Research Tool

Indian Journal of Extension Education
Vol. 62, No. 3 (July–September), 2026, (292-300)

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

A Novel Framework for Constructing a Robust Octa-Dimensional Climate-Smart Agriculture Index

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HIGHLIGHTS

- An Octa-dimensional Climate-Smart Agriculture Index (ODCSAI) comprising 47 indicators across eight dimensions was developed and content validated.
- The Alfares and Duffuaa model ensures a weight of 100 for the top-ranked dimension, eliminating value dilution in index construction.
- Crop Smart emerged as the most critical CSA dimension with the highest cardinal weight (W = 93.73).
- Supplementary reliability triangulation using Spearman-Brown (0.872), Guttman split-half (0.829), and Cronbach's alpha (0.848) confirmed internally stable scoring.

ARTICLE INFO

Keywords: Climate change, Climate-smart agriculture, Cronbach's alpha, Index, Reliability, Spearman-brown.

https://doi.org/10.48165/IJEE.2026.623RT04

Citation: 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. https://doi.org/10.48165/IJEE.2026.623RT04

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ABSTRACT

Escalating climate variability induced risks in agriculture dependent economies necessitated a standardised composite index to measure farm level adoption of Climate-Smart Agriculture (CSA) practices. The study, conducted in 2024, developed the Octa-dimensional Climate-Smart Agriculture Index (ODCSAI) by combining the established cardinal weight assignment model of Alfares and Duffuaa with the min-max normalisation protocol of the Food and Agriculture Organisation (FAO). Eight CSA dimensions viz. Crop Smart, Weather Smart, Water Smart, Carbon Smart, Energy Smart, Nutrient Smart, Knowledge Smart, and Market Smart were delineated through a structured review of seven CSA frameworks and operationalised using 47 indicators. Ordinal rankings elicited from 120 subject matter experts were converted into cardinal weights, with Crop Smart registering the highest weight (W = 93.73), followed by Weather Smart (W = 87.20) and Water Smart (W = 84.17), while Market Smart recorded the lowest (W = 48.03). Content validity was established using a six-member expert panel (S-CVI = 0.935), and psychometric reliability, assessed on 50 farmers across two Climate Smart Villages in Bihar, was triangulated through the Spearman-Brown coefficient (0.872), Guttman split-half coefficient (0.829), and Cronbach's alpha (0.848). The ODCSAI thus constituted a content-validated instrument for quantifying farm-level CSA adoption.

INTRODUCTION

Agriculture in climate dependent economies faces intensifying threats from erratic weather patterns, prolonged droughts, and flood events, all of which jeopardise long term food security and rural livelihoods (Raghuvanshi et al., 2020; Phebe et al., 2024). Climate-Smart Agriculture (CSA) offers a comprehensive, evidence-based strategy to simultaneously enhance agricultural productivity,

Received 07-06-2026; Accepted 22-06-2026

strengthen adaptive capacity, and reduce greenhouse gas emissions (Borah et al., 2025). As CSA interventions are implemented at scale across diverse agro-ecological settings, the ability to assess and compare the climate smartness of individual farmers and farming systems has become increasingly critical for guiding policy, targeting extension efforts, and evaluating the outcomes of completed projects (Meena et al., 2023; Kumar & Saxena, 2024; Pathak et al., 2024). CSA consists of multiple interrelated dimensions viz., crop management, water use, carbon sequestration, energy efficiency, market integration, and knowledge dissemination that differ in their relative importance across contexts, making a multidimensional, weighted measurement approach essential for meaningful cross site comparison (Shitu et al., 2018a; Shitu et al., 2018b; Harikrishna et al., 2019; Chouksey et al., 2021).

Although composite measures of farm-level climate smartness have begun to appear (Singh et al., 2024), they typically derive dimension weights through schemes such as the analytic hierarchy process that dilute the proportional value of the highest-ranked dimension, leaving a need for a transparent, proportionally weighted tool capable of quantifying farm-level CSA adoption in a standardised and reproducible manner. The construction of composite indices to operationalise complex socio-agricultural constructs is well established in development research. Environmental sustainability (Sands et al., 2000), food and human security (Carolan, 2012), livelihood vulnerability (Madhuri et al., 2014), rural development (Michalek & Zarnekow, 2012), and sustainable livelihood security (Singh & Hiremath, 2010) have each been captured through multidimensional index frameworks. Despite this precedent, a rigorous, replicable, and universally adaptable methodology for index construction remains elusive, and several prevailing approaches exhibit inherent structural limitations that compromise the validity and comparability of the resulting scores (Lal et al., 2017).

Garrett's (1979) ranking technique, for instance, restricts the maximum attainable weight of the top ranked dimension to 78 rather than 100 in a seven-criterion framework, systematically undervaluing the most critical element. The method also requires field researchers to carry printed conversion tables, posing a logistical inconvenience. Alkire and Foster's (2011) widely adopted Multidimensional Poverty Index methodology, though theoretically grounded, excludes households with composite deprivation scores below one-third from the final computation, resulting in structural under coverage of the target population. Collectively, these limitations reveal the need for an index construction approach that is computationally transparent, assigns full proportional value to the highest ranked criterion, and incorporates all respondents irrespective of their overall score. It is posited that adapting the Alfares and Duffuaa (2009) cardinal weighting model in conjunction with the FAO min-max normalisation protocol provides a transparent and proportional basis for constructing a multidimensional CSA index, one that assigns full value to the highest-ranked dimension and retains all respondents and that the resulting instrument can be shown to be internally reliable. T h e contribution of this study lies in application and validation rather than in the derivation of new weighting mathematics. First, it operationalises an established weighting-normalisation confluence, previously applied to livelihood security (Lal et al., 2017), for measuring farm-level Climate-Smart Agriculture adoption. In contrast to existing farm-level CSA indices that derive dimension weights through the analytic hierarchy process (Singh et al., 2024), the Alfares–Duffuaa formulation assigns a full weight of 100 to the top-ranked dimension, thereby avoiding value dilution. Second, it synthesises eight CSA dimensions from a review of seven frameworks and renders them measurable through 47 scored indicators, yielding a concrete and reusable assessment tool. Third, it subjects the resulting index to a three-way reliability triangulation (Spearman–Brown, Guttman split-half and Cronbach's alpha), supplemented by ANOVA with Cochran's test, thereby providing psychometric evidence that earlier single-coefficient index studies have often omitted.

METHODOLOGY

The present study, conducted in 2024, delineated eight Climate-Smart Agriculture (CSA) dimensions viz., Crop Smart, Weather Smart, Water Smart, Carbon Smart, Energy Smart, Nutrient Smart, Knowledge Smart and Market Smart through a structured review of CSA frameworks. A structured literature review was conducted in Scopus (2018–2023), restricted to the title, abstract, and keyword fields, using the query: ("Climate Smart Agriculture" OR "Climate-Smart Agriculture" OR CSA) AND ("CSA Index" OR "Composite Index" OR indicator OR framework OR metric) AND (dimension OR pillar OR component). This was supplemented by backward citation searching (snowballing) of the retrieved records. Of the 87 records screened, seven frameworks (Appendix Table 1) met the inclusion criterion i.e., decomposition of CSA into discrete, named dimensions that are operationalisable through measurable indicators. Sources specifying no such structure, or describing CSA goals (e.g., adaptive capacity, food and nutrition security, mitigation) rather than measurable practice domains, were excluded. The retained set spanned international (Aggarwal et al., 2018; Anuga et al., 2019; Ghimire et al., 2022; Antwi-Agyei et al., 2023) and Indian (Bhattacharyya et al., 2020; Singh et al., 2021; Chakraborty et al., 2023) contexts. Rather than adopting any single scheme, the eight dimensions were synthesised across the seven frameworks and synonymous labels were matched (e.g., 'Nitrogen Smart' with 'Nutrient Smart'; 'Seed/Breed' and 'Planting' with 'Crop Smart'), composite labels were disaggregated where treated separately (e.g., 'Carbon/Nutrient Smart', 'Institutional/Market Smart'), and outcome-oriented categories were excluded as non-operationalisable, yielding eight unique dimensions recurring across the literature. A standardised questionnaire soliciting ordinal ranks from 1 to 8 was administered to 138 subject-matter experts, of whom 120 responded (response rate 87.0%); these were randomly selected extension scientists, subject-matter specialists, agronomists and research scholars from agricultural universities, KVKs and ICAR institutes across India.

Ordinal ranks were converted into cardinal weights using the Alfares and Duffuaa (2009) model, adopted here in preference to earlier rank-based weight-approximation methods (Stillwell et al., 1981; Barron, 1992; Lootsma, 1999) because it assigns full proportional value to the top-ranked criterion (Lal et al., 2017). The slope (Sn) declines non-linearly with the number of criteria (n), derived by least-squares regression as:

$S_n = 3.19514 + 37.75756 / n$

which gave Sn = 7.914835 for n = 8. With a weight of 100 assigned to the first-ranked dimension, the weight of a dimension ranked r is:

$W_{r,n} = 100 – S_n (r – 1), 1 \le r \le n$

where $W_{r,n}$ is the cardinal weight at rank r, S_n the slope constant, and r and n integers. The aggregate weight of dimension d was obtained as the frequency-weighted mean of the rank weights:

$W_d = \Sigma (W_{r,n} f_{r,d}) / \Sigma f_{r,d}$

where $f_{r,d}$ is the number of experts assigning rank r to dimension d, the denominator equalling 120.

As the indicators used different measurement units, each was standardised to a 0 to 1 scale by min-max normalisation (Sullivan et al., 2010):

$Z_i = (X_i – X_{min}) / (X_{max} – X_{min})$

where X_i is the observed value of indicator i, and X_{min} and X_{max} its minimum and maximum attainable values. For each respondent j, each dimension score (Zij) was computed as the mean of the normalised values (Zi) of its constituent indicators. The composite score of respondent j was the weighted mean of the normalised dimension scores (Sullivan et al., 2010):

$CSA_j = \Sigma (W_i Z_{ij}) / \Sigma W_i$

where W_i is the cardinal weight of dimension i and Z_{ij} its normalised score for respondent j.

Expanded across the eight dimensions, this becomes:

$$CSA_j = (W_{CrS} \cdot CrS_j + W_{WeS} \cdot WeS_j + W_{WaS} \cdot WaS_j + W_{CaS} \cdot CaS_j + W_{ES} \cdot ES_j + W_{NS} \cdot NS_j + W_{KS} \cdot KS_j + W_{MS} \cdot MS_j) / (W_{CrS} + W_{WeS} + W_{WaS} + W_{CaS} + W_{ES} + W_{NS} + W_{KS} + W_{MS})$$

Where, CrS, WeS, WaS, CaS, ES, NS, KS and MS are the normalised scores of Crop Smart, Weather Smart, Water Smart, Carbon Smart, Energy Smart, Nutrient Smart, Knowledge Smart and Market Smart, respectively, for respondent j, and the corresponding W terms their cardinal weights.

Content validity was established before reliability testing using Lynn's (1986) method. Six experts from Agricultural Extension and Agronomy rated an initial pool of 52 indicators for relevance on a four-point scale (1 = not relevant to 4 = highly relevant); five items were removed on their judgement, retaining 47 indicators. The item-level content validity index (I-CVI) was the proportion of experts rating an indicator 3 or 4, and the instrument-level index their mean:

S-CVI = Σ(I-CVI) / n

where n is the number of indicators. An I-CVI of 0.83 or above (Lynn, 1986) and an S-CVI of 0.90 or above (Polit & Beck, 2006) denoted item retention and excellent content validity, respectively.

Reliability was assessed on 50 randomly drawn farmers (25 each from Climate Smart Village (CSV) Phulhara, Samastipur and CSV Ojhaul, Darbhanga, Bihar) using three internal-consistency coefficients. Split-half reliability used the Spearman-Brown formula (Spearman, 1910; Brown, 1910):

$r_{SB} = 2r_{hh} / (1 + r_{hh})$

where r_{hh} is the Pearson correlation between the two halves. The Guttman split-half coefficient was computed in SPSS (Version 27), and Cronbach's alpha (Cronbach, 1951) was also employed. As the index is a multidimensional composite, its full-scale alpha indexes overall internal consistency rather than one-dimensionality (Schmitt, 1996). The 47 items were split into Part 1 (S1 to S24) and Part 2 (S25 to S47), the unequal division reflecting the odd item total. Johanson and Brooks (2010) consider 30 respondents adequate for pilot reliability estimation, which this sample exceeded; the pilot used non-sample villages to avoid contaminating the main study population.

RESULTS

An analysis of Table 1 indicated that among the eight dimensions of the CSA index, Crop Smart possessed the highest weightage of 93.73 with four indicators, followed by Weather Smart at 87.20 with six indicators, Water Smart at 84.17 with nine indicators, Carbon Smart at 77.57 with five indicators, Energy Smart at 67.62 with five indicators, Nutrient Smart at 63.92 with five indicators, Knowledge Smart at 56.14 with seven indicators, and Market Smart at 48.03 with six indicators. Notably, a dimension ranked first is assigned a weight of 100, ensuring no loss of value.

Validity and reliability statistics of the indicator statements

Content validity was established following Lynn's (1986) methodology. Item-level content validity indices (I-CVIs) for the

Table 1. Cardinal weights of CSA index dimensions based on ordinal rankings (n=120)

Ranks	CrS	WeS	WaS	CaS	ES	NS	KS	MS	$W_{r,n}$
1	83	19	3	9	0	5	1	0	100.000
2	15	68	17	6	3	3	5	3	92.085
3	7	12	86	8	1	3	2	1	84.170
4	4	6	10	82	9	4	1	4	76.255
5	4	3	0	9	89	6	8	1	68.341
6	5	3	3	3	8	92	6	0	60.426
7	1	6	1	0	7	7	88	10	52.511
8	1	3	0	3	3	0	9	101	44.596
Σf	120	120	120	120	120	120	120	120	
$\Sigma W_{r,n}$ f	11248.09	10464.52	10100.44	9308.96	8113.82	7670.59	6736.63	5763.11	
1/Σf	0.00833	0.00833	0.00833	0.00833	0.00833	0.00833	0.00833	0.00833	
W	93.73	87.20	84.17	77.57	67.62	63.92	56.14	48.03	

W= Weightage; S_n = 7.914835; M_c (Mean of W) = 72.2980775; Standard Error for M_c = 5.658202049; f=frequency

Table 2. Reliability statistics of the indicator statements

Cronbach's α	P 1	Value	0.565
		Total Items	24
	P 2	Value	0.817
		Total Items	23
		Grand total	47
Cronbach's α value			0.848
Cronbach's α based on standardised items			0.863
Correlation b/w forms			0.772
Spearman-Brown Coefficient		Equal Length	0.872
		Unequal Length	0.872
Guttman Split-Half Coefficient			0.829
ANOVA with Cochran's Test		420.837	0.000

a. The items are: S1, S2, S3…S24.
b. The items are: S25, S26, S27…S47.

initial 52 indicators ranged from 0.667 to 1.00. Five indicators failed to meet the retention criterion (I-CVI ≥ 0.83 for six experts) and were therefore removed, yielding a final set of 47 indicators (Appendix Table 2). The scale-level content validity index (S-CVI) was 0.935, exceeding the 0.90 benchmark indicative of excellent content validity (Polit & Beck, 2006).

Beyond content validity, the internal consistency of the 47-item set as administered was examined as a supplementary check on score stability. As evident from Table 2, the index was divided into two halves of 24 (Part 1) and 23 (Part 2) items. The Pearson correlation was 0.772, which on Spearman-Brown correction yielded 0.872 for both equal and unequal length forms; the Guttman split-half coefficient was 0.829, with both estimates significant at the 1% level. Cronbach's alpha for the full 47-item scale was 0.848, within the 'good' range per George and Mallery (2003), and 0.863 for standardised items. Dimension-wise Cronbach's alpha (α) ranged from 0.511 to 0.758 (Weather Smart = 0.511, Crop Smart = 0.571, Water Smart = 0.606, Knowledge Smart = 0.620, Energy Smart = 0.657, Nutrient Smart = 0.669, Market Smart = 0.751, Carbon Smart = 0.758), and the part-wise estimates were 0.565 (Part 1) and 0.817 (Part 2). These subscale values are necessarily modest, as each dimension comprises only four to nine largely binary indicators, for which alpha is mathematically depressed (Cortina, 1993; Tavakol & Dennick, 2011). Because the dimensions form a composite that defines, rather than reflects, climate-smart adoption, internal consistency is not the defining quality criterion for the index, and high within-dimension inter-item correlation is neither expected nor required. Content validity accordingly carries the principal evidential weight, with criterion and construct validation identified as the next stage. The coefficients are reported here for completeness and for comparability with extension instruments that conventionally report them. Their close agreement, supported by a significant ANOVA with Cochran's test ($F = 420.837$, $p < 0.01$), indicates that the item set as administered yields internally stable scores.

DISCUSSION

Crop Smart received the highest cardinal weight among the eight dimensions, a result consistent with the centrality of crop management in climate-adaptive strategies (Sain et al., 2017; FAO, 2013). In the rice-wheat systems of Bihar and the wider Indo-Gangetic Plains, the crop is the most immediate point of climate exposure and the most readily adjusted, through stress-tolerant varieties, diversification and improved cropping systems, upon which water, nutrient and energy management subsequently build. The ranking, however, reflects expert priority rather than demonstrated field performance or actual farmer adoption, particularly as the panel was dominated by agronomists and extension scientists who may favour the practices closest to their own training (Ghanghas et al., 2015).

The weights are also conditioned by the study setting. Climate-smart agriculture is highly context-specific, and the practices that matter most differ across farming systems and agro-ecological zones (Tabe-Ojong et al., 2024a); a panel situated in a water-scarce or flood-prone region might therefore rank the dimensions differently. The weights reported here are accordingly specific to this setting rather than fixed. This is a property of the method rather than a limitation, since the Alfares and Duffuaa approach permits the weights to be re-estimated for any region through a fresh round of expert ranking, allowing the structure of the index to transfer even where the weights themselves cannot.

The comparatively low weights assigned to Knowledge Smart and Market Smart merit attention, as they sit at odds with the wider literature. These dimensions capture the enabling conditions, namely information access, farmer organisation, value addition and market linkage, that many studies identify as principal barriers to adopting and scaling climate-smart agriculture (Tabe-Ojong et al., 2024b; Agyekum et al., 2024). In India, Mishra et al. (2026) report that limited knowledge and skills, weak finances and insecure land tenure rank among the most common barriers to adoption, and that cooperative membership lowers them. The low weights may thus reflect a tendency among technical experts to prioritise biophysical practices over these institutional and market dimensions.

Reliability was examined through three complementary coefficients. The Spearman-Brown coefficient corrects the underestimation arising from halving a scale, the Guttman split-half coefficient provides a conservative lower-bound estimate, and Cronbach's alpha measures overall internal consistency across all 47 items; their close agreement, together with the significance of the Spearman-Brown and Guttman values at the 1% level, indicates that the result does not depend on any single test. The estimates are consistent with comparable extension instruments. Shukla et al. (2024) reported an alpha of 0.801 and a Spearman-Brown of 0.828 for the Standardised Information Need Index, Panigrahi et al. (2024) a split-half of 0.81, a Spearman-Brown of 0.89 and an alpha of 0.83 for an agripreneurial performance scale, and Sahu et al. (2026), using a similar non-sample-village design, an alpha of 0.951 and a Spearman-Brown of 0.936. As Schmitt (1996) cautions, alpha alone is insufficient; the split-half coefficients and the significant ANOVA with Cochran's test are therefore reported alongside it as supplementary checks.

In practical terms, the index offers extension functionaries a means to identify the dimensions on which a farmer or village is weak, to compare households and locations, and to monitor and evaluate climate-smart agriculture interventions. Its limitations are nonetheless acknowledged, the weights are expert-derived and context-bound, and reliability was assessed on only 50 farmers in a single state, warranting confirmation on larger and more diverse samples. As demonstrated for other extension scales (Meethal & Thomas, 2024), exploratory factor analysis with convergent and criterion validation on a larger sample represents the natural next step.

CONCLUSION

By combining the established Alfares and Duffuaa weighting model with the Food and Agriculture Organisation min-max normalisation protocol, this study delivers a content-validated and reliability-tested instrument, the Octa-dimensional Climate-Smart Agriculture Index, for quantifying farm-level Climate Smart Agriculture adoption. The adopted weighting approach retains a full weight of one hundred for the highest-ranked dimension, avoiding the value dilution inherent both in rank-based alternatives such as Garrett's technique and in the analytic-hierarchy weighting used by recent farm-level CSA indices. The resulting eight-dimensional index, comprising forty-seven indicators and supported by content validity and triangulated reliability, constitutes a standardised tool for assessing the climate-smart status of farm households. Crop-related practices emerged as the foremost priority among the experts consulted, underscoring the centrality of crop management in climate-adaptive strategies. The index provides a transferable structure that remains adaptable across regions through context-specific alterations, offering a practical resource for policymakers, extension workers, and researchers advancing resilient and sustainable agriculture.

DECLARATIONS

Ethics approval and informed consent: Informed consent was sought from the 120 judges who contributed in assigning ranks to the proposed dimensions, the 50 farmers from two non-sample villages during the course of the data collection and the 6 judges who contributed in content validity.

Conflict of interest: The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest. The authors declare that during the preparation of this work, they thoroughly reviewed, revised, and edited the content as needed. The authors take full responsibility for the final content of this publication

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APPENDIX

Table 1. Climate Smart Agriculture dimensions as suggested by various researchers

S.No.	Name of the researcher(s)	No. of dimensions	Name of the dimensions	
1	Aggarwal et al. (2018)	5	1) 'Weather Smart' 2) 'Water Smart' 3) 'Seed/Breed Smart' 4) 'Carbon/Nutrient Smart' 5) 'Institutional/Market Smart'	
2	Anuga et al. (2019)	6	1) 'Weather Smart' 2) 'Water Smart' 3) 'Carbon Smart' 4) 'Nitrogen Smart' 5) 'Energy Smart' 6) 'Knowledge Smart'	
3	Bhattacharya et al. (2020)	6	1) 'Weather smart' 2) 'Water smart' 3) 'Crop smart' 4) 'Nutrient smart 5) 'Carbon/energy smart' 6) 'Institution/Knowledge smart.'	
4	Singh et al. (2021)	6	1) 'Community Smart'	i) 'Community Service Centre' ii) 'Seed Bank' iii) 'Machine Bank' iv) 'Fodder Bank'
			2) 'Knowledge Smart'	i) 'Farmer-Scientist Interface' ii) 'Weather Smart'
			3) 'Input Smart'	i) 'Water Smart' ii) 'Nutrient Smart' iii) 'Energy Smart' iv) 'Carbon Smart'
			4) 'Adaptive Capacity' 5) 'Food and Nutrition Security' 6) 'Mitigation'	
5	Ghimire et al. (2022)	6	1) 'Nutrient Smart' 2) 'Water Smart' 3) 'Crop Smart' 4) 'Information Smart' 5) 'Energy Smart' 6) 'Future Smart'	

Appendix Table 1 contd...

S.No.	Name of the researcher(s)	No. of dimensions	Name of the dimensions
6	Antwi-Agyei et al. (2023)	7	1) 'Weather Smart' 2) 'Water Smart' 3) 'Carbon Smart' 4) 'Nitrogen Smart' 5) 'Energy Smart' 6) 'Knowledge Smart' 7) 'Planting Smart'
7	Chakraborty et al. (2023)	6	1) 'Weather Smart' 2) 'Water Smart' 3) 'Carbon Smart' 4) 'Nitrogen Smart' 5) 'Energy Smart' 6) 'Knowledge Smart'

Table 2. Indicator Statements to measure Climate Smart level of farmers

	Indicators	Responses from farmers	I-CVI
1) Weather Smart	Draw on personal experience to anticipate weather conditions.	Yes= 1; No= 0	1
	Usage of TV/Mobile phone/Internet/Radio for weather information	Phone/ Internet= 1 TV/Radio= 0.5 No weather information= 0	0.83
	Received training/education on how to access weather information	Yes=1; No= 0	1
	Obtained weather updates via the Community Information Centre.	Yes= 1; No= 0	1
	Beneficiary of Weather Index-Based Insurance (IBI)	Yes= 1; No= 0	0.83
	Weather-related information received from University/Krishi Vigyan Kendra (KVK)	Regularly= 1 Occasionally= 0.5 Never= 0	1
2) Water Smart	Practice of mulching to reduce excessive use of water	Yes=1; No= 0	1
	Reduce water wastage while irrigating fields	Very efficient=1 Moderately efficient= 0.5 Inefficient= 0	0.83
	Rainwater harvesting on the farm	Yes= 1; No= 0	1
	Direct Seeded Rice (DSR)	Yes = 1; No= 0	1
	Raised bed planting of major crops (Maize, Pigeon Pea and Wheat)	3/3 crops= 1 2/3 crops= 0.67 1/3 crops= 0.33 0/3 crops= 0	1
	Laser land levelling	Once in 2-3yrs= 1 Once in 4-5yrs= 0.67 Once in >5yrs= 0.33 Not at all= 0	0.83
	Alternate wetting/drying irrigation in rice	Yes= 1; No= 0	1
	Field bunding in rice	Yes= 1; No= 0	0.83
	Community irrigation	Yes= 1; No= 0	1
3) Carbon Smart	Optimum utilisation of equipment on the farm (minimum tillage)	Optimum = 1 Sub-optimum= 0.5 Poor utilisation= 0	0.83
	Use plants and animal manure on my farm (Organic manuring)	Yes= 1; No= 0	1
	Plant trees in and around the farm (Agro-forestry)	Yes= 1; No= 0	1
	No tillage	Yes= 1; No= 0	0.83
	Residue management	Yes= 1; No= 0	0.83
4) Nutrient Smart	Legume integration	Yes= 1; No= 0	1
	Calculate the exact dosage of fertiliser or manure needed at the time of application.	Accurate= 1 Approximate= 0.5 Uncalculated= 0	1

Appendix Table 2 contd..

	Indicators	Responses from farmers	I-CVI
	Customise nutrient application according to soil type for each field, using decision-support tools like Nutrient Expert.	Yes= 1; No= 0	0.83
	Use Leaf Colour Chart	Yes= 1; No= 0	1
	Use Green seeker (NDVI sensor) to monitor the Vegetative Index	Yes= 1; No= 0	1
5) Energy Smart	Use of fuel-efficient farm equipment/vehicles	Very efficient= 1 Moderately efficient= 0.67 Less efficient= 0.33 Inefficient= 0	0.83
	Composting of residues after harvesting	Yes= 1; No= 0	1
	Convert residue into bioenergy	Yes= 1; No= 0	1
	Use solar-powered equipment in farming	Yes= 1; No= 0	1
	Eliminate/Reduce Puddling in Rice	Eliminate= 1 Reduce= 0.5 Puddling= 0	0.83
6) Crop Smart	Stress- tolerant varieties (Drought/Flood/ Nutrient stress etc)	Yes= 1; No= 0	1
	Input-efficient varieties	Yes= 1; No= 0	0.83
	Cropping system optimisation	Multiple cropping/ Intercropping/ Crop rotation/ Relay cropping = 1 Monocropping= 0	1
	Diversification of crops	Yes= 1; No= 0	0.83
7) Knowledge / Institutional Smart	Engage in personal information sharing with peers (farmer-to-farmer learning).	Yes= 1; No= 0	1
	Belong to farmer associations	Yes= 1; No= 0	1
	Save seeds for the next season or unexpected situations using a seed storage system.	Yes= 1; No= 0	0.83
	Empowering women by incorporating them into the knowledge pool.	Yes= 1; No= 0	0.83
	Use of ICT tools for information gathering	Yes= 1; No= 0	1
	Attended Capacity development programmes	Yes= 1; No= 0	1
	Access to Custom Hiring Centres (CHCs)	Yes= 1; No= 0	1
8) Market Smart	Ability to conduct Market research and analysis	Yes= 1; No= 0	0.83
	Production of Value-added products	Yes= 1; No= 0	1
	Supply chain integration (to reduce middlemen)	Elimination= 1 Reduction= 0.5 No elimination/reduction= 0	0.83
	Flexibility and adaptability	Yes= 1; No= 0	1
	Collaboration and networking through Farmer Producer Organisations (FPOs)	Yes= 1; No= 0	0.83
	Obtain information on market prices for crops and agricultural inputs.	Proper information= 1 Partial information= 0.5 No information= 0	1