Research Article

Indian Journal of Extension Education
Vol. 62, No. 4 (October–December), 2026, (8-14)

ISSN 0537-1996 (Print)
ISSN 2454-552X (Online)

Social Networks of Indigenous Climate Knowledge: Ecological Memory and Resilience in Saora Tribal Communities

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HIGHLIGHTS

- Among the Saora farmers, ecological memory was the most significant factor in climate resilience.
- Social network analysis identified knowledge brokers facilitating intergenerational knowledge transmission.
- Enabling local knowledge networks can enhance tribal community climate adaptation and resilience.

ARTICLE INFO

Keywords: Ecological memory index, Climate resilience, Indigenous knowledge systems, Social network analysis, Knowledge transmission.

https://doi.org/10.48165/IJEE.2026.62402

Citation: Reddy, J. S., Deb, A., Pradhan, V., Bhadra, P., & Suman, S. (2026). Social Networks of Indigenous Climate Knowledge: Ecological Memory and Resilience in Saora Tribal Communities. *Indian Journal of Extension Education*, *62*(4), 8-14. https://doi.org/10.48165/IJEE.2026.62402

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ABSTRACT

Rainfed tribal farming systems are increasingly affected by climatic variability, with indigenous knowledge being a key element to adaptation. This study explored the structure, transmission and ecological memory's contribution to climate resilience of Saora tribal farmers of village Linga in Gajapati district, Odisha, during 2024 to 2026. Household surveys, participatory rural appraisal, seasonal calendars, oral history and key-informant interviews were conducted to collect data with 120 farming households. An Ecological Memory Index (EMI) and Climate Resilience Index (CRI) were created and computed with the application of correlation, regression and t-test statistical analysis, and Social Network Analysis (SNA) was applied to map the pathways of knowledge transmission. Results showed that ecological memory was significantly associated with climate resilience, with ecological memory being the strongest contributing component of climate resilience, with the highest standardised weight ($\beta = 0.61$) among all CRI pillars. Central bridging roles in the knowledge network were occupied by elders, healers and seed keepers who played a significant role in intergenerational knowledge transfer. The study has concluded that the local knowledge network (LKN) can help to improve the climate resilience of a tribal agroecosystem.

INTRODUCTION

Among the livelihoods that are most vulnerable to climate change in South Asia are the smallholder and the tribal farming systems that rely on rain-fed agriculture (Aryal et al., 2020). Formal climate information services are also limited, and adaptation in such contexts is mostly shaped by ecological memory, or the aggregate of observations, stories and practices relating to environmental change that a community and its members accumulated over time and passed on to the next generation (Berkes, 2017). Indigenous lifeways are characterised by their ability to adapt to climate change and remain resilient (Kumar & Saxena, 2024) before it, ranging from the Zabo system in Nagaland to the methods of saving seeds in the Himalayas, but they are under growing stress as climate change exceeds traditional adaptation capacity (Bhattacharjee & Behera, 2021; Mondal & Palit, 2022; Petzold et al., 2024). Oldest among Odisha's Adivasi groups, the Saora have a sophisticated understanding of rainfall forecasting, seed saving, biodiversity

Received 05-06-2026; Accepted 09-07-2026

management and pest control using plants. However, the threat of out-migration, market integration and loss of intergenerational learning runs against its continuity (Damodaran, 2015; Mondal & Palit, 2022). Tribal farm women's limited access to agricultural information and advisory services also poses similar challenges, limiting knowledge sharing and adaptive capacity within tribal communities, as observed by Bahubalendra et al. (2025).

Many TEK scholarship documents content of knowledge, but leaves its social structure under-examined. Knowledge is transmitted through the networks of social relations, and their distribution and movement, as well as their quantity, are important (Crona & Bodin, 2017). There are tools to make this architecture visible, such as social network analysis (SNA), which can determine influential and bridging actors, and community detection, which can detect sub-cultural clustering. Previous research demonstrates how people who occupy "hub" positions in knowledge networks influence the interpretations of eco-signals (Crona & Bodin, 2017) and how an individual's position in a knowledge network tends to hold local ecological knowledge (Calvet-Mir et al., 2012).

India is home to a large indigenous population with their traditional knowledge systems and technologies that have evolved over centuries in tune with their habitats (Lenka & Satpathy, 2020; Bheemappa et al., 2022). IK is deeply rooted in the cultural, social and ecological histories of specific Indigenous communities and is strongly associated with Indigenous connection to land, environment and traditional practices and ways of life (Radcliffe et al., 2021; Kusumastuti et al., 2023). There is a need to critically evaluate the knowledge levels of the tribal farmers to have an insight into the effectiveness of indigenous and livelihood-related practices, as was highlighted in previous studies (Johnson et al., 2023). In addition to scientific knowledge, the use of IK has proven to be an efficient way to improve climate change adaptation and enhance resilience of Indigenous communities in the midst of a changing climate (Chen & Cheng, 2020). There are few studies that provide evidence on the process of how ecological memory is passed across social networks and how it contributes to climate resilience among the Saora tribal community.

METHODOLOGY

A cross-sectional study was conducted in a tribal village called Linga, in Gajapati district, Odisha, a purposively selected representative village of the Saora community where there is a well-defined farming community, high forest dependence, and documented traditional ecological practices and it was found to be well suited for an in-depth sociometric network study. A mixed-methods Participatory Action Research (PAR) design was selected that incorporated both quantitative work related to index construction and statistical analysis, as well as a qualitative community-participatory approach. The study population constituted all the farming households in village Linga, which formed a census-based bounded network (N = 120), as this represented the total farming population of the village. Purposive sampling was used to select knowledge-rich respondents (elders, healers and seed keepers) as key knowledge actors. Relational data were collected in the bounded population by using the name-generator questions. A participatory awareness intervention was implemented over one agricultural season and pre- and post-intervention awareness scores were obtained based on a structured knowledge test. Ecological memory in this study is the household's capacity to remember historical rainfall patterns, drought events, biodiversity changes, traditional forecasting methods, and how often the memory of these forecasts is shared with others (the five dimensions of the EMI built in this study).

Structured household surveys and participatory rural appraisal (PRA) methods such as seasonal calendars, ecological timelines, resource mapping, oral history, focus group discussions, key-informant interviews and participant observation were used to collect data. Network ties were mapped across all 120 nodes, using name-generator questions: (i) "From whom do you learn about traditional farming and ecological practices?"; (ii) "Who do you consult to get information about rainfall prediction and decisions related to the climate?"; (iii) "Who taught you how to save seeds and manage biodiversity?"; (iv) "Who do you turn to for advice when you have problems with your farming? The interview schedule was pre-tested with 15 non-sample respondents and modified prior to data collection.

The Ecological Memory Index (EMI) was constructed from five indicators: historical rainfall knowledge, drought memory, biodiversity memory, traditional forecasting ability and frequency of knowledge transmission. Crop diversity, indigenous adaptation practices, seed self-sufficiency, livelihood diversification and ecological memory were added to the Climate Resilience Index (CRI). Both the indices were computed as arithmetic means of the normalised indicator scores equally weighted across the five indicators: $EMI = (I_1 + I_2 + I_3 + I_4 + I_5)/5$, $CRI = (P_1 + P_2 + P_3 + P_4 + P_5)/5$, where each indicator was scaled to a 0-100 scale before aggregation. Descriptive statistics, Pearson correlation, multiple linear regression and paired t-test were carried out in IBM SPSS Statistics 29 ($p < 0.05$). Normality, homoscedasticity, multicollinearity and independence of errors were tested using regression diagnostics. The social network analysis was performed in UCINET 6 and the visualization in Gephi with a force-directed layout. Network properties (density, average degree, diameter, clustering coefficient) and actor properties (degree, betweenness, closeness, eigenvector) were calculated. The Louvain modularity algorithm was chosen for community detection because it is efficient when applied to medium or large networks, and has been widely adopted in social network analysis.

RESULTS

Table 1 showed that respondents were experienced smallholders (mean age 46.2 years; 24.5 years' farming experience; household size 5.8; landholding 1.72 ha). Ecological memory was unevenly distributed: 42.5% of households scored High, 39.2%

Table 1. Distribution of Ecological Memory Index scores (mean EMI = 72.4; n = 120)

EMI category	Frequency	Percentage
Low	22	18.3
Medium	47	39.2
High	51	42.5
Total	120	100.0

Medium and 18.3% Low, with a mean EMI of 72.4. This concentration foreshadows the centralised network structure reported below.

Perceived climate change and adaptation

Farmers reported pervasive change delayed monsoon (86.7%), rising temperature (81.5%), increased drought frequency (72.4%) and higher pest incidence (69.3%) and responded with memory-rooted adaptations dominated by millet cultivation (91.2%), mixed cropping (88.4%), seed conservation (84.7%), botanical pesticides (79.5%) and water harvesting (65.3%), consistent with adaptive portfolios reported across Indian tribal communities.

Ecological memory as a predictor of resilience

Table 2 represents that Ecological memory was strongly associated with resilience (Pearson $r = 0.73$, $p < 0.001$). Ecological memory had the highest standardised weight ($\beta = 0.61$, $p < 0.001$) amongst the five CRI components, followed by crop diversity ($\beta = 0.38$) and education ($\beta = 0.19$), meaning that this component has the greatest impact on the overall climate resilience score, landholding was non-significant. The model explained 62% of variance ($R^2 = 0.62$; $F = 38.42$; $p < 0.001$). High-memory households achieved markedly higher resilience (CRI = 0.74) than low-memory households (CRI = 0.48). Multicollinearity diagnostics showed no evidence of collinearity among predictor variables, with all VIF values well below the threshold of 10 (EMI = 1.82, Crop Diversity = 1.64, Education = 1.31, Landholding = 1.19). Regression diagnostics further confirmed that model assumptions were satisfied, with normally distributed residuals (Shapiro–Wilk $p = 0.21$), homoscedasticity (Breusch–Pagan $p = 0.34$), and no autocorrelation (Durbin–Watson = 1.94), indicating that the model was statistically robust and suitable for interpretation.

Table 2. Multiple regression predicting the Climate Resilience Index

Predictor	Beta (β)	p-value
Ecological memory	0.61	< 0.001
Crop diversity	0.38	0.002
Education	0.19	0.041
Landholding	0.12	0.083

A participatory awareness intervention produced significant gains in climate awareness (54.8 → 78.5; paired $t = 7.93$, $p < 0.001$) and biodiversity awareness (58.3 → 80.2; paired $t = 8.74$, $p < 0.001$), indicating that memory-based learning is responsive to facilitation.

Network architecture of ecological knowledge

The relational structure of ecological knowledge was examined through six complementary networks, which together depict a centralised, modular system sustained by a small core of elders, healers and seed keepers.

General transmission sociogram

The transmission network consisted of 120 nodes and 487 directed edges, with all nodes representing the complete census of farming households in village Linga, forming a closed and bounded network with an average degree of 8.12, clustering coefficient of 0.41, diameter of 6 and density of 0.034. This resulted in a few direct connections between actors and an efficient structure with the majority of actors being reachable within 6 steps. The main centres were Elder Farmer A (42), Traditional Healer B (39) and Seed Keeper C (37). The knowledge-transmission sociogram is presented in Figure 1, with the size of the nodes, the colour coding, and the direction of the flow of knowledge.

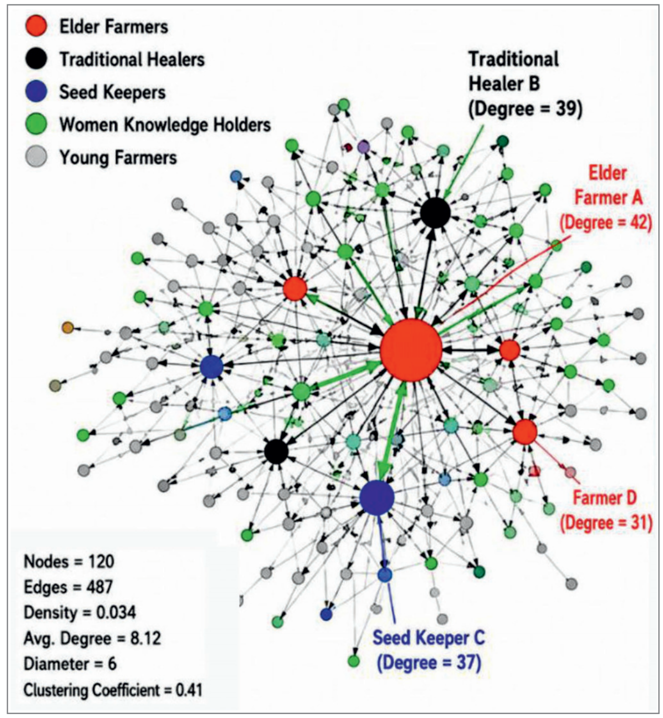


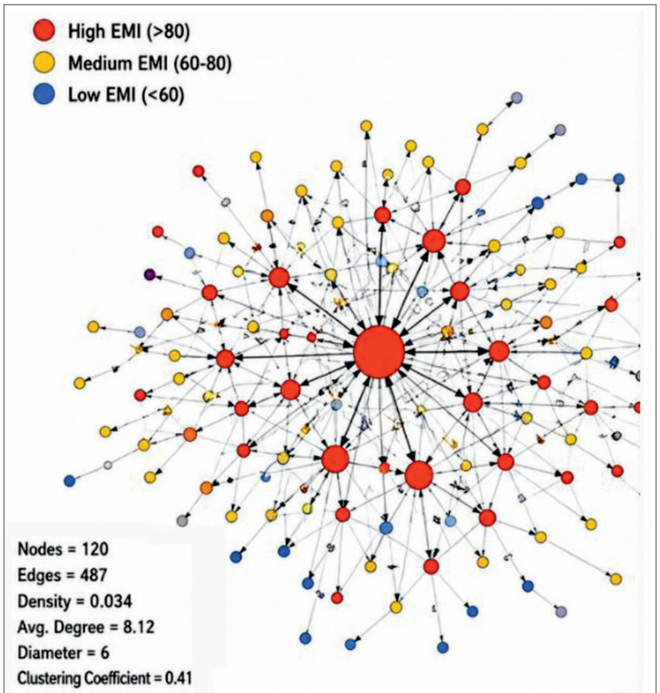
Figure 1. Knowledge-transmission sociogram (120 nodes, 487 edges)

Ecological-memory overlay

By re-colouring the network using the EMI, a clear core-periphery structure emerged: i.e. low (low-EMI, <60) and high (high-EMI, >80) EMI actors were concentrated at the periphery and core of the network respectively. The degrees of centrality had strong and positive Pearson correlation with the knowledge measured by EMI ($r = 0.68$, $p < 0.001$), suggesting that the most knowledgeable individuals are also the most influential in their networks. The concept of ecological-memory overlay is illustrated in Figure 2 with red, amber and blue colours corresponding to high, medium and low EMI levels.

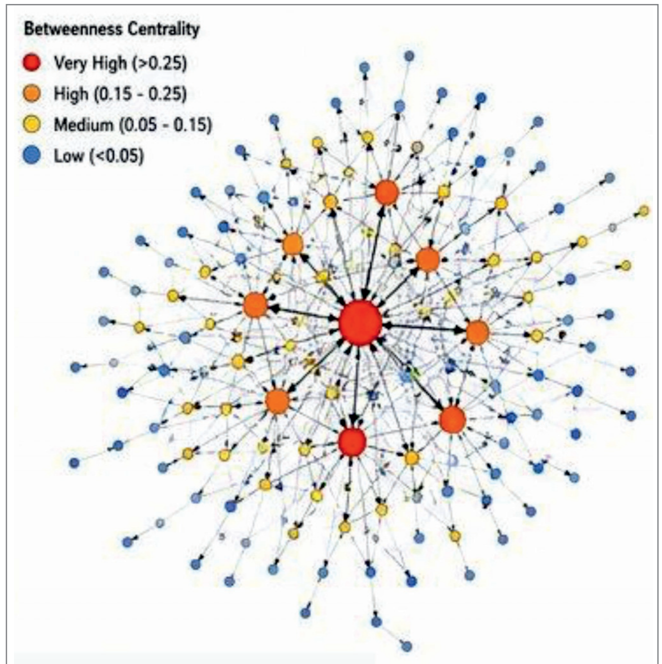
Betweenness centrality and structural vulnerability

The analysis of betweenness showed a varying degree of bridging role of actors in the ecological knowledge network. Normalised betweenness centrality values on the normalised betweenness centrality range (0-1) were used to divide actors into four categories: Low (<0.05), Medium (0.05-0.15), High (0.15-0.25), and Very High (>0.25), in line with the approach of equal interval classification of the observed score distribution adopted for categorisation in SNA studies (Crona & Bodin, 2017). There



Degree centrality positively correlated with EMI (r = 0.68, p < 0.001)

Figure 2. Ecological-memory overlay coloured by EMI



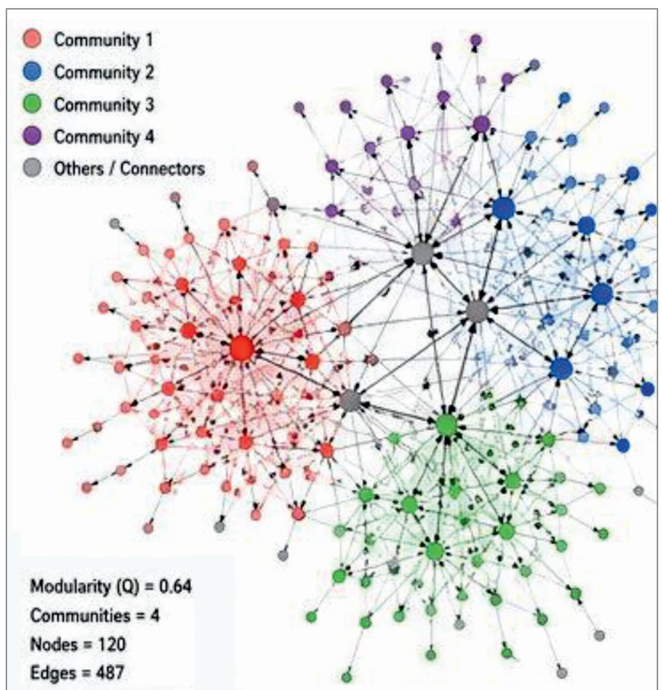
High betweenness actors act as bridges connecting different knowledge clusters

Figure 3. Betweenness Centrality Map

was a high proportion of actors in the low and medium categories, meaning that they had limited involvement in bridging between different knowledge clusters, while a few actors occupied the high and very high betweenness positions and were important bridges in the network. The highest normalized betweenness centrality value was for Elder Farmer A, who had a score of 0.381, indicating that he was in the very high range. This implies that the elimination of this actor might have the effect of breaking up the network and decrease the access of younger farmers to deeper ecological memory source. An example of the distribution of betweenness centrality is shown in Figure 3.

Community structure

The community detection algorithm Louvain identified a well-modular network (Q = 0.64) with four different knowledge communities and connector nodes. The high modularity indicates semi-autonomous sub-cultures, probably around the elder farmers, seed saving, healing knowledge and among the younger farmers. A narrow network of intermediaries connected these communities, allowing for inter-community transactions while also supporting intra-community resilience. The community-detection sociogram is presented in Figure 4, and the colours denote the communities; grey nodes represent connectors that link communities.

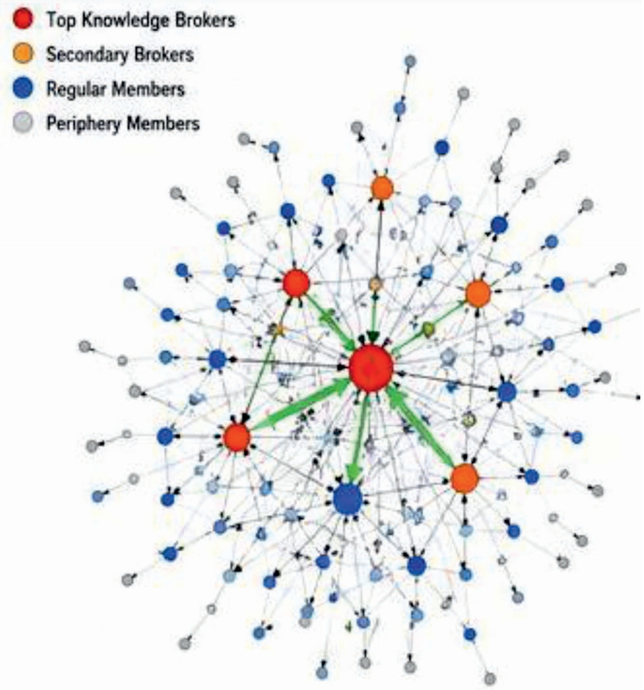


High modularity indicates will-structured knowledge communities

Figure 4. Community-detection sociogram

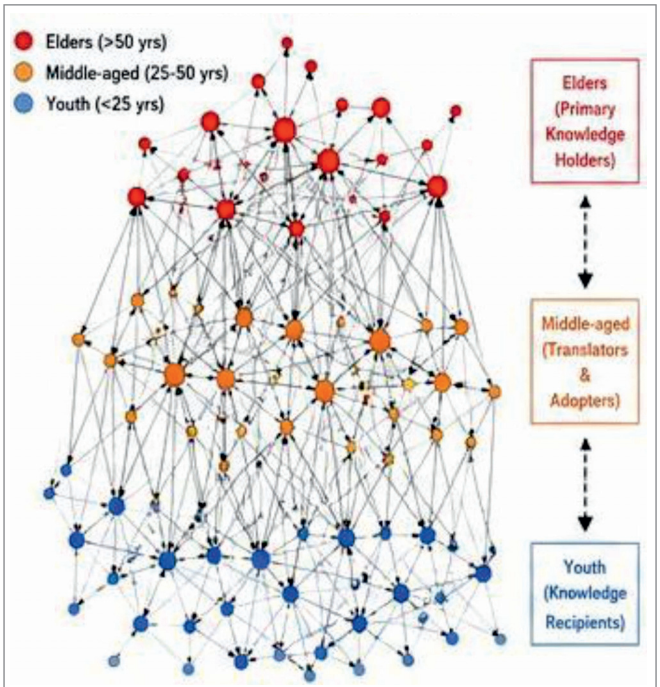
Knowledge-broker influence

When considering only influences, a pattern emerges of a few “big guys” on top, some secondary players, the regular members and a periphery. Strength of influence paths concentrates on top brokers, revealing that knowledge of adaptation comes in first through a well-known expert elite, then radiates outwards. The knowledge-broker influence network is presented in Figure 5, where nodes are sized by influence, red and orange highlight the top and secondary knowledge-brokers, blue highlights are regular members, grey are at the periphery, and highlighted edges represent the strongest influence paths.



Node size ~ Influence (Degree)
Green edges = Strong influence paths

Figure 5. Knowledge-broker influence network



Knowledge flows from Elders → Middle-aged Youth, ensuring intergenerational knowledge continuity.

Figure 6. Temporal knowledge-flow network

Temporal, age-stratified flow

When sorted by age, there is an obvious intergenerational knowledge-transfer pathway in the community. A key role of the elders (aged 50+ years) is to be the master custodians of ecological knowledge, maintaining long-term environmental records, farming methods and cultural practices. The middle-aged (25-50 years) can be considered as a crucial link that takes the knowledge, adapts it, interprets it and passes it on to the younger generations. These exchanges are the main source of information and learning for youth (<25 years). The network is a layered one (from young to elder, from young to middle-aged and from middle-aged to elder) which emphasises the need for intermediary actors to ensure continuity and which signifies vertical and oblique cultural transmission processes.

Centrality of major knowledge holders

Table 3 illustrates that across measures, the same actors dominate. Elder Farmer A leads on every dimension (degree = 42; betweenness = 0.381; closeness = 0.612; eigenvector = 0.842), followed by Traditional Healer B (degree = 39; betweenness = 0.324; closeness = 0.584; eigenvector = 0.791), Seed Keeper C (degree = 37; betweenness = 0.287; closeness = 0.571; eigenvector = 0.765) and Farmer D (degree = 31; betweenness = 0.223; closeness = 0.539; eigenvector = 0.692), confirming that ecological memory is held by cultural repositories rather than evenly diffused.

High closeness centrality values show that the key actors have the potential to reach other actors in the network efficiently, and high eigenvector centrality values suggest that they have strong ties with other influential knowledge holders.

Table 3. Centrality measures of major knowledge holders in the transmission network

Actor	Degree	Betweenness	Closeness	Eigenvector
Elder Farmer A	42	0.381	0.612	0.842
Traditional Healer B	39	0.324	0.584	0.791
Seed Keeper C	37	0.287	0.571	0.765
Farmer D	31	0.223	0.539	0.692

DISCUSSION

The convergence of index-based and network evidence shows that ecological memory is the central adaptive asset of the Saora farming system and that its value is realised through a specific social architecture. The dominance of ecological memory in the resilience regression ($\beta = 0.61$) elevates it above conventional drivers such as landholding, consistent with evidence that flexible, knowledge-rich adaptation enhances community resilience (Petzold et al., 2024) and reinforces Berkes's concept of ecological-memory reservoirs (Berkes, 2017).

Crucially, the networks show this memory is neither evenly held nor freely circulating. It is concentrated in a core of elders, healers and seed keepers, channelled through broker pathways, organised into modular sub-cultures and transmitted along an age gradient mediated by middle-aged translators. The strong centrality–EMI correlation ($r = 0.68$) and high modularity ($Q = 0.64$) imply both strength and fragility: the system is efficient and locally robust yet acutely dependent on a few high-betweenness bridges whose loss would fragment transmission (Crona & Bodin, 2017; Singh et al., 2023).

The results of betweenness centrality were complemented by closeness and eigenvector centrality that offered additional insights into the functioning of the indigenous knowledge network. Those who were closer to other network members on average, or had higher closeness centrality, could easily access and pass on ecological knowledge. This indicates that elders, healers and seed keepers, not only served as knowledge holders, but also as efficient communicators within the network. Likewise, high eigenvector centrality values suggest that these actors also had links to other influential well connected actors, which further increased their overall influence within the knowledge system. The high closeness and eigenvectors scores of key actors then show that they are also knowledgeable and influential actors in terms of climate resilience and ecological memory.

This structural reading reframes adaptation policy. Rather than treating TEK as a diffuse cultural background, interventions can target the actors and ties that carry it, documenting elder and healer knowledge, supporting seed keepers, and strengthening the middle-aged translator layer that connects elders to youth. Identifying brokers also offers an efficient entry point for extension: engaging central actors can accelerate the diffusion of validated practices through the wider network. The findings suggest that strengthening climate resilience requires community-owned knowledge commons to preserve ecological knowledge held by elders, healers and seed keepers. Enhancing intergenerational learning, particularly through middle-aged knowledge transmitters and youth engagement, is essential. Furthermore, protecting key knowledge brokers and leveraging central actors for extension can improve the diffusion of climate-resilient practices within tribal communities.

Limitations include the single-village scope and reliance on self-reported network and memory data. Because ecological memory is a factor of CRI, the regression does not necessarily indicate any independent prediction. It would be good to develop separate indices to validate this relationship in future studies. Future work should extend the multi-layer network approach across villages and incorporate longitudinal data to observe transmission and its disruption over time.

CONCLUSION

The ecological memory plays an important role in the resilience to climate change among Saora tribal farmers and the indigenous knowledge is shared with the elders, healers and seed keepers. Social Network Analysis revealed that the knowledge network was centralized and modular with some actors exerting dominant influence in the transmission of knowledge. The betweenness centrality identified some actors that are critical bridges and thus the network is vulnerable if these actors are absent. The closeness centrality revealed some key actors who are connected to each other and can be easily reached to share ecological knowledge at a faster rate across the community whereas high eigenvector centrality highlighted strong relationships of these key actors with other key actors. There is a need for further research on similar indigenous knowledge networks in other tribal communities and to evaluate changes in transmission of indigenous knowledge over time in the era of modernization and climate change pressures.

DECLARATIONS

Ethical consideration and consent to participate: Every procedure involving human subjects was conducted in respective manner, and each participant gave their informed consent before any data was collected. Confidentiality, privacy, and voluntary involvement were all fully respected during the interview process.

Conflict of interest: The authors reported that there were no known competing financial interest and personal relationships to disclose that could have appeared to influence the work reported in this paper.

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