



Comparative Analysis of Climate Change Awareness in Climate-smart and Non-climate-smart Villages in the Middle Gangetic Plains of India

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ABSTRACT

This ex-post facto study was conducted from January to August, 2024 in Samastipur and Darbhanga districts of Bihar, India lies within the Middle Gangetic Plains (Agro-Climatic Zone IV) of the Indo-Gangetic Plain, the sole zone where the Climate Smart Agriculture programme had been operationalized. Reliable instruments for quantifying climate change awareness among Indian smallholder farmers remain scarce, limiting the monitoring of adaptation programmes. Hence, the study aimed to adapt, contextualize and validate a 35-item climate change awareness scale and to compare awareness between Climate Smart Village and non-programme farmers. The scale was adapted from an existing climate-awareness interview schedule; the response format was expanded to a five-point continuum, items were re-worded for smallholder farmers, and a fossil-fuels theme was added. Content validity (Lawshe's ratio, 15 experts) reduced an initial pool of 42 items to 35. The schedule was administered to 200 randomly selected farmers, evenly split between Climate Smart and non-programme villages. Reliability was confirmed through Cronbach's alpha (0.843), Spearman-Brown split-half (0.762) and Guttman split-half (0.748) coefficients, all significant at the 1% level and supported by analysis of variance with Cochran's test. Climate Smart Village farmers recorded a significantly higher mean awareness score (93.63) than non-programme farmers (70.33), with lower variance. Among Climate Smart Village farmers, 59% fell in the medium awareness category and 30% in the high, whereas 47% of non-programme farmers remained low. The findings provide a replicable measurement tool and confirm the Climate Smart Village model as effective for building climate literacy.

KEYWORDS: Climate change awareness, Cronbach's alpha, climate-smart agriculture

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1. INTRODUCTION

The world's food systems are confronting an increasingly hostile climate. Rising temperatures, erratic rainfall, and extreme weather events are undermining crop yields and threatening the livelihoods of millions who depend on farming for survival (Anonymous, 2022; Lenka et al., 2023; Lobell et al., 2008). Although climate change is a natural phenomenon, human-induced activity has markedly accelerated it in recent years (Borah et al., 2026; Mallick et al., 2025). In South Asia, where much of the population relies on rain-fed agriculture, the costs of this disruption fall hardest on those with the fewest resources to absorb them (Challinor et al., 2014; Vermeulen et al., 2012). Nair et al. (2025) observed that these impacts have intensified markedly, compounding pressures on already fragile agrarian economies. Bihar illustrates this picture. As one of India's most populous and agriculturally dependent states, it faces a threefold threat of erratic monsoons, recurrent floods, and prolonged droughts, often within a single crop year. Tesfaye et al. (2017) documented that heat stress, waterlogging, and rising temperatures pose near- and mid-term risks to both kharif and rabi cropping systems, with serious implications for food security and rural incomes. For smallholder farmers, who form the backbone of Bihar's agricultural economy, adapting to these pressures is an immediate challenge whose consequences arrive every season. Effective adaptation, however, requires awareness: farmers must understand what is changing in the climate and why it matters, since no practice or technology can be meaningfully adopted without first understanding the problem it addresses (Smit and Wandel, 2006). Yet evidence consistently shows that large shares of Indian farmers lack this awareness or hold fragmented, inaccurate understandings of climate change and its drivers. Ghanghas et al. (2015) found low to moderate awareness even among extension professionals in Haryana, a troubling finding given their role in transferring knowledge to farmers. Pathak et al. (2024) identified significant knowledge gaps among Uttar Pradesh farmers regarding the systemic causes of warming, while Kumar and Saxena (2024) showed that awareness across the Indo-Gangetic Plain is closely linked to socio-economic and demographic circumstances, so the farmers most exposed to climate risk are often the least informed. The literature has addressed less thoroughly how to measure farmer awareness rigorously and which institutional pathways most effectively raise it. Most assessments treat awareness as binary or rely on unvalidated instruments that cannot be compared across studies, a gap that impedes tracking changes in awareness or evaluating intervention programmes. Against this backdrop, the Climate Smart Village approach becomes relevant. Conceptualised by the CGIAR Research Program on Climate Change, Agriculture and Food Security, the

programme builds climate resilience through participatory testing of climate-smart agricultural technologies at the community level (Khatri-Chhetri et al., 2017). In Bihar, Aryal et al. (2018) documented significant adoption of climate-smart practices under this framework, and Mishra et al. (2024) confirmed that farmers in Climate-Smart Villages in Haryana consistently showed higher climate-related knowledge than non-programme counterparts. Borah et al. (2025) and Yadav et al. (2025) have since extended this evidence base, examining farmer constraints and adaptation strategies within and beyond the programme corridor. Despite this evidence, a systematic, rigorously measured comparison of climate change awareness within and outside the Climate Smart Village framework in Bihar has not previously been conducted. The present study addresses this gap directly. Its specific objectives are: (i) to adapt, contextualise, and establish the reliability and validity of a 35-item climate change awareness scale; (ii) to delineate awareness levels among Climate Smart Village and non-programme farmers in Samastipur and Darbhanga districts; and (iii) to examine the comparative distribution of respondents across awareness categories and test whether programme membership produces a statistically significant difference in awareness outcomes.

2. MATERIALS AND METHODS

2.1. Selection of the study locale

The study followed an ex-post facto design, since the independent variable, membership of a Climate Smart Village, had occurred before data collection and was not manipulated by the researcher. It was conducted in two phases: first to adapt and validate a scale for quantifying climate change awareness among smallholder farmers, and second to compare awareness between farmers in Climate Smart Villages and those in non-programme villages. Bihar, which falls within the Middle Gangetic Plains Region (Agro-Climatic Zone IV) of the Indo-Gangetic Plain, was purposively selected as the study state because the Climate Smart Village programme of the CGIAR Research Program on Climate Change, Agriculture and Food Security (CCAFS) had been operationalised exclusively in Bihar within this agro-climatic zone, rendering it the only viable setting for a within-zone comparison of programme and non-programme farmers. Data were collected from January to August, 2024 in Samastipur (25.8560°N, 85.7868°E) and Darbhanga (26.1542°N, 85.8918°E) districts of Bihar, the two districts comprising the state's first CSV corridor. Implementation covered Kalyanpur block in Samastipur and Hanumannagar and Bahadurpur blocks in Darbhanga, giving three study blocks. From Kalyanpur, two CSVs (Mirzapur, Birsingpur) and two non-CSVs

(Harpur Zakhra, Malipur) were randomly selected; from Darbhanga, Dihlali and Taralahi (CSV) and Nayanagar and Ahila (non-CSV) were selected from the two blocks respectively. Twenty-five farmers were randomly drawn from each of the eight villages, giving a final sample of 200, equally split between 100 CSV and 100 non-CSV farmers (Figure 1 and 2).

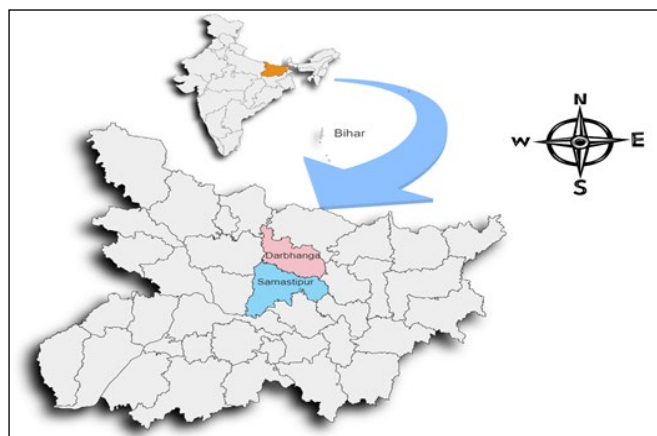


Figure 1: Map of Bihar showing Samastipur and Darbhanga districts

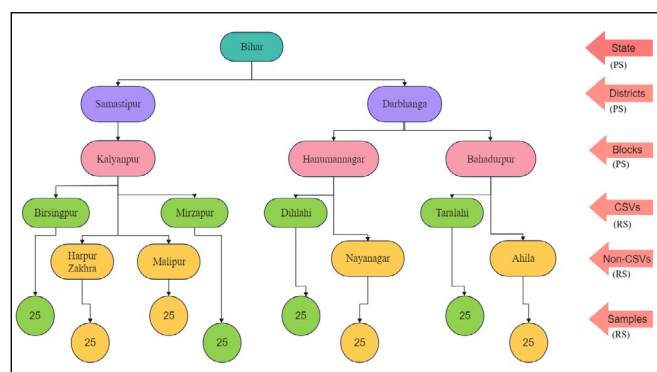


Figure 2: Type and plan of sampling

2.2. Awareness about climate change

Awareness was operationalised as the comprehended knowledge a farmer holds that aligns with valid facts, the foundational step in the knowledge, attitude and practice continuum underlying behavioural change in agriculture (Rogers, 2003); in this study, it referred specifically to knowledge of climate change and its implications for sustainable agriculture in Bihar. It was measured with a structured 35-item schedule scored on a five-point continuum: 'well aware' (4), 'aware' (3), 'somewhat aware' (2), 'not aware' (1) and 'not at all aware' (0). An aggregate score was computed for each respondent, and respondents were classified into low, medium and high awareness groups using the mean $\pm$ standard deviation. The scale was adapted from the climate-awareness interview schedule of Manjeet (2013), originally developed for extension personnel in

Haryana. The three-point response format was expanded to the five-point continuum above, items were reworded and contextualised for smallholder farmers in Bihar, redundant items were removed, and a theme on fossil fuels and climate change was added. The adapted pool was then subjected to content validity and reliability testing.

2.3. Validity of the scale

Content validity, the degree to which an instrument's content represents the subject matter it intends to measure (Kumar et al., 2025), was established before fieldwork using Lawshe's Content Validity Ratio (CVR), which tests whether each item is essential to the construct (Lawshe, 1975). A panel of 15 subject-matter experts, comprising agricultural extension scientists, agronomy specialists and social science researchers, rated every item as 'essential', 'useful but not essential', or 'not necessary'; items rated 'essential' were scored 1 and the other two categories 0. Following Lawshe's criterion for a 15-member panel, only items with a CVR of 0.49 or higher were retained, and the remaining items were removed.

2.4. Reliability of the scale

A scale is reliable when it gives consistently the same results when applied to the same sample. The processed set of thirty-five statements/questions were administered on a five-point continuum to a fresh group of fifty farmers (25% of the sample size of $n=200$) from other regions of non-sample area. From Samastipur district a CSV named Phulhara (25.9084474°N 86.1108220°E) was randomly selected and from Darbhanga district another CSV named Ojhaul (26.1208426°N 85.8513559°E) was also selected randomly. Twenty-five farmers from each village were randomly selected as respondents.

Reliability was calculated using the formula of Spearman (1910) and Brown (1910).

$r_{SB} = (2r_{hh}) / (1 + r_{hh})$, where r_{hh} = Pearson correlation between the two halves of the scale.

The split-half Spearman-Brown procedure has been a standard method of test analysis for forty years. However, the traditional split-half method has faced persistent criticism, with a primary objection being that split-half coefficients do not convey the same information as the correlation between two forms administered at separate intervals (Cronbach, 1946). Cronbach's alpha (α), the most prevalent and esteemed coefficient for evaluating internal consistency, was employed (Cronbach, 1951). The equation is:

$$\alpha = \frac{K}{K-1} \left(1 - \frac{\sum_{i=1}^{i=k} \sigma^2 Y_i}{\sigma^2 x} \right)$$

K= Number of items in the scale

$\sigma^2 y_i$ = The variance of item i for the current sample of respondents

$\sigma^2 x$ = The variance of the scale.

2.5. Z test to compare means

The Z-test is a statistical technique employed to ascertain the presence of a statistically significant disparity between the means of two groups or between a specified sample mean and a known population mean (Cuemath, 2024).

Z-statistic is computed by the following formula:

$$Z = \frac{\bar{X} - \mu}{\frac{\sigma}{\sqrt{n}}}$$

Where,

$\bar{X}$ = Sample mean

μ = Population mean under the null hypothesis

σ = Population standard deviation

n = Sample size

3. RESULTS AND DISCUSSION

3.1. Content validity and reliability statistics of the scale

An initial pool of 42 items was compiled by adapting the schedule and supplementing it with additional items, including a fossil-fuels theme. Experts independently assessed each item and provided scores. Following this review, 7 items were dropped on grounds of low CVR score (<0.49). The revised instrument thus comprised 35 items, which were subsequently used for reliability testing on a sub-sample of farmers drawn from outside the study area.

The correlation between the two halves was 0.615, yielding a Spearman-Brown coefficient of 0.762, while the Guttman split-half coefficient was 0.748, as shown in Table 1. Both values were shown to be significant at the 1% level, so strengthening the index's reliability. The reliability was explained by Cronbach's alpha, which produced a score of 0.843, categorising it inside the 'good' range as per the criteria of George and Mallery (2003).

Schmitt (1996) emphasised four cautions about the proper application of the Cronbach alpha coefficient. One of these cautions highlights that only providing alpha values is insufficient when examining connections among various metrics. It is essential to augment alpha values with inter-correlations. In this context, ANOVA with Cochran's test was applied to assess the significance level of different reliability values, with the results, as presented in Table 1, deemed significant.

3.2. Theme wise performance of the CSV and non-CSV farmers

Table 2 represents the theme wise performance of the respondents across the items.

Table 1: Triangulation of reliability statistics of the scale

Cronbach's alpha	Part 1	Value	.821
		N of items	18
	Part 2	Value	.743
		N of items	17
		Total N of items	35
Cronbach's alpha			0.866
Cronbach's alpha based on standardised items			0.843
Correlation between forms			0.615
Spearman-brown coefficient	Equal length		0.762
	Unequal length		0.762
Guttman split-half coefficient			0.748
ANOVA with Cochran's test		537.034	<0.001

a. The items are: S1, S2, S3..., S18; b. The items are: S19, S20, S21..., S35.

3.2.1. Climatic factors affecting agricultural production

CSV farmers were markedly more aware of directly observable factors like rainfall, temperature, sunshine and wind speed where "well aware" responses exceeded those of non-CSV farmers by 30–50 percentage points, yet awareness of less visible factors such as air moisture and atmospheric CO₂ stayed low in both groups. Farmers attuned to observable seasonal shifts are less equipped to grasp invisible atmospheric processes that require scientific mediation (Rogers, 2003). The programme thus reinforced experiential knowledge but extended awareness less effectively beyond immediate sensory reach (Kumar and Saxena, 2024).

3.2.2. Reasons for temperature rise

Awareness that pollution (47 vs 3% well aware) and industrialisation (43 vs 9%) drive warming was higher among CSV farmers, but understanding of greenhouse gases (GHGs) as the underlying cause remained modest in both groups. This gap between visible drivers and the GHG mechanism suggests extension messaging should build progressively from locally observable phenomena toward greenhouse science, particularly where formal education is limited.

3.2.3. Monsoon and rainfall patterns

CSV farmers showed stronger knowledge of monsoon behaviour, but awareness of average local rainfall was poor in both groups, with 47% of non-CSV farmers reporting none at all. Without a rainfall benchmark, farmers cannot judge whether a season is anomalous or decide when to adapt. Pathak et al. (2024) reported the same gap in Bundelkhand, underlining the need for location-specific, quantitative climate training.

Table 2: Frequency distribution of various statements to evaluate the level of awareness about climate change among the respondents of CSVs and non-CSVs

Sl. No.	Particulars	f (%) (CSVs)					f (%) (non-CSVs)				
		Not at all aware (0)	Not aware (1)	Somewhat aware (2)	Aware (3)	Well aware (4)	Not at all aware (0)	Not aware (1)	Somewhat aware (2)	Aware (3)	Well aware (4)
1. Do you know about these factors of climate that affect agriculture production in your area?											
	(a) Rainfall?	0	3	11	32	54	0	6	54	35	5
	(b) Temperature?	0	4	7	32	57	0	7	50	32	11
	(c) Sunshine?	0	4	17	34	45	0	2	62	22	14
	(d) Wind speed?	0	1	20	31	48	0	4	53	31	12
	(e) Air moisture?	0	7	18	63	12	0	43	46	6	5
	(f) High CO ₂ level?	0	4	33	62	1	0	10	64	21	5
2. Do you know about the reasons for the temperature rise in the last few years?											
	(a) High GHG gases produced?	0	4	26	66	4	0	12	66	14	8
	(b) High pollution rate?	0	4	8	41	47	0	0	46	51	3
	(c) High rate of industrialization?	0	7	12	38	43	0	5	42	44	9
3. Monsoon and rainfall pattern											
	(a) Do you know about the monsoon pattern in your area?	0	5	24	64	7	0	26	58	5	11
	(b) Do you know in which month the monsoon reaches your area?	0	4	22	66	8	0	19	66	10	5
	(c) Do you know the month in which maximum rainfall has occurred in your area?	0	7	9	25	59	0	2	49	42	7
	(d) Do you know about the average rain fall in your area?	7	20	69	4	0	47	42	1	2	8
	(e) Do you know that Indian agriculture is a gamble with monsoon?	0	8	29	59	4	7	34	47	8	3
	(f) Do you know that Indian agriculture is dependent on monsoon?	0	5	12	40	43	1	15	64	10	10
4. Weather forecasting											
	(a) Do you know about weather forecasting services?	0	1	52	47	0	15	47	28	5	5

Table 2: Continue...

Sl. No.	Particulars	f (%) (CSVs)					f (%) (non-CSVs)				
		Not at all aware (0)	Not aware (1)	Somewhat aware (2)	Aware (3)	Well aware (4)	Not at all aware (0)	Not aware (1)	Somewhat aware (2)	Aware (3)	Well aware (4)
	(b) Do you know about any Agro-meteorological observatory in your area?	0	18	80	2	0	20	50	20	3	7
	(c) Do you know about any weather assessment tools?	6	31	63	0	0	42	39	9	3	7
<u>5. Agriculture and climate change</u>											
	(a) Do you know that excessive uses of natural resources like water, soil, forest, etc. also affect the climate adversely?	1	6	45	46	2	10	38	40	3	9
	(b) Do you know the excessive use of insecticides/pesticides also affects the climate and soil health?	0	5	12	38	45	1	6	63	21	9
	(c) Do you know that by use of plastic material/gunny bags also leads to climate degradation?	0	3	16	35	46	0	1	44	52	3
	(d) Do you know that the burning of crop residue is the main reason for climate pollution?	0	6	39	51	4	0	42	50	2	6
	(e) Do you know that excessive use of nitrogenous fertilizer also affects climate degradation?	0	5	40	53	2	6	25	56	8	5
<u>6. Greenhouse gases and climate change</u>											
	(a) Do you know about the greenhouse gases?	2	28	65	5	0	29	51	3	5	12
	(b) Do you know about GHG emissions affect climate soundness?	1	7	45	47	0	2	27	58	6	7
	(c) Do you know that crop rice also produces GHG gas?	13	31	56	0	0	30	41	14	2	13

Table 2: Continue...

Sl. No.	Particulars	f (%) (CSVs)					f (%) (non-CSVs)				
		Not at all aware (0)	Not aware (1)	Somewhat aware (2)	Aware (3)	Well aware (4)	Not at all aware (0)	Not aware (1)	Somewhat aware (2)	Aware (3)	Well aware (4)
	(d) Do you know that farm animals also produce methane (GHG gas)?	3	25	69	3	0	19	44	17	6	14
	(e) Do you know CO ₂ level which is increasing is harmful for climate?	1	5	21	32	41	1	12	50	28	9
	(f) Do you know that industrialization is also the main cause of GHG?	1	1	16	48	34	0	7	47	32	14
	(g) Are you aware of the average temperature increasing every year?	1	6	8	46	39	0	9	45	37	9
7. Fossil fuels and climate change											
	(a) The majority of anthropogenic CO ₂ emissions are attributed to the combustion of fossil fuels.	0	2	55	43	0	1	32	46	7	14
	(b) Are you aware that nitrogen monoxide (NO) emitted by gasoline or engines in vehicles contributes to global warming	0	34	65	1	0	5	50	6	6	33
	(c) Are you aware that reduction in energy use, as long as it is obtained from fossil fuels, has the effect of decelerating global warming?	0	2	11	51	36	0	23	56	5	16
	(d) Are you aware that global climate change will generate drought in your country?	0	8	37	53	2	2	29	42	4	23
	(e) Do you know that climate change is happening right now	0	3	12	45	40	2	4	40	31	23

* Since no of respondents (n=100), the value of frequency is the same as the value of the percentage

3.2.4. Weather forecasting services

Only 0–6% of CSV farmers had no awareness of forecasting services, whereas 15–42% of non-CSV farmers had none; however, “well aware” responses were modest on both sides, especially for agro-meteorological observatories and assessment tools. Awareness of a service is not the ability to use it. The programme introduced the concept but not yet the institutional familiarity needed for farmers to act on forecasts, a gap acute in Bihar, where digital connectivity lags the national average.

3.2.5. Agriculture and climate change

CSV farmers were considerably more aware that their own practices like pesticide use, plastic and gunny-bag use harm soil and climate. Yet awareness of crop-residue burning's effects reached only the “aware” band even among CSV farmers, despite its prominence as an agri-environmental issue in northern India. Sharpening messaging on the agriculture–climate feedback loop, through demonstrations or farmer-to-farmer extension approach, may prove more effective than conventional advisories.

3.2.6. Greenhouse gases and climate change

This was the weakest theme in both groups: no CSV farmer was “well aware” of greenhouse gases, and awareness of methane from paddy and livestock was especially poor. The results expose a consistent boundary between farmers' experiential environmental awareness and their scientific literacy about climate mechanisms. Ghanghas et al. (2015) found the same gap among Haryana extension professionals, implying that weak GHG understanding at the farm level mirrors limitations within the extension cadre itself. Bridging it requires visual demonstrations and community-based experiential learning rather than more of the same information.

3.2.7. Fossil fuels and climate change

CSV farmers were more aware that fossil-fuel combustion drives anthropogenic CO₂ emissions (43% aware vs 14% well aware among non-CSV) and that cutting fossil-fuel energy use slows warming. A counterintuitive reversal appeared for vehicle NO emissions and drought, where non-CSV farmers

scored higher, most plausibly reflecting selective media exposure rather than systematic understanding. Curriculum-guided CSV training, by spreading awareness more evenly, may reduce the false confidence that accompanies such selective recall.

3.3. Comparative distribution of respondents across awareness categories

Table 3 shows 59% of CSV farmers in the medium awareness category and 30% in the high, against only 11% in the low; among non-CSV farmers, the distribution reversed (47% low, 44% medium, 9% high). This shift from low to medium without consistently reaching high is consistent with Chouksey et al. (2021); moving further likely requires longer, more intensive formats such as farmer field schools or peer-learning circles. That 53% of non-CSV farmers nonetheless scored above low, i.e., well beyond the 38% awareness Sarkar and Padaria (2010) reported in coastal West Bengal, suggests rising climate discourse has had a diffuse effect even without intervention. The CSV model's contribution, however, is structural: a consistent, locally embedded learning environment accelerates awareness-building in ways media exposure alone cannot (Mishra et al., 2024).

3.4. Z-test comparison of climate change awareness between CSV and non-CSV farmers

CSV farmers recorded a higher mean awareness score (93.63) than non-CSV farmers (70.33) with lower variance (163.77 vs 205.66); the Z-statistic of 12.12 far exceeded the 1% critical values, rejecting the null hypothesis (Table 4). The 23-point gap places CSV farmers in the medium band and non-CSV farmers at the upper edge of the low band, while the lower dispersion indicates the programme raised both the level and the consistency of awareness characteristic of curriculum-guided interventions (Chouksey et al., 2021). Aryal et al. (2018) documented strong adoption of climate-smart practices in the same corridor; the present results suggest this adoption is both reflected in and partly enabled by a higher, more uniform awareness base. Awareness is thus both an outcome and an enabler of the CSV approach (Kumar and Saxena, 2024), supporting expansion of the model beyond its current Bihar corridor.

Table 3: Categorisation of participants of CSVs and non-CSVs into low, medium, and high groups based on their awareness levels

Variable	Category	CSV f (%)	Mean ± SE	Non-CSV f (%)	Mean±SE	Pooled f (%)	Mean±SE (Range)
Awareness	Low (≤64.09)	11 (11)	93.63±1.28	47 (47)	70.33±1.41	58 (29)	81.98±1.27 (55–119)
	Medium (64.10–99.87)	59 (59)		44 (44)		103 (51.5)	
	High (>99.87)	30 (30)		9 (9)		39 (19.5)	

Figures in parentheses in columns 3, 5, and 7 represent percentages

Table 4: Z-test to compare awareness levels

Parameters	CSV	Non-CSV
Mean	93.63	70.33
Known Variance	163.7708	205.6577
Observations	100	100
Hypothesized mean difference	0	
z	12.12	
P(Z<=z) one-tail	<0.001	
z Critical one-tail	2.33	
P(Z<=z) two-tail	<0.001	
z Critical two-tail	2.58	

4. CONCLUSION

The 35-item scale, adapted from an existing interview schedule and validated through Cronbach's alpha (0.843), Spearman-brown (0.762) and Guttman split-half (0.748) coefficients, proved a reliable and replicable tool for measuring climate change awareness in agrarian settings. Climate smart village farmers scored significantly higher (93.63) than non-programme farmers (70.33), with greater uniformity. Awareness of greenhouse gases, weather forecasting and fossil fuels remained weak in both groups, warranting targeted extension programming.

5. REFERENCES

- Anonymous, 2022. IPCC, 2022. Climate Change 2022: Impacts, Adaptation and Vulnerability. Contribution of Working Group II to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge, 3056. DOI: <https://doi.org/10.1017/9781009325844>.
- Aryal, J.P., Jat, M.L., Sapkota, T.B., Khatri-Chhetri, A., Kassie, M., Rahut, D.B., Maharjan, S., 2018. Adoption of multiple climate-smart agricultural practices in the Gangetic plains of Bihar, India. *International Journal of Climate Change Strategies and Management* 10(3), 407–427. DOI: <http://dx.doi.org/10.1108/IJCCSM-02-2017-0025>.
- Borah, A., Lal, S.P., Das, D., 2026. A novel framework for constructing a robust octa-dimensional climate-smart agriculture index. *Indian Journal of Extension Education* 62(3), 292–300. DOI: <https://doi.org/10.48165/IJEE.2026.623RT04>.
- Borah, A., Lal, S.P., Singh, K.M., Prakash, S., 2025. Assessing farmers' impediments in climate-smart and non-climate smart villages: Kendall's W approach. *Journal of Economic Plants* 12(6), 01–08. DOI: <https://doi.org/10.23910/2/2025.6021>.
- Brown, W., 1910. Some experimental results in the

correlation of mental abilities. *British Journal of Psychology* 3(3), 296–322. Available from: <http://jhanley.biostat.mcgill.ca/bios601/Surveys/1910-brownReliability.pdf>.

- Challinor, A.J., Watson, J., Lobell, D.B., Howden, S.M., Smith, D.R., Chhetri, N., 2014. A meta-analysis of crop yield under climate change and adaptation. *Nature Climate Change* 4(4), 287–291. DOI: <https://doi.org/10.1038/nclimate2153>.
- Chouksey, R., Singh, K.C., Singh, C., Birla, Y., 2021. Adaptation of farmers regarding climate resilient technologies in Rewa block of Rewa district in Madhya Pradesh. *Indian Journal of Extension Education* 57(1), 26–31. Available from: https://iseeiari.org/Journalpdf/IJEE_57_1/IJEE_57_1_5.pdf.
- Cronbach, L.J., 1946. A case study of the split-half reliability coefficient. *Journal of Educational Psychology* 37(1), 473–480. DOI: https://doi.org/10.1037/h0054328?urlappend=%3Futm_source%3Dresearchgate.net%26utm_medium%3Darticle.
- Cronbach, L.J., 1951. Coefficient alpha and the internal structure of tests. *Psychometrika* 16(3), 297–334. DOI: <https://doi.org/10.1007/BF02310555>.
- Cuemath, 2024. Z test: formula, definition, examples, types. Available from: <https://www.cuemath.com/data/z-test/>. Accessed on 2 June 2026.
- George, D., Mallery, P., 2003. SPSS for windows step by step: a simple guide and reference. 4th Edn. Allyn and Bacon, Boston, 218. Available from: <https://dl.acm.org/doi/abs/10.5555/557542>.
- Ghanghas, B.S., Shehrawat, P.S., Nain, M.S., 2015. Knowledge of extension professionals regarding impact of climate change in agriculture. *Indian Journal of Extension Education* 51(3&4), 125–129. Available from: <https://epubs.icar.org.in/index.php/IJEE/article/view/144237>.
- Khatri-Chhetri, A., Aggarwal, P.K., Joshi, P.K., Vyas, S., 2017. Farmers' prioritization of climate-smart agriculture (CSA) technologies. *Agricultural Systems* 151, 184–191. DOI: <https://doi.org/10.1016/j.agsy.2016.10.005>.
- Kumar, A., Manhas, J.S., Lal, B., 2025. A scale to measure perception of farmers towards weather based agro-advisory services. *Gujarat Journal of Extension Education* 39(2), 151–156. DOI: <https://doi.org/10.56572/gjoe.2025.39.2.0025>.
- Kumar, A., Saxena, S.P., 2024. Farmers' awareness and perception about climate change in the Indo-Gangetic Plain region of India. *Indian Journal of Extension Education* 60(4), 101–106. DOI: <https://doi.org/10.48165/IJEE.2024.60418>.

- Lawshe, C.H., 1975. A quantitative approach to content validity. *Personnel Psychology*, 28(4). Available from: <https://parsmodir.com/wp-content/uploads/2015/03/lawshe.pdf>.
- Lenka, S., Patnaik, B.R., Dash, S.R., 2023. Impact of NICRA project on knowledge, skill and attitude (KSA) of farmers on climate-resilient agrotechnology's in the NICRA operated district of Odisha. *International Journal of Bio-resource and Stress Management* 14(1), 132–137. DOI: <https://doi.org/10.23910/1.2023.3276a>.
- Lobell, D.B., Burke, M.B., Tebaldi, C., Mastrandrea, M.D., Falcon, W.P., Naylor, R.L., 2008. Prioritizing climate change adaptation needs for food security in 2030. *Science* 319(5863), 607–610. DOI: <https://doi.org/10.1126/science.1152339>.
- Mallick, B., Lal, S.P., Behera, B., 2025. Adaptive behavior of farmers in cyclone vulnerable state of India: Global Priorities Weightage Analysis. *International Journal of Bio-resource and Stress Management* 16(6), 01–07. DOI: <https://doi.org/10.23910/1.2025.6161>.
- Manjeet, 2013. Impact of climate change on agriculture. M.Sc. Thesis. Extension Education, Chaudhary Charan Singh Haryana Agricultural University, Hisar, 111. Available from: <https://krishikosh.egranth.ac.in/items/cac2f2da-106e-4635-8e90-9366dafba4fd>.
- Mishra, A., Malik, J.S., Chikkalaki, A.S., Niwas, R., 2024. A comparative study on knowledge level of climate smart agricultural practices (CSAP) among paddy farmers in Eastern Haryana. *Indian Journal of Extension Education* 60(3), 77–82. DOI: <https://doi.org/10.48165/IJEE.2024.60315>.
- Nair, A.S., Kumar, P.G., Reddy, H., Sumathi, V., Lakshmi, T., 2025. Building resilient food system: a comprehensive review of community supported agriculture. *Journal of Community Mobilization and Sustainable Development* 20(4), 1045–1052. Available from: [https://mobilization.org.in/images/Journal%20of%20Mobilization%20Vol.%2020\(4\)%20October-December,%202025_final%20book%2031.1.26.pdf](https://mobilization.org.in/images/Journal%20of%20Mobilization%20Vol.%2020(4)%20October-December,%202025_final%20book%2031.1.26.pdf).
- Pathak, D.K., Gupta, B.K., Verma, A.P., Shukla, G., Kalia, A., Mishra, D., Mishra, B.P., 2024. Assessing farmers' awareness of climate change impact: a case of the Bundelkhand region, India. *Indian Journal of Extension Education* 60(4), 77–82. DOI: <https://doi.org/10.48165/IJEE.2024.60414>.
- Rogers, E.M., 2003. *Diffusion of Innovations*. 5th Ed. Free Press, New York, 551. DOI: <https://doi.org/10.1016/j.jmig.2007.07.001>.
- Sarkar, S., Padaria, R.N., 2010. Farmers' awareness and risk perception about climate change in coastal ecosystem of West Bengal. *Indian Research Journal of Extension Education* 10(2), 32–38. Available from: <https://api.seea.org.in/uploads/pdf/v10207.pdf>.
- Schmitt, N., 1996. Uses and abuses of coefficient alpha. *Psychological Assessment* 8(4), 350–353. DOI: <https://doi.org/10.1037/1040-3590.8.4.350>.
- Smit, B., Wandel, J., 2006. Adaptation, adaptive capacity and vulnerability. *Global Environmental Change* 16(3), 282–292. DOI: <https://doi.org/10.1016/j.gloenvcha.2006.03.008>.
- Spearman, C., 1910. Correlation calculated from faulty data. *British Journal of Psychology* 3(3), 271–295. Available from: <https://search.proquest.com/openview/9e46330dba2285dea63dd35588155383/1?pq-origsite=gscholar&cbl=1818401>.
- Tesfaye, K., Aggarwal, P.K., Mequanint, F., Shirsath, P.B., Stirling, C.M., Khatri-Chhetri, A., Rahut, D.B., 2017. Climate variability and change in Bihar, India: challenges and opportunities for sustainable crop production. *Sustainability* 9(11), 1998. DOI: <https://doi.org/10.3390/su9111998>.
- Vermeulen, S.J., Campbell, B.M., Ingram, J.S.I., 2012. Climate change and food systems. *Annual Review of Environment and Resources* 37, 195–222. DOI: <https://doi.org/10.1146/annurev-environ-020411-130608>.
- Yadav, P., Barman, B., Pavan, P., Mahananda, C.C., Saurav, S.K., Meena, B.S., Yeasin, M., 2025. Examining adoption of feed and fodder related adaptation strategies for climate change using classification and regression tree (CART) analysis. *Journal of Community Mobilization and Sustainable Development* 20(4), 1303–1309. Available from: [https://mobilization.org.in/images/Journal%20of%20Mobilization%20Vol.%2020\(4\)%20October-December,%202025_final%20book%2031.1.26.pdf](https://mobilization.org.in/images/Journal%20of%20Mobilization%20Vol.%2020(4)%20October-December,%202025_final%20book%2031.1.26.pdf).