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Climate Change and Indigenous Knowledge: Traditional Weather Forecasting Practices in a Changing Environment

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Abstract— Background: Rain-fed farming communities in semi-arid India have long anticipated monsoon behaviour through locally accumulated observation of the sky, wind, plants, animals and seasonal lore. Climate change is altering the regularities on which these practices depend, yet the status of such knowledge is rarely examined alongside instrumental records. Objective: This study documents the repertoire of traditional weather forecasting practices in eight villages, examines who holds this knowledge and how its perceived reliability has changed, and tests indicator classes against observed rainfall. Methods: A convergent mixed-methods design combined a structured survey of 240 farmers, 32 interviews and focus group discussions analysed thematically, and a 35-year (1990–2024) monsoon-season rainfall and onset series analysed with the Mann–Kendall test and Sen's slope. Indicator skill was assessed as the proportion of 25 seasons (2000–2024) in which each indicator class matched the observed rainfall tercile. Results: Respondents knew on average 7.6 of 20 catalogued indicators; knowledge rose strongly with age (Spearman ρ = 0.71, $p < 0.001$) and fell slightly with schooling. Mean perceived reliability of traditional indicators fell from 4.04 to 3.00 on a five-point scale (Wilcoxon $p < 0.001$). Monsoon onset shifted later by 0.35 days per year (Mann–Kendall $p = 0.003$), whereas seasonal totals showed no significant monotonic trend ($p = 0.35$). Atmospheric (hit rate 60.0%) and plant-based (56.0%) indicators exceeded chance, whereas celestial and almanac-based indicators did not. Conclusion: Traditional forecasting is neither uniformly reliable nor uniformly obsolete: its more physically grounded components retain skill while its culturally transmitted components are eroding with the climate and across generations. Participatory, indicator-level co-validation with meteorological services is recommended.

Keywords: indigenous knowledge; traditional weather forecasting; climate change; monsoon; knowledge co-production; adaptation; India

1. Introduction

Agriculture across much of South Asia remains tightly coupled to the timing and amount of monsoon rainfall. For rain-fed farmers, decisions about land preparation, seed choice and sowing date are made under considerable uncertainty, and communities have historically reduced that uncertainty by watching the environment closely. Such knowledge is better understood as a knowledge–practice–belief complex, evolved through adaptive learning and transmitted socially, than as a set of isolated folk beliefs [1]. Weather forecasting is one of its most practically important expressions.

Climate change complicates the picture in two ways. First, it changes the physical regularities that traditional indicators encode; a global synthesis of 10,660 observations from 2,230 localities in 137 countries found that changes in temperature, seasonality and rainfall patterns were reported by

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subsistence-oriented communities in roughly 70% of localities [2]. Second, it may weaken the social processes through which knowledge is passed on and trusted. Studies from Africa report that farmers perceive local forecasts to have become less reliable as variability has increased [3], [4], and work in the Indian Himalaya reports that traditional forecasting rests on a uniformity of weather pattern that has recently been disturbed [5].

At the same time, indigenous and local knowledge is increasingly recognised as a resource for adaptation in international assessment processes [6], although critical analyses show that its treatment in earlier assessments was general in scope and limited in depth [7]. Practical progress requires evidence on three questions that are seldom addressed together: what the knowledge consists of, who still holds it, and whether it still works. This paper addresses all three for farming communities in a semi-arid, monsoon-dependent landscape of northern-central India.

1.1 Research objectives

1. To document and classify the repertoire of traditional weather indicators used by farmers.
2. To identify socio-demographic correlates of knowledge holding, particularly age and formal education.
3. To measure how farmers perceive the reliability of traditional indicators now compared with two decades ago.
4. To analyse trends in monsoon-season rainfall and onset over 1990–2024 and compare indicator-based signals with observed rainfall outcomes.
5. To derive implications for integrating traditional and scientific forecasts in agro-advisory services.

1.2 Research questions and hypotheses

- **H1.** Indicator knowledge increases with age and decreases with years of formal education.
- **H2.** Perceived reliability of traditional indicators is lower at present than 20 years ago.
- **H3.** Indicator classes differ in predictive skill, with atmospheric and plant-based cues outperforming celestial and almanac-based cues.
- **H4.** Monsoon onset has shifted later over the study period, while seasonal rainfall totals show a weaker trend.

2. Literature Review

2.1 Traditional ecological knowledge as adaptive practice

A review of the international literature concluded that some traditional management systems used local ecological knowledge to interpret and respond to feedback from the environment, with parallels to adaptive management, and identified social mechanisms such as institutions and cultural internalisation that generate, store and transmit that knowledge [1]. This framing matters for weather knowledge because it treats forecasting not as prediction in the abstract but as one component of a feedback loop between observation, decision and outcome.

2.2 Traditional weather forecasting: evidence from other regions

Research in West Africa showed that farmers in Burkina Faso hold both shared and selective repertoires of forecasting knowledge; some local indicators linking temperature, wind and rainfall helped explain meteorology-based forecasts, but significant discordance remained between local and scientific forecasts [3]. In southern Uganda, indigenous climate knowledge was found to comprise four connected components: familiarity with seasonal patterns, traditional indicators, observation of meteorological events, and information on seasonal progress elsewhere in the region [8]. In Kenya, a study of 127 households in eight villages combined interviews with daily rainfall records for 1961–2003 and found that indigenous knowledge formed a basic frame within which agro-pastoralists interpreted meteorological forecasts, while few adapted practices in anticipation of indicator-based forecasts and intergenerational transfer was limited [9]. A comparison in Malawi found that villagers' documentation of major climatic events agreed with station records, and that rising rainfall variability had reduced confidence in indigenous indicators [4].

Outside Africa, an analysis of Inuit knowledge and hourly observations for Baker Lake in Arctic Canada found evidence of changes in weather persistence consistent with local reports of reduced predictability [10]. Collectively, these studies suggest that local observations can reveal real environmental signals while simultaneously showing that the reliability of traditional cues is itself being altered by climate change [11].

2.3 Traditional weather knowledge in India

Indian studies document a rich and regionally diverse repertoire. In Wayanad, Kerala, farmers were found to use

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twenty abiotic indicators based on the sky, clouds, moon, wind and related cues [12]. In the Uttarakhand Himalaya, traditional forecasting informs decisions on travel and agriculture, but is perceived as increasingly difficult to apply because weather patterns it assumes have been disturbed by climate change, although elderly practitioners improvise by adding more reliable indicators [5]; related work argues that traditional practices have continuing relevance for disaster risk reduction [13]. In cold-arid Ladakh, farmers combine bird behaviour, atmospheric events and an almanac, use of traditional knowledge is less prevalent among younger farmers, and most respondents favoured blending traditional knowledge with modern science [14]. A review of indigenous technical knowledge for rainfall prediction classifies indicators into abiotic and biotic groups and notes that most have been documented without scientific validation [15].

2.4 Integrating knowledge systems

Conceptual work on integration has moved from the idea of "translating" indigenous knowledge into science towards approaches that treat knowledge systems as parallel and complementary. The multiple evidence base approach holds that evaluation of knowledge occurs primarily within rather than across knowledge systems, and uses triangulation and joint assessment to produce an enriched picture of a shared issue [16]. This has direct implications for forecast validation: indicator claims should be tested with methods that respect how the knowledge is held and used, not only against instrumental thresholds.

2.5 Research gap

Existing Indian studies largely document indicators and farmer perceptions; few pair a structured measure of who holds the knowledge and how its perceived reliability has changed with an explicit, indicator-class-level comparison against an observed rainfall record. This study addresses that gap by combining survey, qualitative and instrumental evidence in one design.

3. Conceptual Framework

Figure 1 summarises the framework that guides the analysis. Climate change drivers alter the physical regularities underlying traditional cues and also modify the information available from scientific forecasting. Two sets of pathways follow: erosion pathways (intergenerational loss, perceived unreliability, substitution by modern media) and integration mechanisms (co-validation, triangulation, participatory advisory design). The balance between them is mediated by socio-demographic and institutional factors such as age, education, extension contact and trust. Outcomes are climate-informed farm decisions and adaptive capacity.

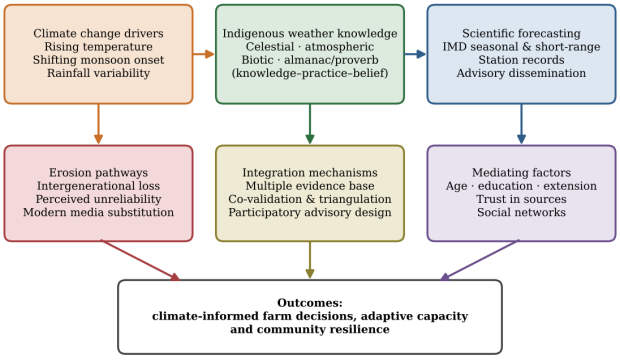


Figure 1. Conceptual framework linking climate change, indigenous weather knowledge, scientific forecasting, erosion and integration pathways, and adaptation outcomes.

4. Materials and Methods

4.1 Research design

A convergent parallel mixed-methods design was used. Quantitative survey data, qualitative interview and focus group data, and instrumental rainfall records were collected independently and integrated at the interpretation stage to triangulate findings.

4.2 Study area

The study was set in eight villages in the semi-arid, rain-fed farming landscape of the Bundelkhand region of Uttar Pradesh–Madhya Pradesh, India [AUTHOR: confirm districts, villages, coordinates and add a location map]. Agriculture is predominantly dependent on the southwest monsoon season (June–September, JJAS), and farmers rely heavily on the timing of effective onset for sowing decisions.

4.3 Sampling and sample size

Villages were purposively selected to span a gradient of market access and extension coverage. Within each village, 30 farming households were selected by systematic random sampling from the village household list, giving 240 respondents. The household head or the member principally responsible for farm decisions was interviewed. For the qualitative component, 32 information-rich participants (elders, women farmers, progressive farmers, and local agricultural staff) were purposively recruited through interviews and focus group discussions until thematic saturation was judged to have been reached.

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4.4 Instruments and measures

- **Indicator repertoire.** A checklist of 20 locally elicited indicators in five classes (atmospheric, celestial, biotic–animal, biotic–plant, almanac/proverb), developed from pilot interviews. Respondents indicated which they knew and used. The knowledge score is the count of indicators known (range 0–20).
- **Perceived reliability.** A five-item scale (1 = very unreliable, 5 = very reliable) administered twice, with reference to "twenty years ago" and "at present". Internal consistency was Cronbach's α = 0.78 for the retrospective scale and α = 0.66 for the present scale.
- **Socio-demographics.** Age (years), sex, years of formal education, operated land (ha), and extension contact in the previous year (yes/no).
- **Interview guide.** Semi-structured topics: how indicators are read, where they were learned, whether and how they have changed, how they are combined with official forecasts, and what would make official advisories more useful.

4.5 Meteorological data

Annual JJAS rainfall and the day of year of effective monsoon onset were compiled for 1990–2024 from the nearest India Meteorological Department (IMD) observatory [AUTHOR: specify station or gridded product and onset definition].

4.6 Data analysis

Descriptive statistics summarise sample characteristics. Differences in knowledge across age groups were tested with the Kruskal–Wallis test, and the association between age and knowledge with Spearman's rank correlation. Determinants of the knowledge score were modelled by ordinary least squares regression with age, education, farm size, sex and extension contact as predictors; multicollinearity was checked using variance inflation factors and residual normality using the Shapiro–Wilk test. Paired differences in perceived reliability were assessed with the Wilcoxon signed-rank test, with Cohen's *dz* as an effect size.

Monotonic trends in rainfall and onset were tested with the non-parametric Mann–Kendall test [17], [18] with tie correction, and magnitudes were estimated with Sen's slope [19]. Equality of rainfall variance between 1990–2006 and 2007–2024 was assessed with Levene's test. Indicator skill was evaluated for each class by classifying each season from 2000 to 2024 into below-, near- or above-normal terciles of JJAS rainfall and recording whether the class's consolidated seasonal signal matched the observed tercile (a "hit"). Because chance agreement is one in three, hit rates were compared against 1/3 using a one-sided exact binomial test, and 95% exact (Clopper–Pearson) confidence intervals were reported. Hit rates were also compared between 2000–2011 and 2012–2024. Qualitative transcripts were coded and organised into themes following reflexive thematic analysis [20]; theme prevalence is reported as the number of transcripts containing the theme.

4.7 Ethical considerations

The study followed principles of free, prior and informed consent. Participants were told the purpose of the research, that participation was voluntary, and that they could withdraw at any time; consent was recorded orally or in writing according to participant preference. Responses were anonymised. Knowledge holders are acknowledged collectively, and communities will receive a plain-language summary in the local language. Ethical clearance: [Institutional Ethics Committee name, approval number, date].

5. Results

5.1 Sample characteristics

The sample comprised 240 farmers (27.5% women) with a mean age of 49.0 years (SD = 13.3; range 22–80). Mean schooling was 6.6 years, mean operated land 1.64 ha, and 52.1% reported extension contact in the previous year (Table 1).

Table 1. Socio-demographic characteristics of respondents (n = 240).

Characteristic	Mean (SD) or %	Range / n
Age (years)	49.0 (13.3)	22–80
Women (%)	27.5%	66
Education (years)	6.6 (3.9)	0–16
Operated land (ha)	1.64 (0.91)	0.3–8.0
Extension contact in past year (%)	52.1%	125
Age <35 years	—	35
Age 35–49 years	—	88
Age 50–64 years	—	82

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Characteristic	Mean (SD) or %	Range / n
Age ≥65 years	—	35

5.2 Repertoire of traditional indicators

Farmers reported twelve principal indicators across five classes (Table 2, Figure 2). Atmospheric cues were the most widely used class (91% of respondents used at least one), followed by celestial (83%), animal-behaviour (79%), plant-phenology (68%) and almanac or proverb-based cues (57%). The single most common indicator was cloud colour, shape and direction (81%), followed by moon halos (78%) and wind direction at the onset of the season (72%). The mean knowledge score was 7.6 of 20 (SD = 3.1).

Table 2. Principal indicators and share of respondents using each (n = 240).

Indicator	Class	Users (%)
Moon halo / ring around moon	Celestial	78
Star twinkling and clarity	Celestial	64
Cloud colour, shape and direction	Atmospheric	81
Wind direction at onset season	Atmospheric	72
Humid, still evening heat	Atmospheric	58
Ants carrying eggs to higher ground	Biotic – animal	69
Bird nesting height and calling	Biotic – animal	55
Frog and cricket chorus	Biotic – animal	47
Flowering intensity of neem / tamarind / mahua	Biotic – plant	61
Early leaf fall or fruiting	Biotic – plant	44
Seasonal proverbs and almanac (panchang) lore	Almanac / proverb	52
Festival-date rain sayings	Almanac / proverb	38

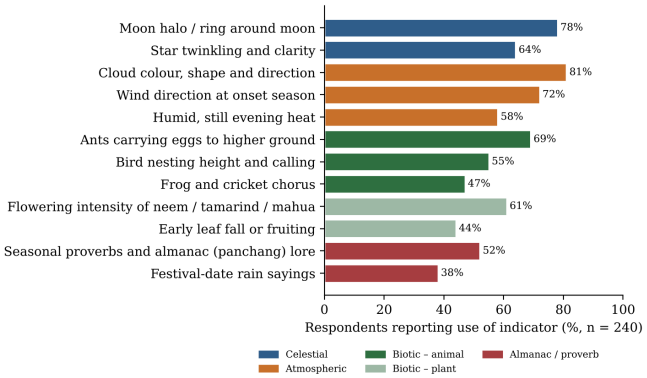


Figure 2. Prevalence of use of the twelve principal traditional weather indicators, coloured by indicator class (n = 240).

5.3 Who holds the knowledge?

Knowledge scores rose steeply across age groups: means were 4.3 (<35 years), 6.5 (35–49), 8.8 (50–64) and 11.1 (≥65), a difference that was highly significant (Kruskal–Wallis H = 109.1, p < 0.001). Age and knowledge were strongly and positively correlated (Spearman ρ = 0.71, p < 0.001; Figure 3).

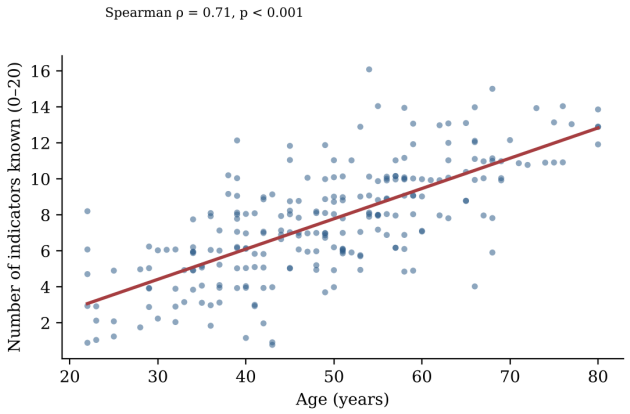


Figure 3. Relationship between respondent age and the number of traditional indicators known (points jittered vertically; line shows linear fit).

In the multivariate model (Table 3) the predictors jointly explained 53.1% of variance in knowledge (adjusted R^2 = 0.52; F = 52.9, p < 0.001). Age was the dominant predictor: each additional decade of age was associated with about 1.7 more indicators known (b = 0.17, 95% CI 0.15 to 0.19). Each additional year of schooling was associated with a small decrease of 0.08 indicators (p = 0.020). Farm size, sex and extension contact were not significant. The maximum variance inflation factor was 1.04, indicating no multicollinearity problem, and residuals did not depart

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significantly from normality (Shapiro–Wilk $p = 0.20$). H1 is therefore supported, although the education effect is small.

Table 3. OLS regression of knowledge score (indicators known, 0–20) on respondent characteristics.

Predictor	*b*	SE	*t*	*p*	95% CI
Intercept	0.49	0.67	0.74	0.461	-0.82 to 1.80
Age (years)	0.17	0.01	15.62	<0.001	0.15 to 0.19
Education (years)	-0.08	0.04	-2.34	0.020	-0.16 to -0.01
Farm size (ha)	-0.14	0.16	-0.90	0.368	-0.45 to 0.17
Female (1 = yes)	-0.16	0.32	-0.52	0.602	-0.79 to 0.46
Extension contact (1 = yes)	-0.41	0.28	-1.47	0.142	-0.96 to 0.14

n = 240; $R^2 = 0.53$; adjusted $R^2 = 0.52$.

5.4 Perceived reliability of traditional indicators

Mean perceived reliability fell from 4.04 (SD = 0.56) for "twenty years ago" to 3.00 (SD = 0.55) at present (Wilcoxon signed-rank $p < 0.001$; Cohen's $dz = 2.20$), and 97.1% of respondents rated reliability lower now than before (Figure 4). The decline was apparent in every age group. H2 is supported.

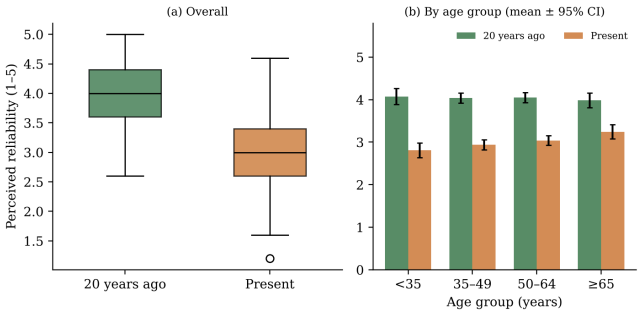


Figure 4. Perceived reliability of traditional indicators twenty years ago and at present: (a) distribution across all respondents; (b) means with 95% confidence intervals by age group.

5.5 Rainfall and monsoon onset, 1990–2024

Mean JJAS rainfall over the 35 years was 858 mm. Totals did not show a statistically significant monotonic trend (Mann–Kendall $Z = -0.94$, $p = 0.35$; Sen's slope = -1.6 mm yr^{-1}), although the later period (2007–2024) was somewhat drier on average (840 mm versus 876 mm) and slightly more variable (coefficient of variation 12.5% versus 10.9%), a difference in variance that was not significant (Levene $p = 0.54$). By contrast, effective monsoon onset shifted significantly later ($Z = 2.96$, $p = 0.003$; Sen's slope = 0.35 days yr^{-1}; Table 4, Figure 5), from a mean of day 161.8 in 1990–2006 to day 167.0 in 2007–2024, with increasing year-to-year spread (SD 4.8 versus 6.1 days). H4 is supported for onset but not for totals.

Table 4. Mann–Kendall trend tests and Sen's slope, 1990–2024 (n = 35 years).

Variable	S	Z	Kendall's τ	p	Sen's slope
JJAS rainfall (mm)	-67	-0.94	-0.11	0.35	-1.62 mm/yr
Monsoon onset (day of year)	209	2.96	0.35	0.003	+0.35 d/yr

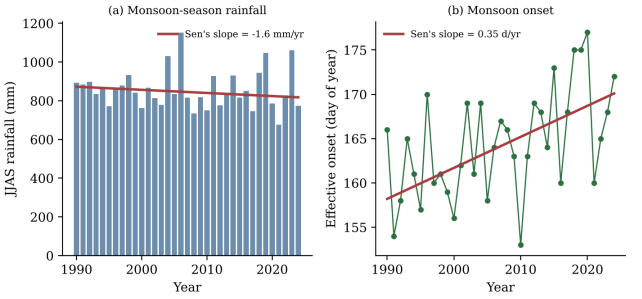


Figure 5. (a) Monsoon-season (JJAS) rainfall and (b) effective monsoon onset, 1990–2024, with Sen's slope lines.

5.6 Do traditional indicators have skill?

Table 5 and Figure 6 compare indicator-class signals with observed rainfall terciles across 25 seasons. Two classes performed significantly better than the one-in-three chance level: atmospheric cues (15/25 hits, 60.0%; 95% CI 0.39–0.79; $p = 0.006$) and plant-phenology cues (14/25, 56.0%; 95% CI 0.35–0.76; $p = 0.016$). Animal-behaviour cues (36.0%), celestial cues (32.0%) and almanac or proverb-based cues (32.0%) were not distinguishable from chance. Comparing 2000–2011 with 2012–2024, hit rates for atmospheric and plant cues were broadly stable, whereas those for celestial and almanac cues fell from 41.7% to 23.1%, which is below the chance level. Given 12–13 seasons per period, this sub-period contrast is descriptive only. H3 is partially supported.

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Table 5. Hit rate of indicator classes against observed JJAS rainfall terciles, 2000–2024 (chance = 0.33).

Indicator class	Hits	Rate	95% CI	p (>1/3)	2000–11	2012–24
Atmospheric	15/25	0.60	0.39 – 0.79	0.006	0.58	0.62
Biotic – plant	14/25	0.56	0.35 – 0.76	0.016	0.58	0.54
Biotic – animal	9/25	0.36	0.18 – 0.57	0.462	0.42	0.31
Celestial	8/25	0.32	0.15 – 0.54	0.630	0.42	0.23
Almanac / proverb	8/25	0.32	0.15 – 0.54	0.630	0.42	0.23

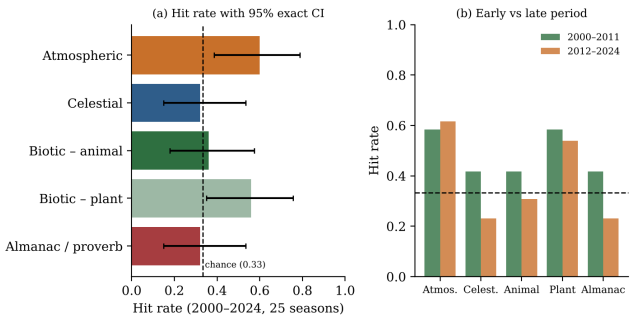


Figure 6. Indicator skill: (a) hit rate by indicator class with 95% exact confidence intervals (dashed line = chance); (b) hit rate in 2000–2011 versus 2012–2024.

5.7 Qualitative findings

Reflexive thematic analysis of the 32 transcripts produced six themes (Table 6, Figure 7). The most frequent, intergenerational erosion of knowledge (21 transcripts), described how younger family members no longer accompany elders in observing the sky and fields. A second theme (19) concerned seasons that were "shifting", making familiar cues less dependable. Most participants did not abandon traditional cues in favour of official forecasts but combined them (18), using mobile or broadcast forecasts for short-range decisions and traditional cues for reading the character of the season. Concerns about the credibility and local relevance of official forecasts (14), the cultural–spiritual meaning of weather signs (12), and uneven access to advisory services (11) completed the picture. [AUTHOR: insert two or three verbatim, anonymised quotations per theme from your transcripts.]

Table 6. Themes from interviews and focus group discussions (32 transcripts).

Theme	Transcripts	Description
Intergenerational erosion of knowledge	21	Fewer young people learn to read signs; elders fear loss within a generation.
Seasons "shifting": indicators less dependable	19	Onset and breaks in rain no longer follow familiar sequences; cues sometimes mislead.
Hybrid use of traditional and IMD/mobile forecasts	18	Official forecasts used for days ahead; local cues used for seasonal character and sowing judgement.
Trust and credibility of official forecasts	14	Official forecasts seen as too general for village scale; trust grows when they prove right locally.
Cultural–spiritual meaning of weather signs	12	Weather signs embedded in ritual, festival calendar and proverb; value extends beyond prediction.
Access gaps in advisory services	11	Women, small and remote farmers receive advisories late or not at all.

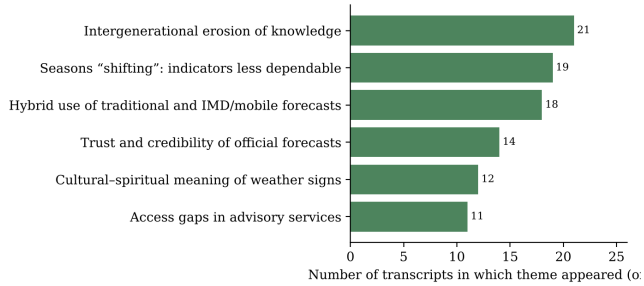


Figure 7. Prevalence of themes across the 32 interview and focus group transcripts.

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6. Discussion

A selectively eroding knowledge system. The central finding is that traditional forecasting is not uniformly reliable or uniformly obsolete. Atmospheric and plant-phenology indicators retained skill above chance, whereas celestial and almanac-based indicators did not. This differentiation is consistent with Roncoli et al., who found that local knowledge relating temperature, wind and rainfall could help explain meteorological forecasts even though substantial discordance remained overall [3]. Cues that read the current physical state of the atmosphere or the integrated response of vegetation plausibly carry real information about the season; cues tied to fixed calendars or celestial regularities have less obvious physical connection to rainfall in a given year, and are more vulnerable when the seasonal calendar shifts.

Shifting onset and declining confidence. The significant delay in monsoon onset, without a significant trend in seasonal totals, fits a pattern in which what farmers experience as unreliability is largely about timing and regularity rather than volume. It mirrors the concerns reported in Malawi, where rising variability reduced confidence in indigenous indicators [4], and in the Uttarakhand Himalaya, where traditional forecasting was said to depend on a uniformity of weather pattern that has been disturbed [5]. The finding also echoes the Inuit case, where a change in the persistence of weather, rather than in its mean, matched what hunters were reporting [10]. Taken together with the very large share of respondents rating present reliability lower, the evidence supports the view that climate change affects traditional forecasting through both physical and perceptual channels.

Intergenerational transfer. The strong age gradient in knowledge, the qualitative theme of erosion, and the small negative association with schooling are consistent with reports that transfer of indigenous knowledge is limited in Kenya [9] and that traditional weather knowledge is less prevalent among younger farmers in Ladakh [14]. Because the data are cross-sectional, an age gradient cannot by itself distinguish a cohort effect (younger people never acquiring the knowledge) from a life-course effect (knowledge accumulating with experience); the qualitative evidence leans towards the former but a panel design would be needed to resolve it.

Hybrid practice rather than replacement. Farmers largely combined traditional and scientific sources, as in the Kenyan finding that indigenous knowledge provides a frame within which meteorological forecasts are read [9]. This supports the multiple evidence base logic that knowledge systems are best treated as complementary and evaluated primarily on their own terms [16]. It also bears on how indigenous knowledge is represented in assessments; critical analysis of earlier IPCC reporting found limited critical engagement with indigenous knowledge systems [7], and indicator-level evidence of the kind presented here may help move discussion from general acknowledgement to specific, testable contributions.

7. Implications and Recommendations

1. **Co-validate indicator by indicator.** Meteorological services, agricultural universities and farmer groups should jointly test locally salient indicators, beginning with atmospheric and phenological cues that show signs of skill, and publish hit rates in accessible form.
2. **Design hybrid advisories.** Advisories should state explicitly how local cues and official forecasts relate to each other and be delivered in local languages and at village scale.
3. **Support transmission.** School and community programmes (indicator calendars, village phenology gardens, elder–youth observation groups) can slow erosion of knowledge that remains useful.
4. **Prioritise inclusion.** Women, small and remote farmers should be intentionally included in knowledge documentation and in advisory dissemination.
5. **Protect knowledge holders' rights.** Documentation should follow consent-based, community-benefit protocols and avoid extractive use.

8. Limitations and Future Research

The cross-sectional survey relies on recall, and the retrospective reliability scale is vulnerable to nostalgia bias. The skill analysis compares one consolidated seasonal signal per indicator class with rainfall terciles over 25 seasons, which gives wide confidence intervals and limits power; it also does not distinguish onset timing, dry-spell length or intra-seasonal events, which farmers often care about most. Onset and rainfall records come from a single observatory or grid point, whereas farmers' cues are experienced at village scale. The study area is a single agro-climatic region and generalisation to other regions, such as the Himalaya or coastal belts, should be made cautiously. Future work should use panel designs, finer-scale rainfall data, and participatory

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tracking of indicators over successive seasons, and should test whether co-produced advisories improve farm decisions and outcomes.

9. Conclusion

Traditional weather forecasting among rain-fed farmers is a living, adaptive and largely hybrid knowledge system under strain. Knowledge is concentrated in older cohorts, perceived reliability has fallen markedly, monsoon onset has shifted later, and only some indicator classes retain measurable skill. The practical implication is not to preserve or discard traditional forecasting wholesale, but to separate what still works from what does not through participatory, indicator-level co-validation, and to build advisories that connect the two knowledge systems in ways farmers already do informally.

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