of the farmers towards natural disasters affecting agriculture in India

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ABSTRACT

In the present paper farmers' resilience index (FRI) was constructed considering the natural disaster using five dimensions including physical, social, economic, human and natural. The scale is administered to the 240 paddy farmers in two coastal districts of Andhra Pradesh. Principal component analysis was performed in order to fix the weightage for each variable. About (39.58%) of farmers are resilient to natural disasters with the highest resilience score for financial capital (0.641) and natural capital with less resilience score (0.401). Confirmatory factor analysis (CFA) was performed to determine how well the generated model of the scale fits the data. The structural equation modelling (SEM) path diagram was developed based on the conceptual model, which uses resilience as a latent variable. The SEM analysis revealed that four dimensions of capital positively affect farmers' resilience except for the human capital which negatively affects resilience. To reduce the effects of natural catastrophes in the upcoming years, the adaptation strategies from the highly resilient places can be examined and put into practice in the less resilient areas. It is imperative that development programmes at all levels incorporate climate awareness and stakeholder capacity building.

Key words: Capitals, Confirmatory factor analysis, Natural disasters, Principal component analysis, Resilience index, Structural equation model

HIGHLIGHTS

- Farmers Resilience Index constructed using five livelihood dimensions.
- Majority of the farmers are resilient to the natural disasters.
- Economic capital has been perceived as important capital contributing to the resilience of farmers.
- Structural equational model analysis revealed resilience of the farmers showed a significant positive association with four (physical, social, financial and natural) capitals except human capital which shows negative significant association with the resilience.

1. INTRODUCTION

India is vulnerable to a wide range of both natural and man-made disasters. Approximately 58.6% of the continent is vulnerable to earthquakes of moderate to very high intensity, floods and river erosion, while nearly 5,700 km of the 7,516 km long coastline is vulnerable to cyclones and tsunamis. Drought is a risk for more than 68% of the cultivable land (National Disaster Management Authority, 2019). However, the eastern coast of India is more vulnerable to disasters than the west. Between 1891 and 2000, the East Coast of India was hit by over 308 cyclones, of which 103 were classified as severe. Over 62 cyclones, including depressions, surges and severe surges, have hit the Andhra Pradesh coast in the last 40 years. There were 32 cyclones that hit the Krishna–Godavari area, which includes the four districts of East Godavari, West Godavari, Krishna and Guntur (Basheer Ahammed & Pandey, 2019).

The recent Gulab cyclone tragedy that occurred in 2021 caused extensive damage to agricultural fields in the coastal states, including Telangana, Odisha and Andhra Pradesh due to cyclone storms and heavy precipitation. At the same time, the flood-affected croplands in Andhra Pradesh were found in several regions (Prakash *et al.*, 2023). Regular cyclones in India result in a significant reversal of the country's developmental progress since they cause a high number of fatalities, lost livelihood chances, loss of both public and private property and severe infrastructural damage.

Andhra Pradesh is a coastal state in southeastern India. It is one of the most exposed states in India to cyclones. Its proximity to the Bay of Bengal and its low-lying topography are compounded by high population density, and poorly maintained flood protection and drainage systems making coastal Andhra Pradesh highly vulnerable to the impacts of cyclones and floods (Rao *et al.*, 2017).

Agriculture is the main and only source of income for a majority of the farmers in Andhra Pradesh, especially in rural areas. It is one of the most disaster-affected sectors. Even though the state is referred to as the 'rice bowl of India,' there are problems with the state's agriculture. Certain areas – particularly the coastal districts – are more likely to experience cyclones and floods, whereas the Rayalaseema regions are more likely to experience persistent drought (NADMP, 2020). Though it is not possible to prevent natural disasters, it certainly is possible to reduce the frequency and intensity of the disasters by evolving appropriate preparedness to counter disaster and initiate mitigation measures.

The Indian Government has set a target of doubling farmers' income by the year 2022, 5 trillion-dollar economy and ease of living by 2024. However, these targets can be achieved by improving the scenario of Indian agriculture and protecting them from natural disasters through adaptation. According to a recent research by the Ministry (2018), if suitable adaptation measures are not implemented in the agriculture sector, climate change is predicted to have a more severe impact on agricultural productivity starting in 2020 and might increase by as much as 40% by 2100 (NADMP, 2020).

2. REVIEW OF LITERATURE

The concept of resilience stems from the Latin 'resilire' to denote 'bouncing back' or 'recoiling'. The IPCC (2007) defined resilience as 'the capacity of a social or ecological system to absorb disturbances while preserving the same fundamental structure and modes of functioning, the capacity for self-organization, and the capacity to adapt to stress and change'. For agricultural production systems to be successful, farmers' capacity to absorb, handle, and recover from a climate disaster is crucial. At the village level, farmer resilience is all about giving them the tools they need to absorb and recover from shocks and pressures that affect their agricultural output and way of life. When anticipating a crisis in the near future, communities can learn from their proactive responses to climate disasters.

As resilience is a dynamic multidimensional concept, its quantification remains controversial (Béné *et al.*, 2016). Measuring resilience is a difficult task and different authors proposed different approaches. Alternative measurement methods or resilience indicators are often used since measuring resilience is not easily possible (Quandt, 2018). The climate disaster resilience (CDR) framework adopted to study the farmers' resilience index which showed that the economic dimension is high (0.58) when compared with the social, technical and physical dimensions which have farmers' resilience index value less than 0.5 (Jayadas & Ambujam, 2021). The Disaster Resilience Place Model (DROP) framework adopted to study the inherent resilience index for Zimbabwe consists of community capital, economic, infrastructure and social and health as indicators

(Mavhura *et al.*, 2021). Access to basic services, assets, social safety nets, and adaptive capacity are the indicators used for developing micro-level resilience index. Natural disasters have a negative impact on education, crop variety, and consumption which is unavoidable as residents are unable to develop enough adopting abilities (Mondal *et al.*, 2023). The study found that social capital (SC), ecological stability and livelihood resources such as cropland, livestock, livelihood diversification, and infrastructure are the main determinants impacting households' resilience to climate induced shocks (Asmamaw *et al.* (2019). The sustainable livelihood framework (SLF) was adopted to study the livelihood resilience in the mining sector. This framework consists of five capitals (Arhin *et al.* 2022). Resilience outcomes are the changes in a household's ability to respond to climate hazards.

With this background, the present study was undertaken with the objective of assessing the farmers' resilience towards natural disasters and developing a disaster management model to overcome the crisis effectively.

3. FRI METHODOLOGY

The state of Andhra Pradesh was selected purposively for the present study. There is a growing consensus in the scientific community to address the resilience of farmers related to climate change, particularly at the regional level. This would enable fine-tuning the hot spot areas that need immediate intervention. The Krishna is the second largest Eastward Draining River in Peninsular India covering vast areas in the States of Maharashtra, Karnataka and Andhra Pradesh. It is the major river passing through Krishna and NTR districts. Thus, the Krishna and NTR (Nandamuri Taraka Rama Rao) districts have been taken for computing farmers' resilience since the districts are highly susceptible to the incidence of disasters (Figure 1). Thus, a total sample size of 240 respondents was selected using a proportionate random sampling technique. After the computation of the

Fig. 1 | Description of the study area.

farmers' resilience index (FRI), Structural Equation Modelling (SEM) was done on the data that had been collected: (1) The convergent and discriminant validity was examined by performing Confirmatory Factor Analysis (CFA) followed by developing a structural path model which explains how each construct in the model is related to one another. The Amos V23 software was used in this study to perform structural equational modelling.

3.1. Computation of FRI

The FRI is based on the SLF designed by Chambers (1983) and later modified by Chambers & Conway (1992). When using livelihood strategies to address vulnerabilities and adapt to them, this paradigm makes complex relationships between diverse types of capital more understandable (Tyas, 2015). The theoretical framework is given in Figure 2.

This framework highlights community social, political, and physical situations as well as the livelihoods that are impacted by trends, shocks, and seasonal changes from the outside world. Disaster resilience is related to the SLF approach, even though it primarily emphasizes the idea of sustainability (Tobin, 1999). Five dimensions make up the resilience tool. There are distinct indicators for every dimension. A farmer is therefore said to be more resilient if he performs on average better in each of these five areas. Overall, the farmers' resilience framework consists of 15 indicators given in Table 1. For example, road connectivity is an indicator of the 'physical dimension'. Better road connectivity leads to faster and more efficient displacement of people from affected areas. Therefore, farmers are more likely to be resilient to shocks.

For the purpose of determining the weights, principal component analysis (PCA) was performed to determine the weightage for each indicator or variable under five dimensions. Based on component loadings of the first principal component with eigenvalue > 1 and a higher percentage of variance, the respondent score has been weighted (Filmer & Pritchett, 2001; Jayadas & Ambujam, 2021). The factor loadings of the first principal component are given in Table 2.

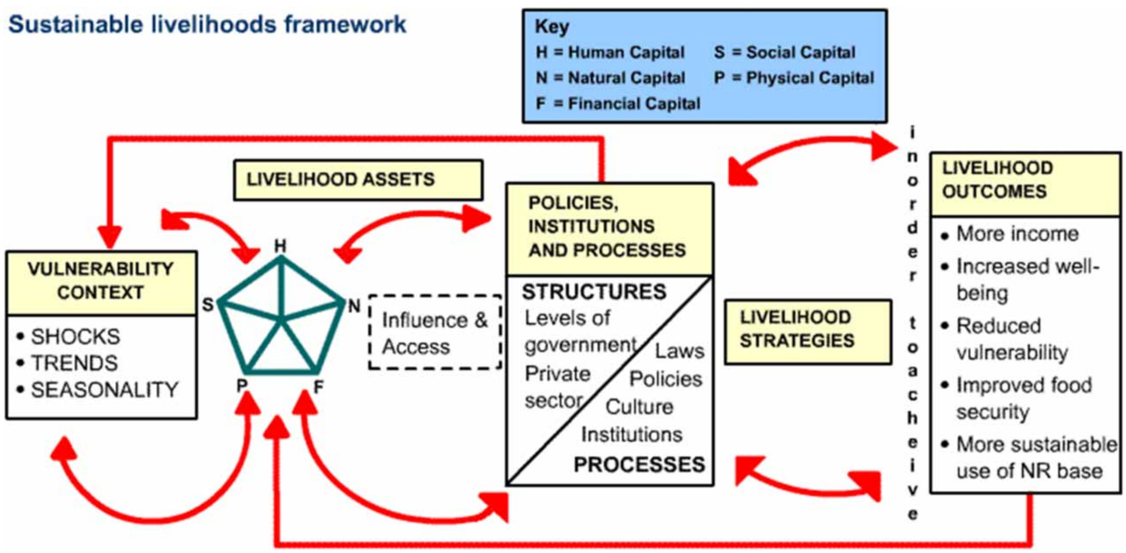

Fig. 2 | Theoretical framework for the farmers' resilience.

Table 1 | Variables underpinning the quantitative study.

S.No	Dimensions	Indicators
1.	Physical	Possession of transportation Access to electricity Road connectivity
2.	Social	Extent of social cohesiveness Use of social networking site Urban connectivity
3	Economic	Access to credit Financial safety Saving part of income
4	Human	Participation in agricultural extension activity Health status No of earning members
5	Natural	Land productivity Water availability Soil fertility status
6	Farmers' resilience	Infrastructure facilities are better to cope with the climate shocks Better access to information and dissemination improve climate change preparedness as well as adaptation Insurance facility minimize risk and compensate loss and helps to get productive inputs in time Better extension activity participation helps to combat the natural disaster and other climatic stress There is better access to drinking water facilities

Table 2 | Factor loadings of first principal component.

S.No	Indicators	Factor loadings	Eigenvalue	% Variance
1	Possession of transportation	0.03	7.314	48.760
2	Access to electricity	0.229		
3	Road connectivity	0.333		
4	Extent of social cohesiveness	0.888		
5	Use of social networking site	0.895		
6	Urban connectivity	0.878		
7	Access to credit	0.673		
8	Financial safety	0.617		
9	Saving part of income	0.725		
10	Participation in agricultural extension activity	0.755		
11	Health status	0.683		
12	No of earning members	0.748		
13	Land productivity	0.172		
14	Water availability	0.276		
15	Soil fertility status	0.096		

The Dimension Resilience Index has been calculated by multiplying the weightage assigned (factor loadings) with the respondent score after each indicator's weights have been fixed. The dimension-wise resilience index is computed using the following equation:

$$\text{Dimension-wise resilience index}_{\text{i}} = \frac{\sum_{\boldsymbol{i}=1}^{\boldsymbol{n}} (\text{Weightage}*\text{Variable score})\boldsymbol{j}}{n} \tag{1}$$

where j is the number of variables falling under a given dimension and i is its dimension (there are five of them). n is the overall number of dimensions.

The financial resilience index, social resilience index, human resilience index, and physical resilience index are all part of the dimension-wise resilience index. The following equation has been used to compute the overall FRI:

$$\text{Farmer resilience index} = \frac{\sum_{i=1}^{n} \frac{(\text{Dimension} - \text{wise resilience index})i}{(\text{Maximum resilience index})i}}{n} \tag{2}$$

where n is the total number of dimensions and i is the dimension (corresponding dimension).

The various resilient indices have been computed, and the indices have been quantized. Table 3 provides the quantile-based classification of farmer resilience.

4. RESULTS

4.1. Resilience index

The resilience index has been calculated for the five dimensions, namely economic, social, human, physical and natural, followed by the FRI for both districts together. The factor loadings of the first principal component along with the eigenvalues and cumulative variance are given in Table 2 for fixing the weightage of each variable.

Table 2 indicated factor loadings of the first principal component with an eigenvalue of 7.314. The percentage of covariance explained by the first principal component is 48.760. The second principal component eigenvalue is 2.029 explained by 13.527% variance followed by the third component, eigenvalue is 1.698 with 11.320% of variance. Since the first principal component has the highest eigenvalue with more percentage variance, the first principal component factor loadings have been chosen for fixing the weightage for each variable. After calculating the dimension-wise resilience index, the overall farmers' resilience index has been calculated by using Equation (2). The overall FRI value for the study area is 0.55. The dimension-wise resilience index values are shown in the spider diagram in Figure 3.

The overall FRI value for the study area is 0.55. Financial capital (FRI value = 0.641) has been perceived as the relatively most important indicator contributing to the resilience of a farmer. Social (0.612) and physical capitals

Table 3 | Distribution of farmers based on the resilience.

FRI	Frequency	Percentage
Less resilient (0–0.37)	63	26.25
Moderately resilient (0.37–0.61)	82	34.17
Highly resilient (0.62–1.0)	95	39.58

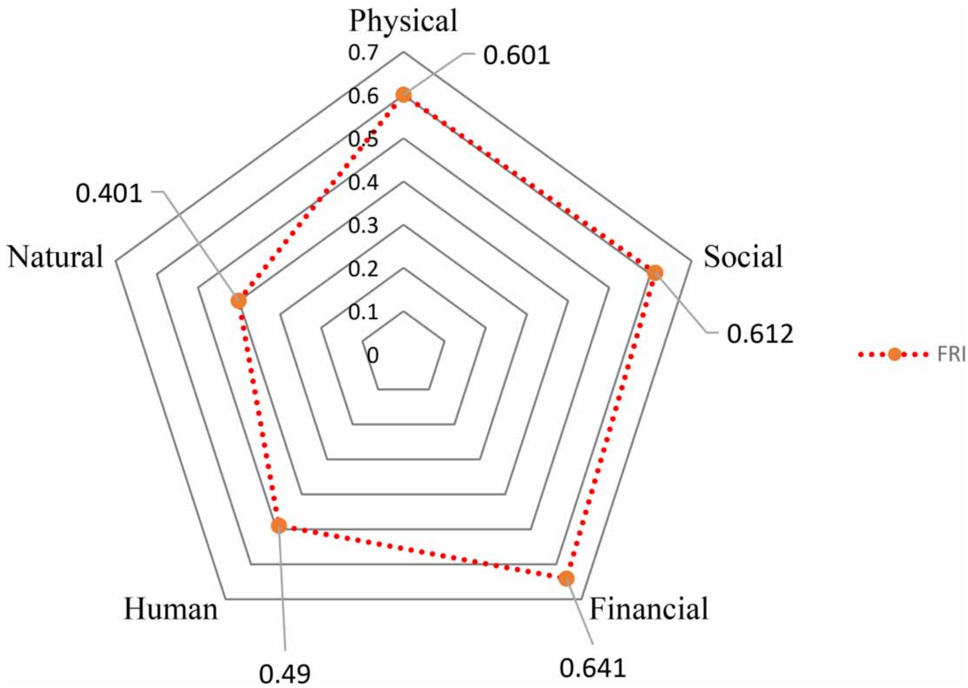

Fig. 3 | Mean scores of capitals.

(0.601) also equally contributed whereas the index value of human (0.496) and natural capitals (0.401) is less than the overall FRI score which means that those two indicators are perceived as least important by the farmer. The resilience index values for all capital are high except natural capital which is 0.401 because in the short run, farmers cannot cope with the effects of natural disasters and it takes time for them to recover from the damage caused to soil and land productivity. Farmers in both districts are financially better and have alternate source of income. It was also found that most of the farmers are semi-medium farmers having a landholding more than 2–4 ha. This might be the reason for the high financial capital index (0.641) which is shown in Figure 3. The findings are in line with Jayadas & Ambujam (2021).

After calculating the different resilient indices, the indices have been grouped into quantiles. The classification of farmer resilience based on the quantile is shown in Table 3.

Table 3 represents the distribution of respondents based on resilience. It was found that nearly half (39.58%) of the respondents had high resilience towards natural disasters followed by medium (34.17%) and low (26.25%), respectively. The results reveal that the majority of the respondents have high resilience towards natural disasters. This is because a majority of the farmers are getting crop insurance from the government and they are practising crop diversification with a range of 0.4–0.6 as a resilient strategy. In addition, farmers in the study area often possess traditional knowledge passed down through generations. This knowledge incorporates practices that have proven effective in managing agricultural risks. This combination of traditional wisdom and innovation allows them to find solutions to challenges posed by natural disasters.

At the same time, these farmers most of the time do not wait for external interventions and develop their own adaptation strategies to cope with disasters. In many cases, there is a good understanding of the challenges and problems faced by the farmers, they also know which strategy to adopt in order to tackle. However, in some cases, they lacked the capacity to implement the necessary changes due to lack of technical knowledge and fatalistic behaviour, which impedes the implementation of resilient strategies. Results are consistent with the results of Reddy *et al*. (2015).

4.2. SEM for FRI

SEM is an advanced statistical technique to study mainly social phenomenon, processes or behaviour by estimating the relationship between latent constructs and their indicator variables. The same was employed here to confirm the theoretical framework developed for the farmer resilience index based on a sustainable livelihood framework.

The internal consistency and reliability were evaluated using Cronbach's alpha (>0.7) for each dimension used for the development of the FRI. After calculating internal consistency, two-step approach of SEM comprising of measurement model and structural model was followed.

The measurement model is developed based on 1. CFA and 2. path diagram obtained is the structural model which is depicted in Figure 5.

4.2.1. Internal reliability of constructs in the model

Cronbach's alpha reliability was employed to identify the internal reliability indices of each construct using SPSS version 26. Table 4 indicates that all the constructs are highly reliable (>0.70) as suggested by George & Mallery (2010) in the model.

4.2.2. Confirmatory factor analysis

CFA was performed with 240 respondents to determine how well the data fit the scale model that was generated in which four measures were assessed to indicate the overall fitness of the measurement model. The four metrics were *P*-value, comparative fit index (CFI), Tucker–Lewis index (TLI) and incremental fit index(IFI), The results from CFA revealed that the model has acceptable fit measures given by Hu & Bentler (1999), shown in Table 5.

Physical capital (PC) indicator variables: PC1 (Possession of transportation), PC2 (Access to electricity) and PC3 (Road connectivity)

Social capital (SC) indicator variables: SC1 (Extent of social cohesiveness), SC2 (Use of social networking sites and SC3 (Urban connectivity)

Economic capital (EC) indicator variables: EC1 (Access to credit), EC2 (Financial safety) and EC3 (saving part of income)

Human capital (HC) indicator variables: HC1 (Participation in agricultural extension activity), HC2 (Health status) and HC3 (No of earning members)

Table 4 | Internal reliability of all dimensions.

S.No	Dimensions	Cronbach's alpha reliability
1.	Physical	0.880
2.	Social	0.864
3.	Financial	0.749
4.	Human	0.947
5.	Natural	0.865

Table 5 | Model fit summary of confirmatory factor analysis.

	Fit measures	Acceptable measures	Obtained fit measures
1	*P*-value	<0.001	0.000
2	Comparative fit index (CFI)	>0.90	0.903
3	Incremental fit index (IFI)	>0.90	0.904
4	Tucker–Lewis INDEX (TLI)	>0.90	0.881

Natural capital (HC) indicator variables: NC1 (Land productivity), NC2 (Water availability) and NC3 (Soil fertility status)

Overall resilience score : RS1, RS2, RS3, RS4 and RS5

It is evident that the computed *P*-value was 0.000 which means that the model accurately represents the data. The current model's incremental fit indices (i.e., CFI = 0.903, IFI = 0.904, TLI = 0.881 and CFI = 0.916) suggested that the model was a perfect fit. As a result, it could be inferred that the constructed scale's proposed model perfectly fits the sample data. The results of CFA insist that the Average Variance Extracted (AVE) of each construct was more than 0.5 and had significant factor loadings as suggested by Bagozzi & Yi (1998). Results also showed that construct reliability (ά) and composite reliability (CR) values for all capitals were more than 0.7, shown in Table 6. This shows that all the five capitals are affecting each other significantly. The CFA path diagram is shown in Figure 4.

4.2.3. SEM results

The structural model was constructed based on the results from the CFA. The assessment of parameters and goodness of fit (GOF) proved that the structural model is good ($P = 0.000$, CFI = 0.838; IFI = 0.839; TLI = 0.814). Table 7 shows the model fit measures for SEM.

Figure 5 portrays the statistically significant estimates and casual paths (hypotheses).

4.2.3.1. Path analysis through SEM. The SEM analysis revealed that the latent variable resilience of the farmers showed a significant positive association with four (physical, social, financial and natural) capitals except HC which shows a negative significant association with resilience. The PC ($\beta = 0.206$, $p = <0.05$), social ($\beta = 0.131$, $p = <0.001$), financial ($\beta = 0.552$, $p = <0.05$), natural ($\beta = 0.184$, $p = <0.05$) and HC ($\beta = -0.435$, $p = < 0.05$) were found significant at 5, 10, 5, 5 and 5% significance (α) levels, respectively. This revealed that any effort to improve these four dimensions would undoubtedly enhance the resilience of the farmers in the two districts. The SEM SPSS AMOS output expressed the relationship between the latent variables – resilience and components which are summarized in Table 8.

5. DISCUSSION

5.1. Path analysis through SEM

The SEM results indicated that four (physical, social, financial and natural) capitals are found to have a positive and significant relationship with resilient score. Hence improvement in those four capitals significantly improves the resilience of farmers' towards natural disasters.

Table 6 | CFA factor loadings, reliability and validity of constructs.

Items	Standardized loadings	CR	AVE	ά value
PC1	0.701	0.964	0.900	0.949
PC2	0.979			
PC3	0.936			
SC1	0.899	0.910	0.775	0.881
SC2	0.872			
SC3	0.970			
EC1	0.828	0.939	0.836	0.915
EC2	0.893			
EC3	0.940			
NC1	0.824	0.918	0.789	0.888
NC2	0.845			
NC3	0.920			
HC1	0.942	0.898	0.746	0.864
HC2	0.935			
HC3	0.969			
RS1	0.549	0.845	0.527	0.726
RS2	0.636			
RS3	0.796			
RS4	0.845			
RS5	0.762			

5.2. HC and resilience

From Table 8, it was found that HC shows negative and significant relationship ($\propto = -0.435$, $p = 0.007$) with resilient score at 1% level of probability. This is due to local farmers not participating in much training programmes regarding disaster coping mechanisms such as disaster preparedness or disaster recovery. This leads to lack of knowledge and skills necessary to adopt modern agricultural practices, manage risks effectively, and make informed decisions. Without adequate knowledge and skills, farmers may struggle to respond and adapt to challenges posed by natural disasters. Lack of knowledge and skill might be the reason for having a negative significant association of HC with resilience.

5.3. SC and resilience

From Table 8, it was found that SC shows a positive and significant relationship ($\propto = 0.131$, $p = 0.005$) with a resilient score at a 1% level of probability. It was found that SC allows farmers in the study area to access valuable information and knowledge through social networks. They can learn from each other's experiences, and exchange information about climate patterns, innovative farming practices, and effective risk management strategies. This enhances their ability to adapt to changing conditions and build resilience. Due to this reason, SC has a positive and significant relationship with resilience score.

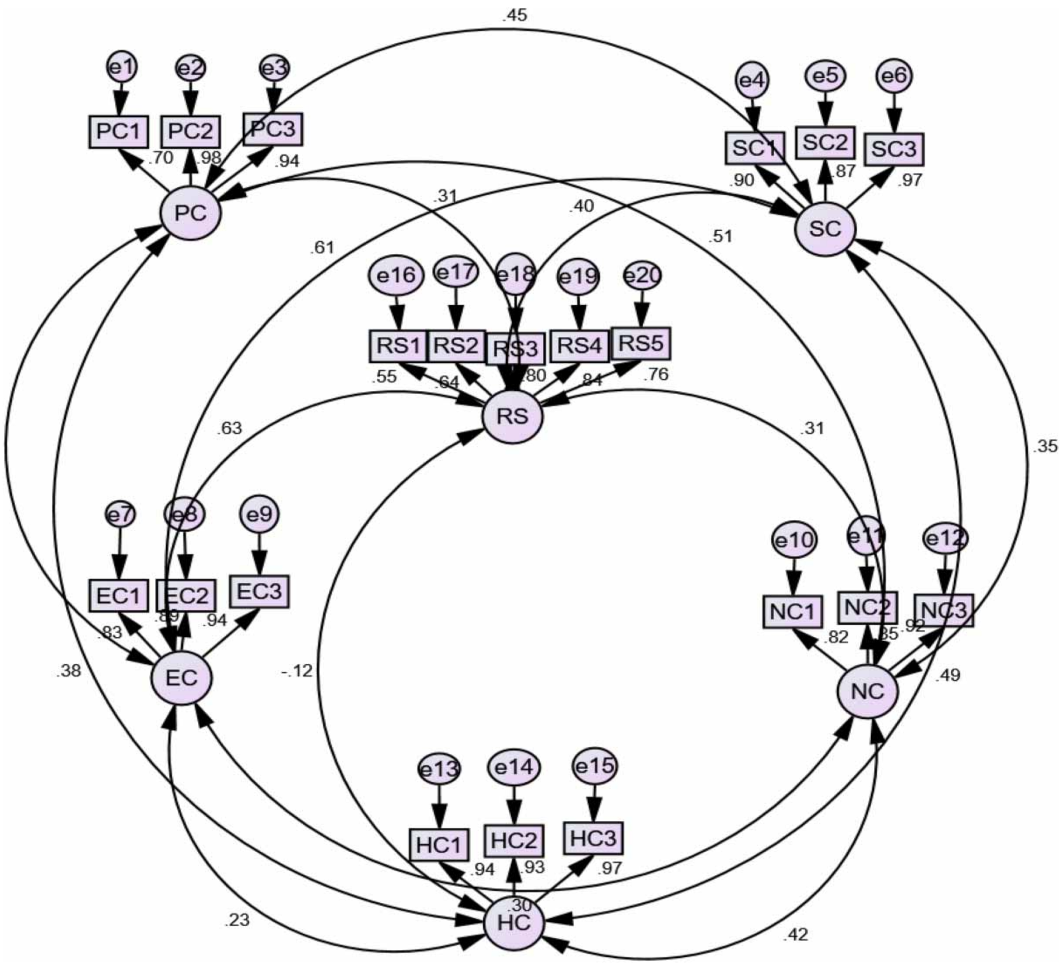

Fig. 4 | CFA path diagram.

Table 7 | Model fit measures for structural equational modelling (SEM).

	Fit measures	Acceptable measures	Obtained fit measures
1	*P*-value	<0.001	0.000
2	Comparative fit index (CFI)	>0.90	0.838
3	Incremental fit index (IFI)	>0.90	0.839
4	Tucker–Lewis index (TLI)	>0.90	0.814

5.4. Financial capital and resilience

From Table 8, it was found that financial capital shows a positive and significant relationship ($\propto = 0.552$, $p = 0.020$) with a resilient score at a 5% level of probability. Similarly, savings are one of the important factors

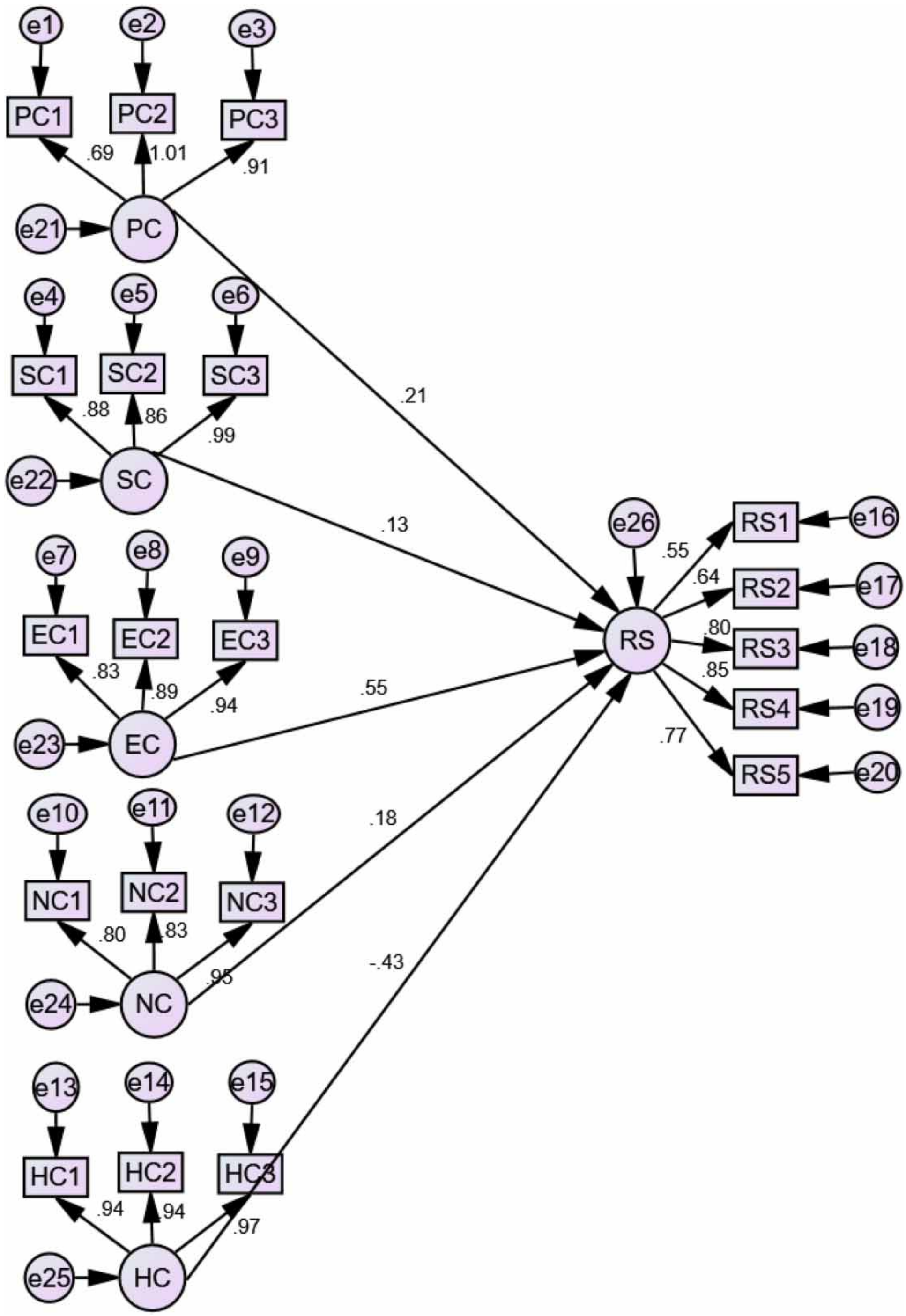

Fig. 5 | Path diagram from structural equation modelling. PC, physical capital; SC, social capital; EC, economic capital; NC, natural capital; HC, human capital; RS, resilience score.

Table 8 | Path analysis through SEM.

Path	Standardized coefficient	SE	CR	Label
PC → RS	0.206	0.052	3.734	YES
SC → RS	0.131	0.005	2.528	YES
EC → RS	0.552	0.020	6.971	YES
NC → RS	0.184	0.060	3.318	YES
HC → RS	−0.435	0.007	6.452	YES

in identifying EC. In the study area, more than half of households have high savings through alternate sources of income. In addition, farmers also have better access to credit from institutional sources which resulted in an improvement in resilience among farmers towards disasters. This is the reason behind positive significant association of financial capital with resilience.

5.5. PC and resilience

From Table 8, it was found that PC shows a positive and significant relationship ($\propto = 0.206$, $p = 0.052$) with a resilient score at a 5% level of probability. Infrastructure facilities like electricity and transportation are good in the study area. This helps in quick displacement from disaster-prone areas to less vulnerable areas. Hence, PC has a positive and significant relationship with resilience score.

5.6. Natural capital and resilience

From Table 8, it was found that PC shows a positive and significant relationship ($\propto = 0.184$, $p = 0.060$) with a resilient score at 5% level of probability. Although the farmers have a less natural capital score, this capital is also significantly affecting their resilience. Since all capital significantly affects the farmers' resilience, it is important for the government to focus on all five capitals which will automatically improve the livelihood of individuals and also their resilience to natural disasters. Capacity building and training programmes in disaster coping mechanisms have to be initiated by the government officials which will help the farmers to cope up with future shocks.

6. CONCLUSION

FRI concluded that half of the respondents under the Krishna and NTR districts are resilient to natural disasters whereas the remaining half are less resilient. The districts that are more vulnerable should be given priority for introducing any interventions. Given the priority for investment, policymakers can start with the most vulnerable locations and work their way down, reducing the overall impact of disasters. Additionally, it is crucial that climate awareness and capacity building become an essential component of all development programmes. The study also showed that four (physical, social, financial and natural) capitals positively and significantly impacted the farmers' resilience towards natural disasters. The developed disaster model may stimulate the policymakers to direct their efforts towards taking effective and sustainable preventive measures before the disaster occurs and ensure prompt response, recovery, and reconstruction during and after the disaster so as to build India's overall disaster resilience.

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DATA AVAILABILITY STATEMENT

All relevant data are available from an online repository or repositories: https://docs.google.com/spreadsheets/d/1eiBJsmOOHq8LEs_5odrFT-NtxfFBwoMF/edit#gid=1161945972.

CONFLICT OF INTEREST

The authors declare there is no conflict.

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