MRV SUPPORT TO CIFF'S INVESTMENT TOWARDS LOW CARBON AGRICULTURE

PROJECT TECHNICAL REPORT

(JANUARY 2022 - AUGUST 2024)

Unnat Kheti

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Technical report in connection to the Low Carbon Agriculture Project

Financial Support:

Children's Investment Fund Foundation (CIFF)

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We acknowledge.......

We are profoundly grateful to the Children's Investment Fund Foundation (CIFF) for the financial support. We would like to express our appreciation for the invaluable support provided by team members from AGA KHAN FOUNDATION (AKF) and AKRSP (AGA KHAN RURAL SUPPORT PROGRAMME, INDIA) for their precious and patient local support during the implementation of the survey instrument and Land Degradation Surveillance Framework (LDSF) survey. Our thanks also extend to staff from the Foundation for Ecological Security (FES), for their sound cooperation, particularly for the LDSF survey. We would also like to acknowledge the support given by the Morsel agency in baseline, follow up and end line data collection, the team of hardworking young guys who implemented the LDSF survey on the ground and the staff of 'Charles Renard Analytical Laboratory (CRAL), International Crops Research Institute for the Semi-Arid Tropics (ICRISAT), Hyderabad' who carried out analysis of soil samples. We cherish this opportunity to extend our heartfelt regards to all involved. We would also like to extend our heartfelt appreciation to Mr. Ajay Kumar Singh for his invaluable contributions to the project report and design.

DISCLAIMER

Abbreviations

AKF	AGA KHAN FOUNDATION
AKRSPI	Aga Khan Rural Support Program India
CAPI	Computer Assisted Personal Interviewing
CIFF	Children's Investment Fund Foundation
CIFOR ICRAF	The Centre for International Forestry Research and World Agroforestry
CRAL	Charles Renard Analytical Laboratory
FAO-Global	Food and Agriculture Organisation Global
FES	Foundation for Ecological Security
FIES	Food insecurity Experience Scale
FYM	Farmyard Manure
GHG	Green House Gas
HCA	High Carbon Agriculture
ICP-OES	Inductively Coupled Plasma-optical Emission Spectrophotometer
ICRISAT	International Crops Research Institute for the Semi-Arid Tropics
IPM	Integrated Pest Management
KPI	Key Performance Indicators
LCA	Low Carbon Agriculture
LCSI	Livelihood Coping Strategies Index
LDSF	Land Degradation Surveillance Framework
MIS	Management Information System
MP-AES	Atomic Emission Spectrometer
MRV	Monitoring, Reporting, and Verification
NF Coalition	National Coalition of Natural Farming
pH	Potential of Hydrogen
SDG	Sustainable Development Goals
SRI Tool Kit	System of Rice Intensification toolkit
SOP	Standard Operating Procedure
SOC	Soil Organic Carbon
TC-TN analyser	Total Organic Carbon and Total Nitrogen Analyser
USD	United States Dollar

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Executive Summary

Through the 'Low Carbon Agriculture' (LCA) program, funded by the Children's Investment Fund (CIFF) and implemented by various implementing partners, CIFOR-ICRAF engaged to producing farming system-based evidence that highlight the environmental and socio-economic benefits of the LCA practices. The project aimed to pilot and scale up LCA practices among 18,000 farmers spread across three agro-ecological zones in the India states of Gujarat, Madhya Pradesh and Uttar Pradesh.

The impact of LCA project was assessed by measuring various key performance indicators (KPIs) namely rate of LCA practice adoption and High Carbon Agricultural (HCA) practice dis-adoption, change in soil health variables, impact on socio-economic wellbeing. The data for these indicators were collected using Land degradation surveillance framework (LDSF) and Farm family and village level survey instruments in the pilot intervention villages. Through LDSF survey, collection of 1288 soil samples and recording various other observations related to land cover, land use, land degradation etc. as per LDSF methodology were carried out from 627 plots covering 56 villages/clusters from project area. The soil samples were analysed for pH, bulk density, texture, total nitrogen and total organic carbon. Farm family and village level surveys recorded detailed information related to household demographics; land characteristics; livestock and other farm and non-farm asset ownership; field-based detailed activities; household coping strategies and food insecurity experiences from 1100 families covering 55 villages at the baseline of which 1046 followed up at the endline. The data collection was carried out three times - baseline, follow up for progress monitoring and endline to assess the changes brought about by LCA interventions.

The results drawn from the analysis of soil health data collected from LDSF survey, showed overall improvement in soil organic carbon and nitrogen content in the LCA intervention plots (LCA plots) compared to non-intervention plots (non LCA plot) in very short period of time. This probably indicates extended adoption of LCA practices on long term basis to achieve sustainable positive change. However, our results show proper selection and long term implementation of ecosystem specific LCA practices can add to the organic carbon and nitrogen content substantially. Slight replacement of high values of sand content by clay in case of Sayla (Gujarat) may add to improvement in soil water holding capacity. Clearly, longer interventions are advised for significant desirable changes in physical properties of soil. Furthermore, shift of soil pH towards neutral class in soils of LCA plot over non-LCA plot at Bahraich, (Risia, Uttar Pradesh) was a good sign possibly leading to higher nutrient availability. In all three project sites, agroforestry systems were less common, with annual crops prevailing over trees. This highlights the need to increase tree cover, which could ultimately lead to improvements in soil and ecosystem health.

Data were collected from the same farm families during both the baseline and endline surveys for selected impact indicators. We assessed changes in these indicators and analyzed the impact using first difference estimation. Recognizing that the status of these indicators likely fluctuates over the seasonal calendar, we compared their status during the same farming seasons. Specifically, we compared data collected during Kharif 2023 at the endline survey with data from Kharif 2021 at the baseline.

The following table summarises the project's endline result, for the selected KPIs.

Indicator Dimension	KPI	Endline highlights
LCA practice uptake/ adoption	• % of farms taking up at least one new LCA practice, disaggregated by type of practice • % of farms dis-adopting at least one HCA practice, disaggregated by type of practice	At the endline 504 (48%) farming families adopted at least one new LCA practice or dis-adopted at least one HCA practice compared to the baseline, as measured by LCA up scaling, i.e positive change in LCA index. Adoption Rate disaggregated by type of practices: • Of the sampled farming families: 324 farmers (31%) used FYM; 155 (15%) incorporated crop residues, 156 (15%) used mulching, 166 (16%) practiced pre-planting soil cover, 93 (9%) applied compost to crop fields, 208 (20%) used boundary trees and only 31(3%) practiced agroforestry, 129 (12%) used natural herbicides and pesticides and 30 (3%) used IPM • Examples of dis-adoption of HCA practices: 146 farmers (14%) dis-adopted chemical fertilizer; 178 (17 %) dis-adopted chemical herbicides and 447 (43%) dis-adopted chemical pesticides
Soil health variables	• % of farms with increases in soil carbon over past 3 years • % of farms with greater vegetative cover over past 3 years • % of farms with enhanced soil infiltrability over previous 3 years	• Overall improvement in soil organic carbon in LCA intervened plots (LCA plots) over non intervened plots (non LCA plot) in very short period. Further nitrogen content showed similar trend. • All the three project areas reported lower occurrence of agroforestry systems, with annual crops dominating over trees • No plot-wise (LCA vs non-LCA) variation recorded.
Socio-economic wellbeing	• % of farming families reporting at least a 10% net reduction in farm expenses, overall year and farming season • % of farming families reporting at least a 10% improvement in their overall farm income, overall year and farming season • % of farming families reporting improvements in their food security situation, overall year and farming season • % of farming families reporting less need to engage in maladaptive coping behaviours, overall year and farming season	• At the endline, 703 farmers (67%) of the sampled farming families reported at least 10% net reduction in farm expenses after adjusting for inflation • 347 farmers (33%) of the sampled farming families reported at least 10% improvement in their crop income, after adjusting for inflation • 531 farmers (51%) of the sampled farming families reported improvement in their food security as measured by the change in FIES • 706 (67 %) of the sampled farming families reported less need to engage in maladaptive coping behaviours as measured by the change in LCSI

1. Introduction

1.1 Project Background:

At the outset we refer to a study conducted by Wang et al., 2017[1] about the Indian agriculture sector. It quotes 'Indian agriculture sector is a significant emitter of greenhouse gases (GHG), with emissions projected to increase by 47% between years 2011 and 2020. This necessitates a rapid and substantial scaling up of mitigation efforts, including the agricultural sector. However, achieving this remains challenging, as mitigation is not currently a priority in Indian agriculture. Despite the availability of numerous mitigation technologies ready for deployment, their adoption and implementation are insufficient to meet the emission targets set by the Government of India. This shortfall is primarily due to the lack of financial incentives, inadequate capacity building for farmers and the absence of an enabling policy framework at various levels'.

In light of these challenges and shortfalls, the 'Low Carbon Agriculture (LCA)' programme initiated by the Children's Investment Fund Foundation (CIFF) appeared to be a promising effort to address these issues. This programme was funded by CIFF and implemented by the Aga Khan Foundation (AKF) and the Aga Khan Rural Support Program India (AKRSPI), in partnership with other organizations such as the Foundation for Ecological Security (FES) and the National Coalition of Natural Farming (NF Coalition).

The project aimed to pilot and scale up LCA practices among 18,000 farmers across three Agro Ecological Zones in Gujarat, Madhya Pradesh, and Uttar Pradesh. AKF led the project implementation in Uttar Pradesh, while AKRSPI was the implementing partner in Gujarat and Madhya Pradesh. Specifically, in Gujarat, the project was implemented within the districts of Surendranagar, Narmada, Devbhoomi Dwarka, and Junagadh. In Madhya Pradesh, it covered the districts of Khandwa and Khargone. Intervention in Uttar Pradesh concentrated in the district of Bahraich.

1.2. Scope of work:

Given the limited evidence on effective pathways and interventions for the sustained adoption of LCA practices in India, CIFF engaged CIFOR-ICRAF to produce farming system-based evidence detailing the environmental and socio-economic benefits of LCA practices.

The impact of the project was assessed using selected key performance indicators (KPIs). These indicators ranged across various dimensions namely, the rate of LCA practices adoption and dis-adoption of HCA practices, soil health indicators, and socioeconomic outcomes. The Land degradation surveillance framework (LDSF) was used for the assessment of changes in soil health indicators.

To assess the changes in the adoption of LCA practices/dis-adoption of HCA practices and its impact on socio-economic outcomes, farm family surveys were conducted. Randomly sampled farm families in the pilot villages were interviewed using computer assisted personal interviews (CAPI) tool. The data collection was carried out three times: baseline to establish the baseline situation for the KPIs; a follow-up survey for progress monitoring, and endline survey for impact assessment. These surveys recorded detailed information related to household, field-based farming activities and input use, asset wealth ownership and food insecurity experiences, which enabled us to measure the indicators.

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[1] Wang, S.W., Lee, W. and Y.S. (2017). Low Carbon Development Pathways in Indian Agriculture. Change Adaptation Socioecol. Syst. 3 : 18–26.

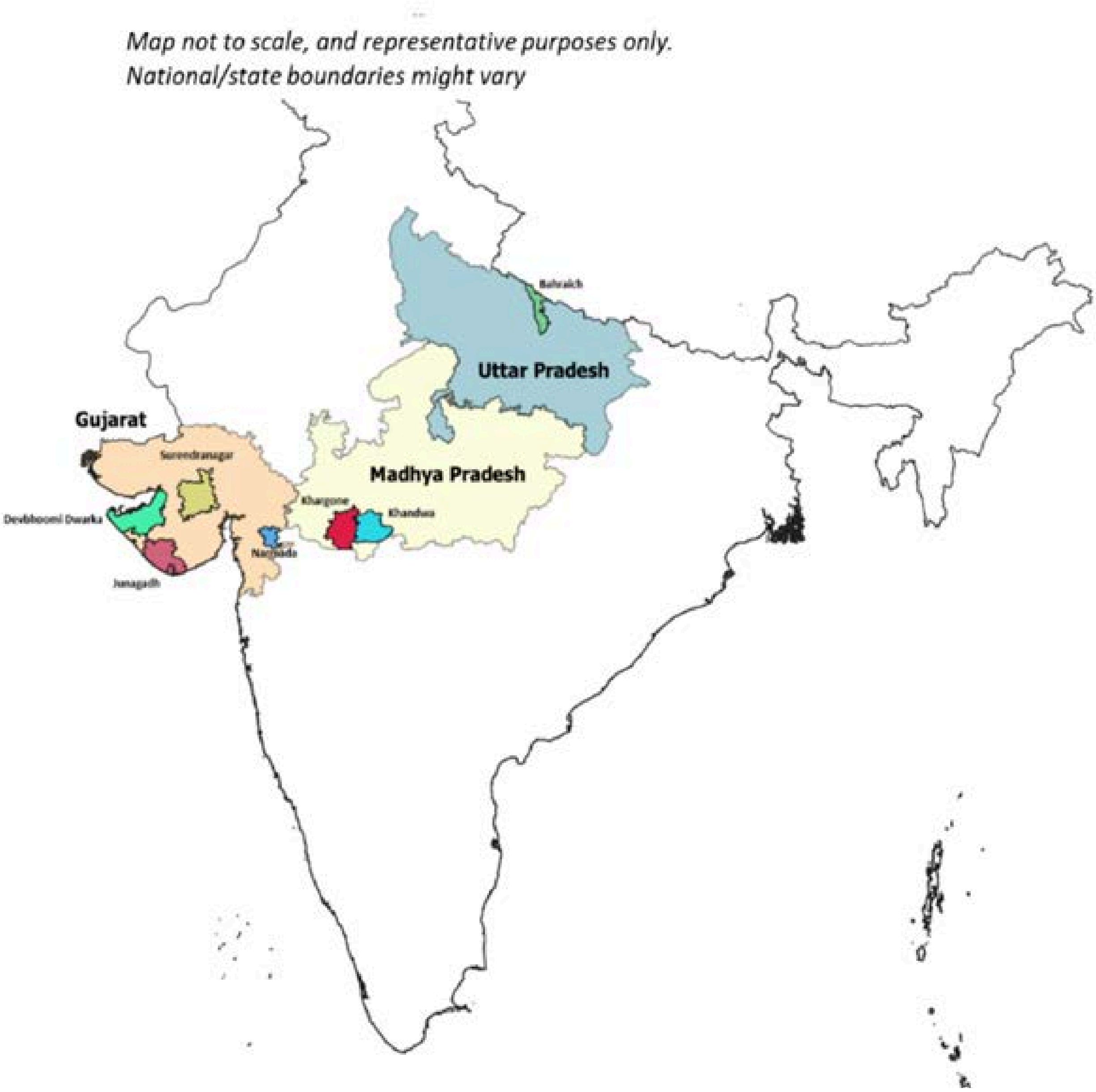


Figure 1: State & District Map of areas where 'Low Carbon Agriculture Project' is being implemented

This report provides highlights of key results based on this assessment. The purpose of this report is threefold:

- To document changes in the adoption of LCA practices and the dis-adoption of HCA practices
- To assess whether changes in the adoption of practices are associated with changes in socio-economic outcome indicators
- To assess and document changes in soil health indicators by comparing LCA intervention sites with non-intervention sites

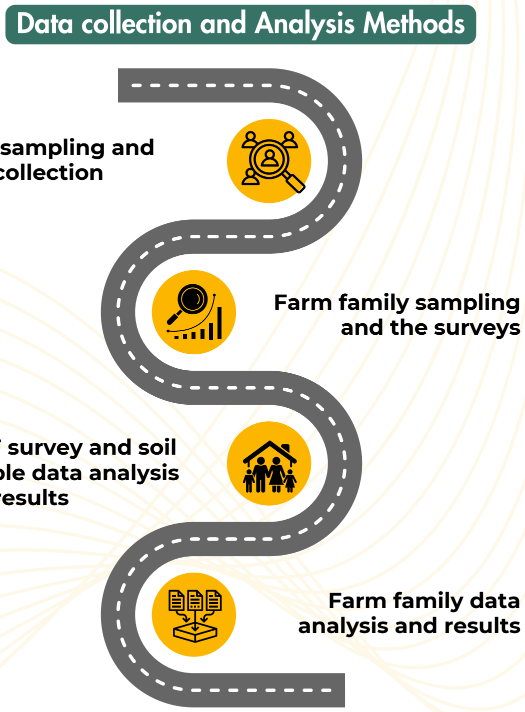
The report begins by describing the methods used for data collection and measurement of the key indicators in Chapter 2. Chapter 3 then presents and discusses key results focusing on the changes in soil indicators, followed by Chapter 4, which presents and discusses key results on the changes in the adoption of LCA and dis-adoption of HCA practices. Finally, Chapter 5 provides a summary of the key findings.

2. Data collection and Analysis Methods:

2.1 The Land Degradation Surveillance Framework:

2.1.1 Concept and purpose of LDSF survey:

The Land Degradation Surveillance Framework provides field protocols for measuring indicators of ecosystem health, including vegetation cover, structure and floristic composition, historic land use, visible signs of soil degradation and soil physical characteristics. Systematic baselines of soil and ecosystem properties allow for a proper assessment of landscape performance and prediction of change over time. The LDSF was designed to provide a biophysical baseline at the landscape level and a monitoring and evaluation framework for assessing processes of land degradation and the effectiveness of rehabilitation measures over time. The concept of LDSF is illustrated in Figure 2 below.



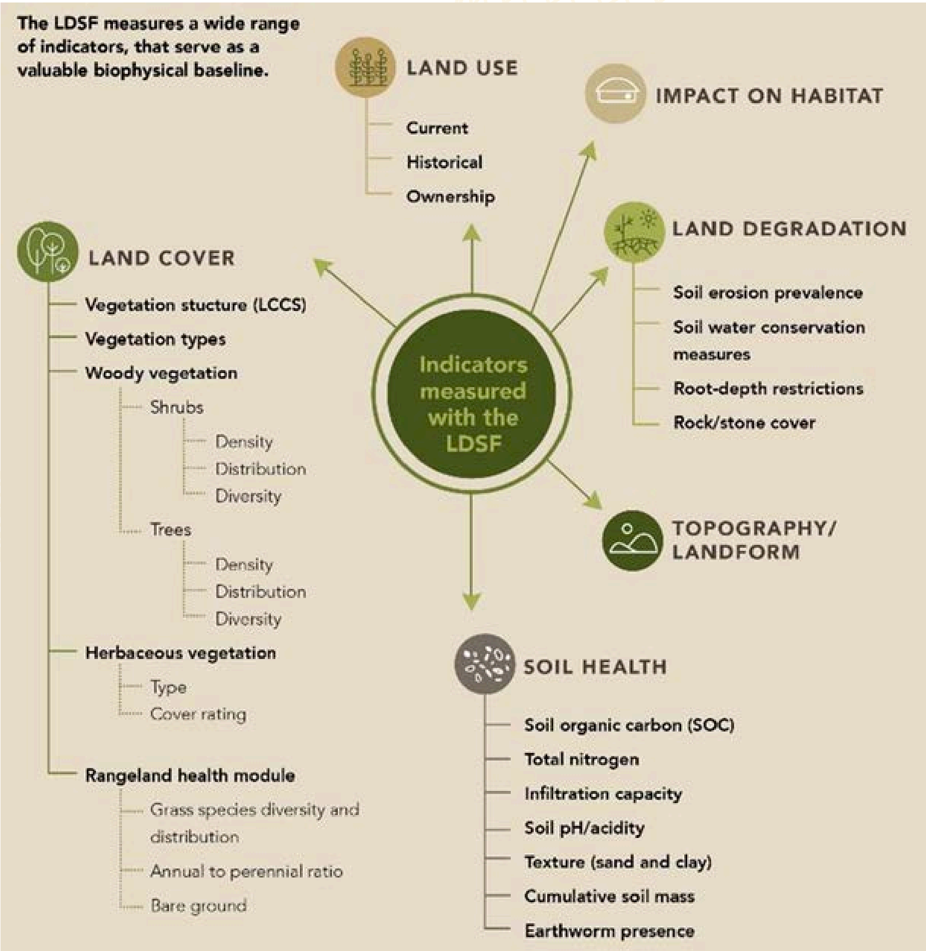


Figure 2: Concept of Land Degradation Surveillance Framework (LDSF)

2.1.2 Sampling for Land Degradation Surveillance Framework (LDSF) ground truthing sites:

For the purpose of this assignment, three LDSF sites were proposed, one for each of the three agro ecological zones covered by the project, ensuring some overlap (co-location) with intervention villages. The LDSF methodology follows a standardized sampling design, wherein each LDSF site spans 100 km^2 and contains 16 clusters, each with 10-1000 m^2 plots, randomly located within each cluster. Each plot has four sub-plots from which field measurements are subsequently taken. For this assignment, the LDSF sites corresponded to a sub-sample of villages targeted for the first phase of baseline data collection, with the plots sampled representing farmers' fields.

The data collected in the LDSF sites supports the assessment of soil health in farmers' fields via remote sensing, with spatial assessments and maps generated across all LCA intervention villages. These derived indicators inform land management interventions and enable the estimation of changes in soil organic carbon, a key opportunity for low-carbon agriculture. Key data points captured in the three LDSF sites included:

- **Soil infiltration capacity**
- **Erosion prevalence**
- **Soil texture**
- **Soil organic carbon**
- **Total nitrogen**
- **pH**
- **Tree and shrub species and densities**

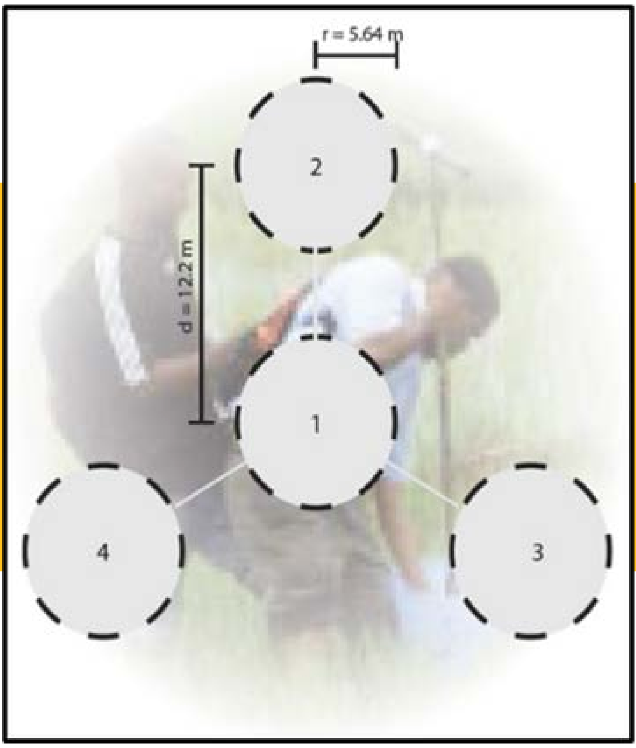


Figure 3: LDSF plot layout
1000 m^2 radial-arm plot layout. The dashed circles represent 100 m^2 sub-plots in which soil surface and vegetative observations were made. Georeferencing and infiltration measurements were conducted in the center of subplot 1

2.1.3 Training to implementing partners:

To introduce the concept of LDSF to implementing partners, we conducted an online training session on February 1, 2022. Additionally, an on-site training and demonstration were held on February 19, 2022, at the FES campus in Anand, Gujarat, for respective field staff from implementing partners. The objectives of these training sessions included briefing participants on the concept, terminologies, purpose, and methodology of LDSF, introduction to LDSF equipment demonstration of plot and subplot selection, sampling of topsoil, subsoil, and cumulative mass soil samples guidelines for filling out information and recording observations in LDSF forms and details of post-sampling procedures. Over 30 participants from AKF and AKRSPI actively participated in both online and offline training sessions.

Figure 4: Glimpses of onsite training cum demonstration on LDSF at FES campus located at Anand, Gujarat on 19th Feb 2022

2.1.4 LDSF survey implementation:

To undertake the LDSF survey, three LDSF sites namely Sayla from Gujarat, Jhirnya from Madhya Pradesh and Bahraich (Risia) from Uttar Pradesh were finalized through discussion with implementing partners. Through randomization technique, 16 clusters/villages per site comprising 15 GPS locations per cluster were selected for the survey (Figures 6-8). Out of these 15 locations, LDSF survey was actually undertaken on 10 locations. These locations were called LDSF plots or other plots that fell on the built area during the randomization step. There were an additional 5 locations per cluster to allow for the omission of inaccessible plots. Out of the selected GPS locations some were LCA farms while some were non-LCA. It was decided to have 3 extra LCA plots per cluster, in case all the locations of that cluster happen to be non-LCA. A minimum of 3 plots per cluster were confirmed to be LCA. This could ensure both LCA and non LCA farms in every cluster to get an inclusive picture. The selected locations were assured by implementing partners for their accessibility. For data collection as per LDSF methodology, a specially developed mobile-based ODK collect app was used.

Cluster-wise maps were prepared to guide the LDSF survey implementing team to identify locations. A team of 4 members from Bhilwara, Rajasthan was identified and trained thoroughly for soil sampling and recording various observations, as per the LDSF methodology. At each site, a local person was also identified with the help of implementing partners who accompanied the team while conducting the survey. With the support of implementing partners, the team completed the LDSF survey at all three sites successfully and on time. During the process, apt monitoring and on-site guidance were provided. Regular data checks, server uploads and resolving incidental queries throughout the survey was also conducted. Collected samples were then transported from the respective sites to the selected laboratory in Hyderabad, for analysis. The LDSF survey was conducted during March to July 2022 as mentioned in Table no 1 and Figure 5.

Table no. 1: Details of conducted LDSF surveys

Sr. No.	Site	Duration (2022)	No. of cluster/villages	Plots sampled	Soil samples collected
1	Sayla	22 Mar-10 Apr	16	207	384
2	Zhirnya	23 May - 10 Jun	24	209	420
3	Risia	20 Jun - 4 Jul	16	211	484
		TOTAL	**56**	**627**	**1288**

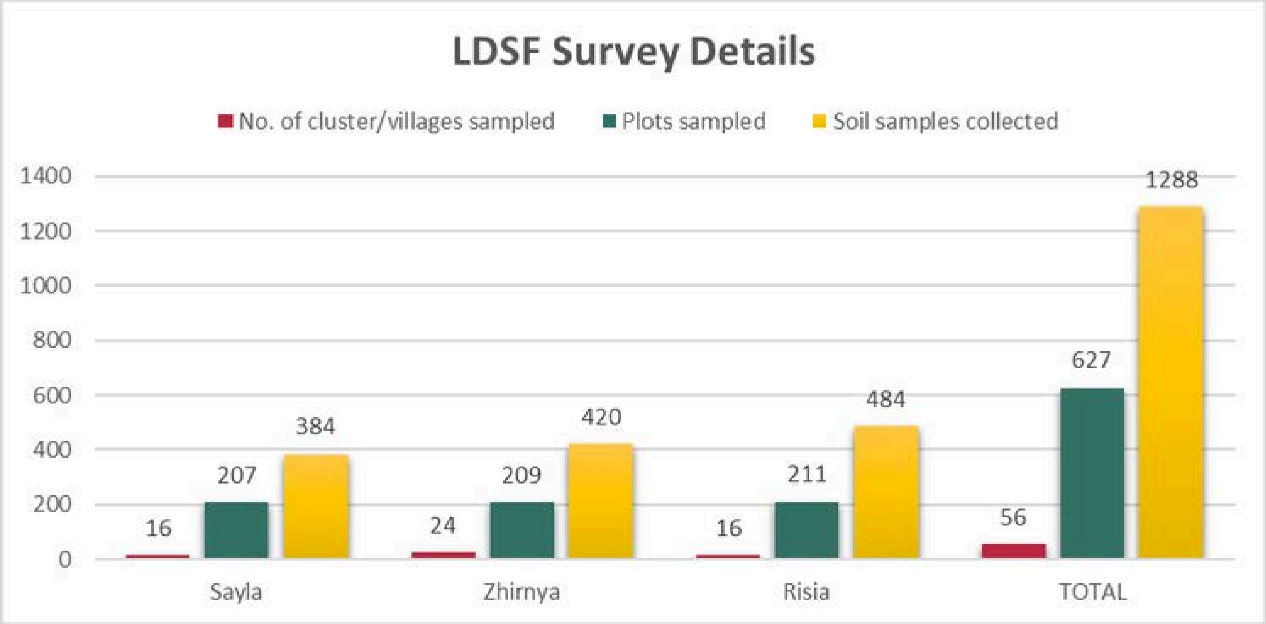
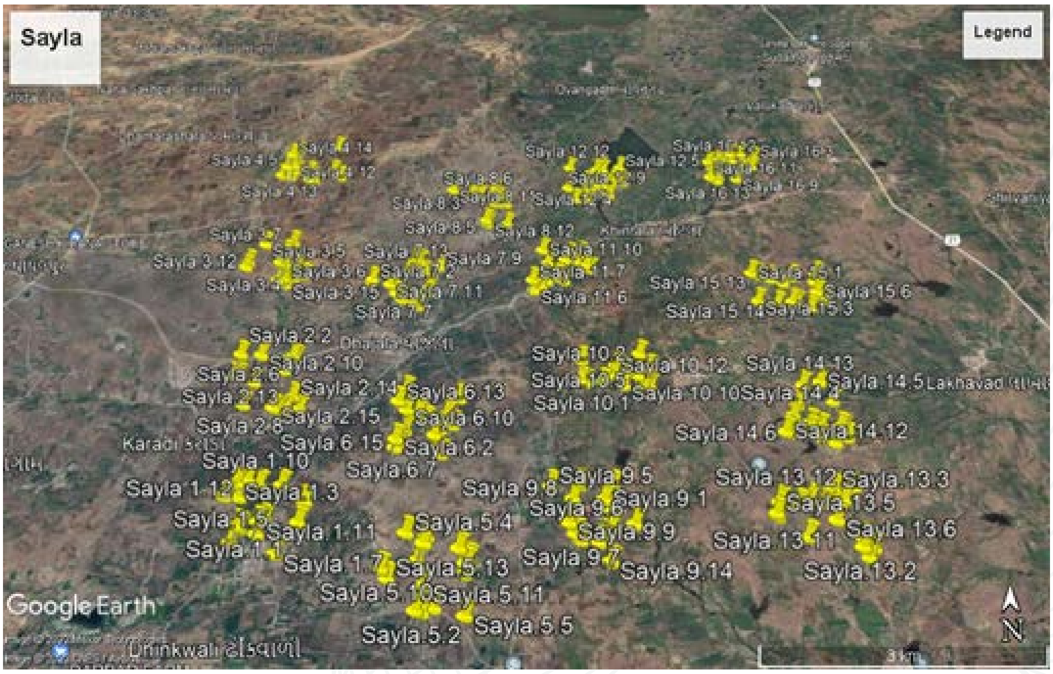
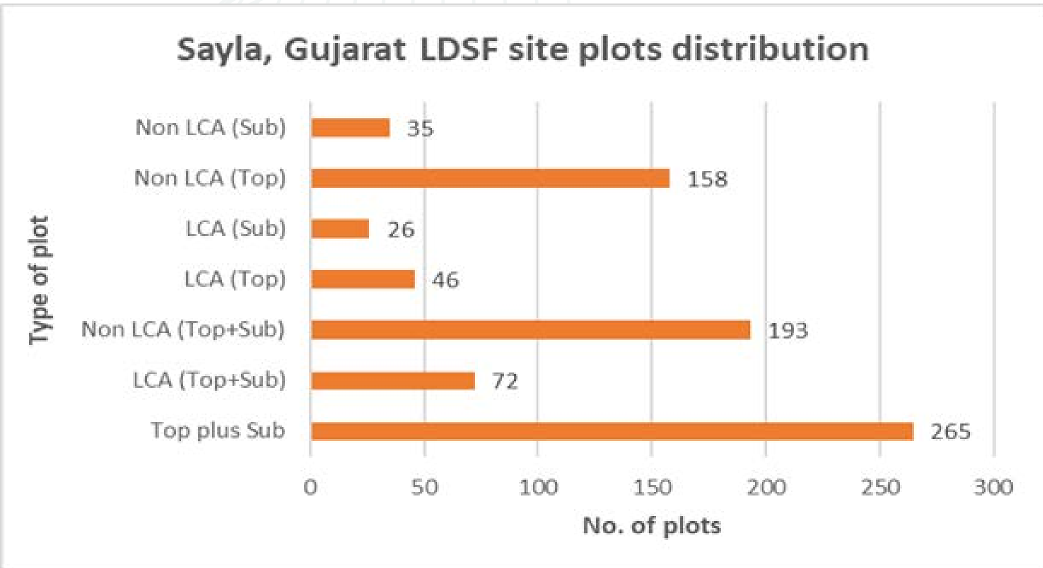


Figure 5: Details of conducted LDSF surveys

Sayla LDSF site, Gujarat

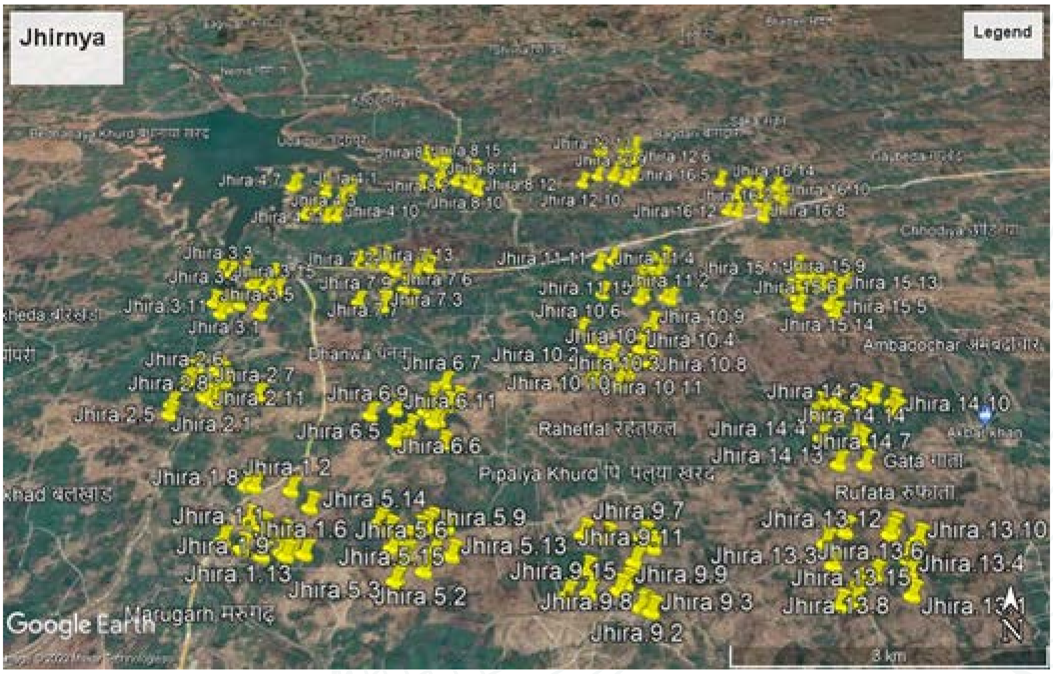


(a)



(b)

Figure 6: LDSF sample locations - The 16 clusters comprising 15 GPS locations per cluster (a) and LDSF LCA and non-LCA plots distribution (b) from Sayla site, Gujarat



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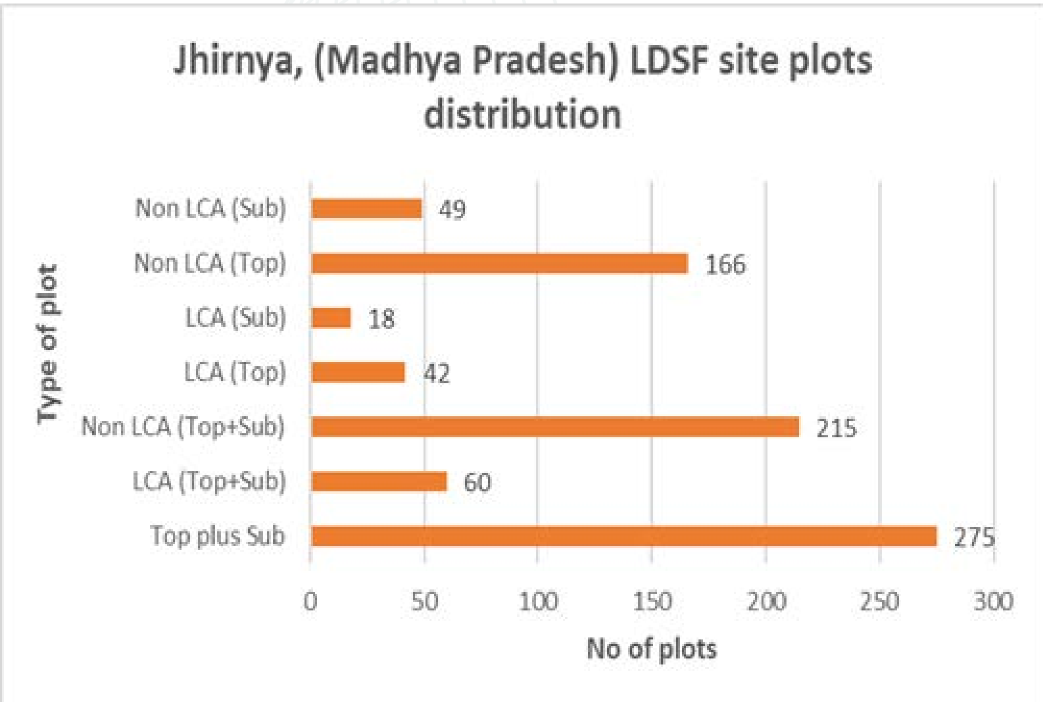
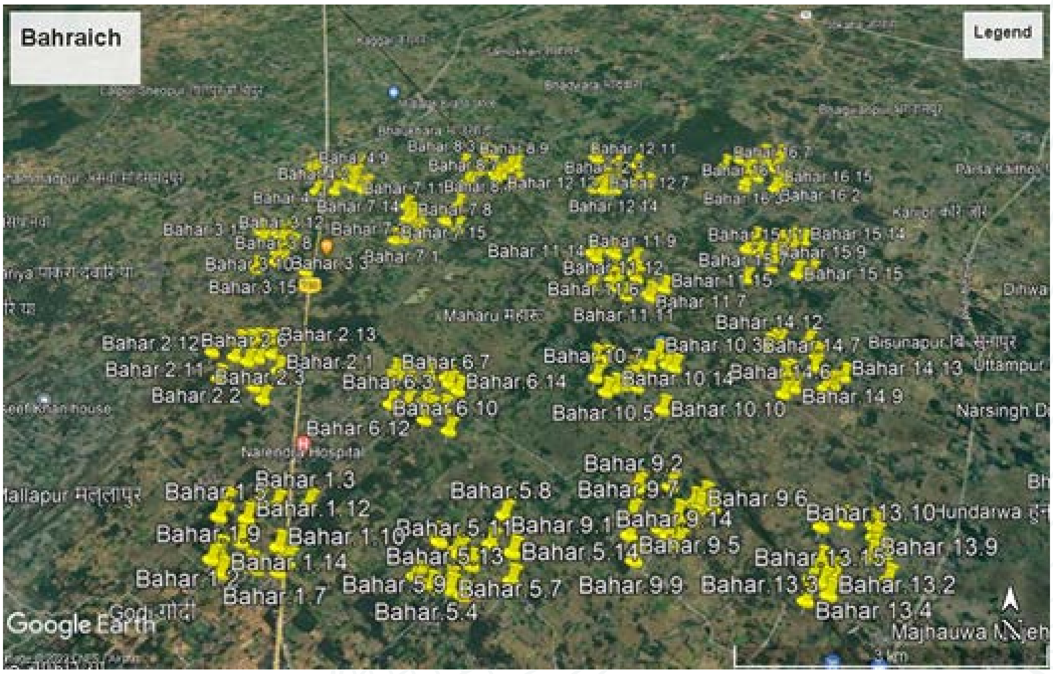


(b)

Figure 7: LDSF sample locations - The 16 clusters comprising 15 GPS locations per cluster (a) and LDSF LCA and non-LCA plots distributions (b) from Jhirnya site, Madhya Pradesh



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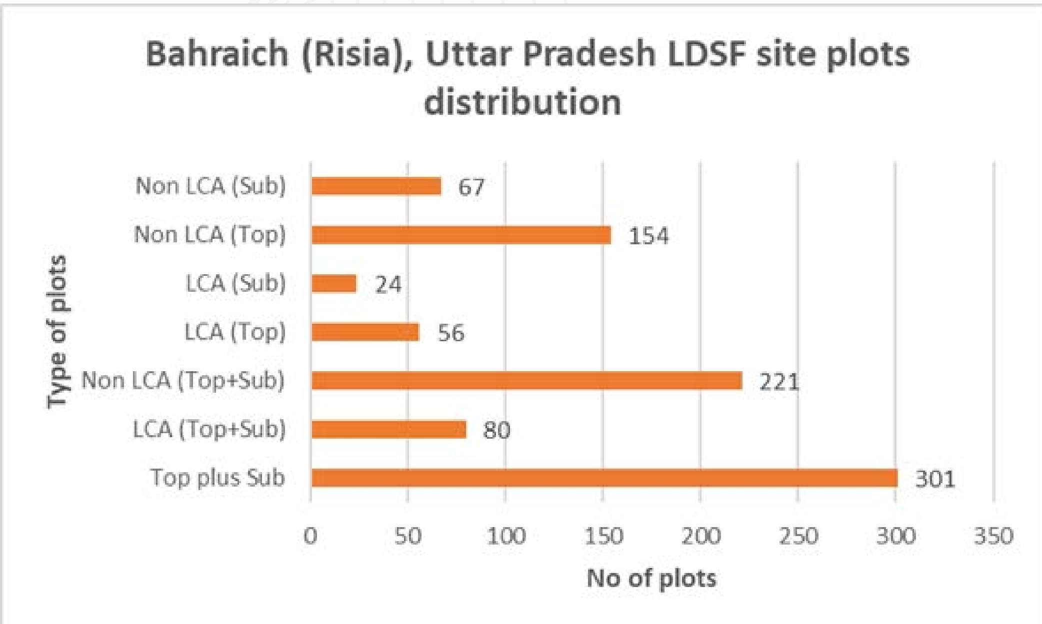


(b)

Figure 8: LDSF sample locations - The 16 clusters comprising 15 GPS locations per cluster (a) and LDSF LCA and non-LCA plots distribution (b) from Bahraich (Risia) site, Uttar Pradesh

Recording observation related to infiltration at Sayla

Recording observations related to the vegetation at Jhirnya

Recording observation related to infiltration at Sayla

Figure 9: Photographs during the LDSF survey at Sayla from Gujarat, Jhirnya from Madhya Pradesh and Risia from Uttar Pradesh

Below is an example of a typical map of the LDSF cluster from Risia block (Figure 10). The location of the sampling plot is randomly determined to capture representativeness at the landscape level and avoid any type of bias.

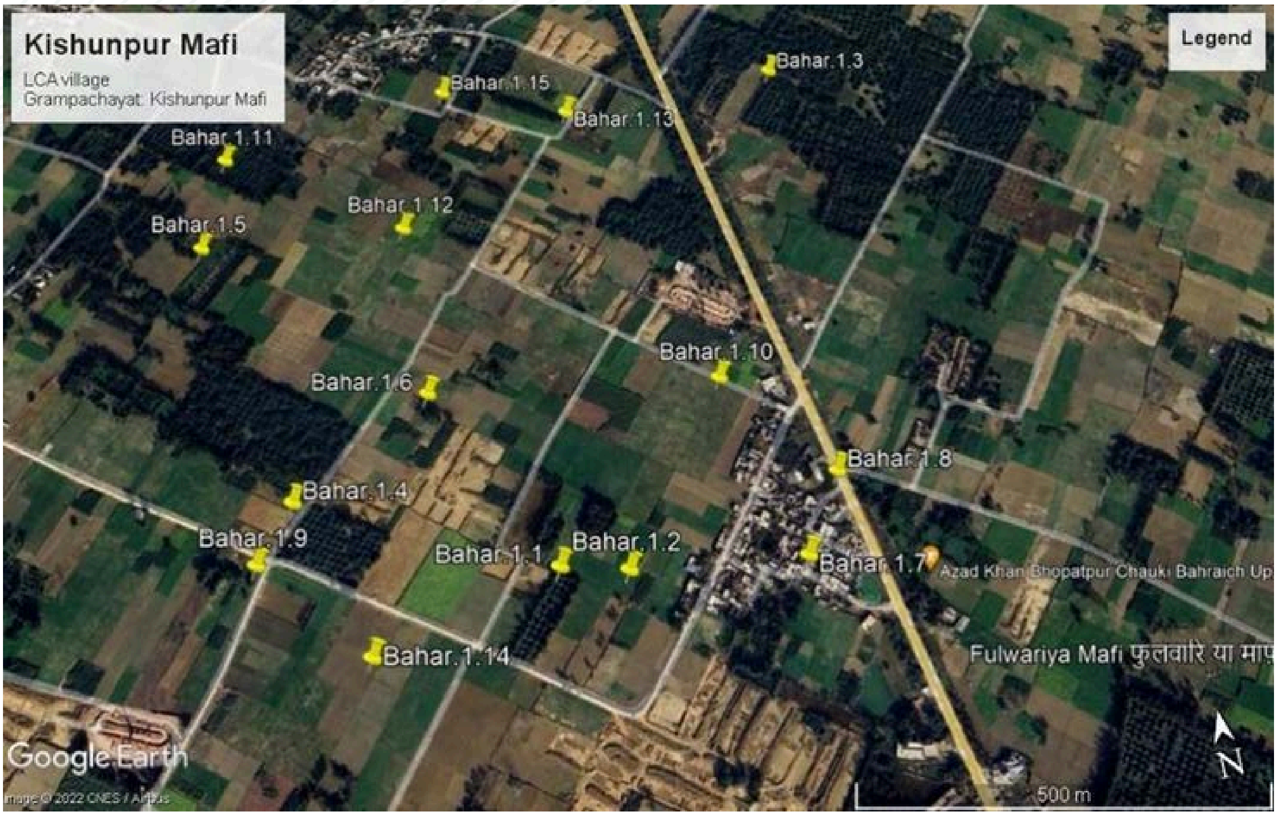
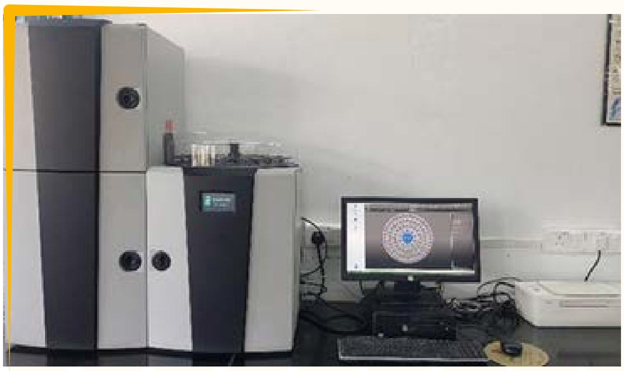


Figure 10: Typical map of LDSF cluster from Risia block, Bahraich district, Uttar Pradesh

2.1.5 Soil samples shifting and analysis:

Soil samples collected from Sayla (Gujarat), Jhirnya (Madhya Pradesh), and Risia (Uttar Pradesh) were transferred to and received by the Charles Renard Analytical Laboratory (CRAL) at the International Crops Research Institute for the Semi-Arid Tropics (ICRISAT), Hyderabad. The Charles Renard Analytical Laboratory, established in 1978, is renowned for its state-of-the-art facilities and expertise in soil, plant, and water analysis. The laboratory has been a member of the FAO-Global Soil Laboratory Network since 2019 (CRAL Online portal: https://analyticalab.icrisat.org).

This laboratory has advanced and sophisticated equipment for soil analysis (Figure 11).



Total organic carbon and total nitrogen analyser (TC – TN analyser)

Analyst from laboratory working on Auto-analyser

Figure 11: Various advanced and highly sophisticated equipment at CRAL, ICRISAT, Hyderabad

Table no. 2: List of soil health parameters

Sr. No.	Name of soil parameter
A	**Physical:**
1	pH
2	Bulk density
3	Soil texture
B	**Chemical:**
1	Total organic carbon
2	Total nitrogen

2.2 Sampling of villages and farming family:

To assess the adoption of low carbon agricultural practices and its environmental and socio-economic benefits using key farm and farmer-level indicators, data were captured from a panel of representative farming families. To account for significant intra-village variation in terms of both farming family characteristics and the uptake of LCA practices, proportional random sampling was used. Using this sampling approach, 20 farming families were selected from each of the 55 pilot villages across the three states resulting in a total sample size of 1100 farming families. For each of the sampled farming families, male and female respondents were identified at random to ensure gender balance for questions addressed to individual respondents. Figure 12 shows the survey locations and the number of farming families interviewed at the baseline.

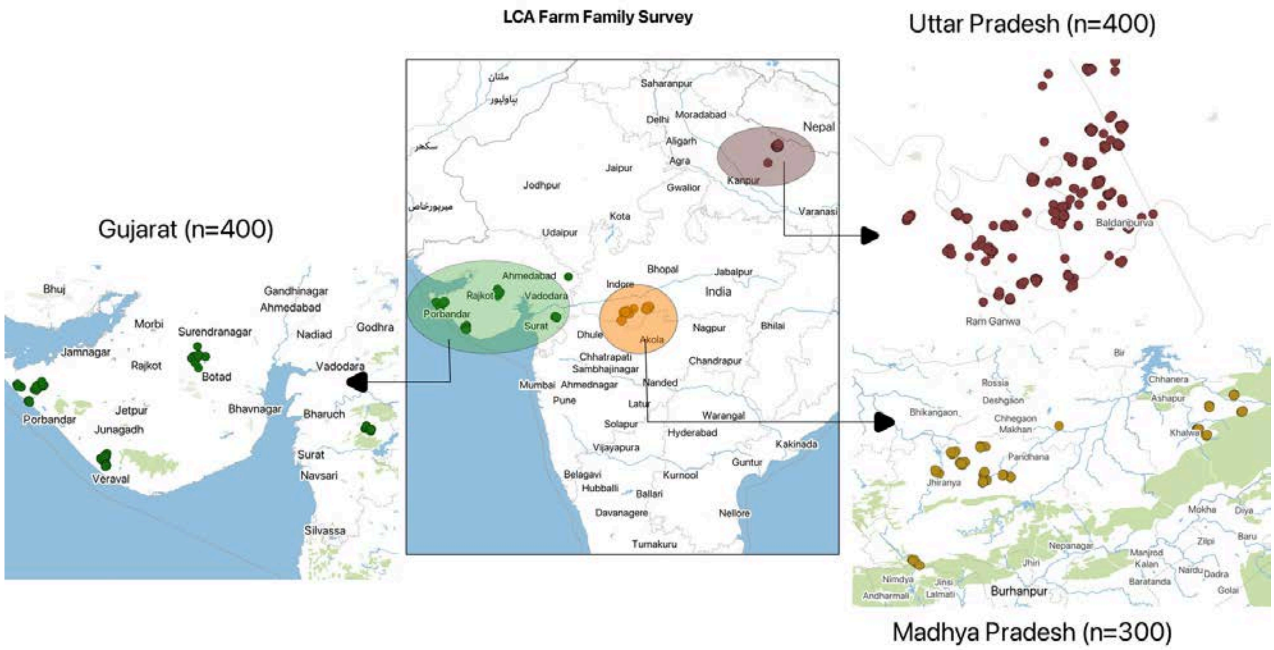


Figure 12: Locations and number of sampled farming families at baseline across the three states.

2.2.1 Baseline, follow up and endline surveys:

The baseline survey was carried out from May to June 2022 across the three states. The baseline aimed to establish farming family socio-economic and biophysical characteristics including the adoption of LCA practices. The baseline data captured key information related to the key indicators at the farm and family levels for the Kharif season 2020, using a recall question, and Kharif season 2021. A streamlined survey instrument for Computer-Assisted Personal Interviewing (CAPI) was designed, in English and translated into local languages, for the data collection at the household and village levels.

The family-level survey consisted of 14 modules, each comprising a set of questionnaires. The modules were designed considering the project interventions outcome targets. Through questionnaires, the modules covered information related to household demographics, land ownership and field-based agricultural practices, asset ownership, participation in social groups, food security status, coping strategies behaviours, use and management of communal resources, women's participation in key decision making at the family level, etc. Field-based data on agricultural practices aimed to track the uptake of practices and scaling back of HCA practices. Household (farming family) and farm characteristics data were used to enable broader analysis of the socio-economic impacts of changes in practices.

The village-level survey, on the other hand, consisted of seven sections, each comprising a set of questions each capturing data related to land, agriculture, marketing, commons, institutions, etc. at the village level to enrich information captured at the farming family level.

A midline follow-up survey was conducted from May to Dec 2023 to assess progress on the key farm and farmer-level indicators and the adoption of LCA practices for adaptive management. A reduced version of the baseline survey tool was used for the follow-up survey.

The endline survey was conducted from April to August 2024 to track and assess changes in the key outcome indicators. Out of the 1,100 Households surveyed at baseline (Figure 13), 1,046 households were successfully tracked, with only 54 households lost to follow-up (< 5 percent attrition) for various factors, including temporary migration and unwillingness to be interviewed. The endline survey captured key information related to the outcome indicators at the farm and family levels for the Kharif 2023 and Rabi 2024 cropping seasons using a revised version of the baseline survey tool.

2.2.2 Implementation of the farming family survey

For the three surveys , CIFOR-ICRAF partnered with a data collection firm called Morsel Agency based in India. After designing the survey instrument, a locally recruited data collection team of enumerators and supervisors was trained on the survey tools and the use of the mobile app to conduct the interviews and collect quality data. The training was held online for the baseline and follow-up surveys, while at the endline in person training was conducted by the CIFOR-ICRAF and MORSEL team at Lucknow, India. The data were collected using SurveyCTO, an ODK-based computer-assisted personal interviews (CAPI) tool. Trained enumerators interviewed respondents in a face-to-face setting and entered responses into an offline application on the tablets or smartphones provided to them. Collected data were sent to SurveyCTO server every evening once an internet connection was available. Then, the data were subjected to a thorough quality assessment by the CIFOR-ICRAF team, and near real-time feedback was provided to the MORSEL field team for rectification of any issues.

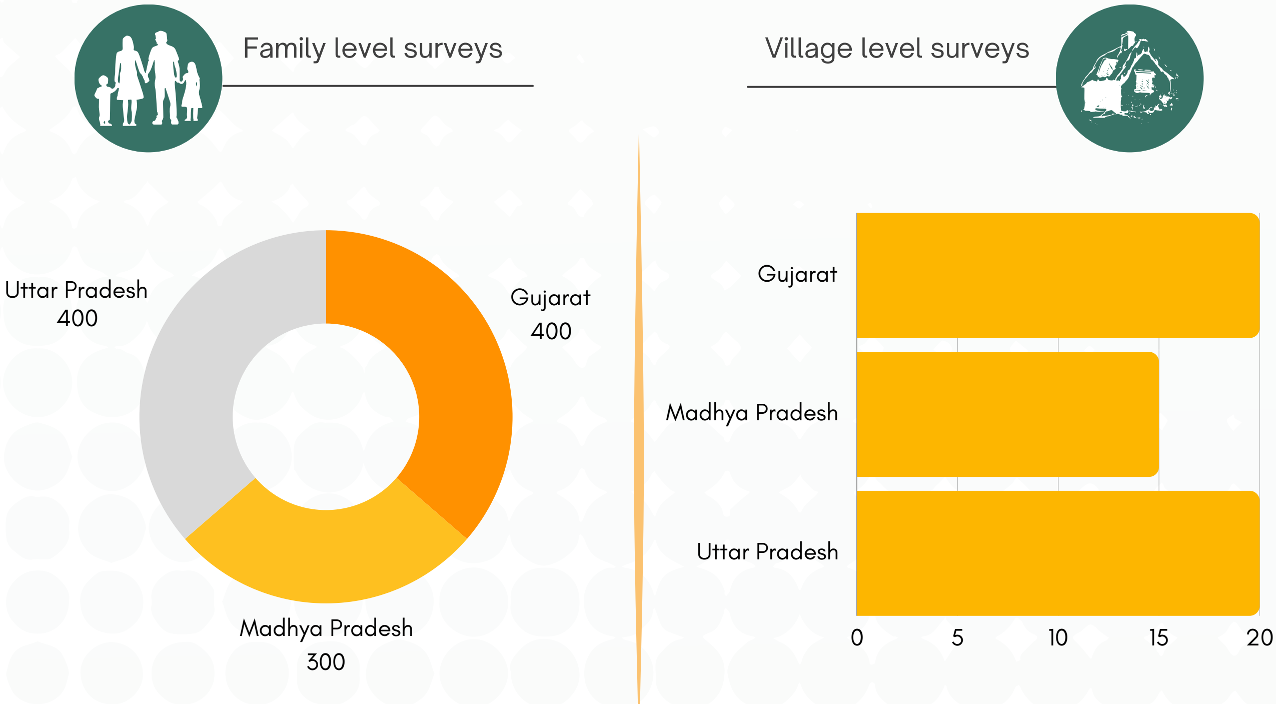


Figure 13: Farm family and village level survey conducted across the three states at the baseline

2.2.3 Survey data cleaning and analysis

Collected data were cleaned, and indicators were constructed using Stata 17, while visualization materials were produced in R[2]. During data cleaning, we removed extreme outliers (values that are more than three times the interquartile range) from the dataset, assuming they were the results of enumerator error.

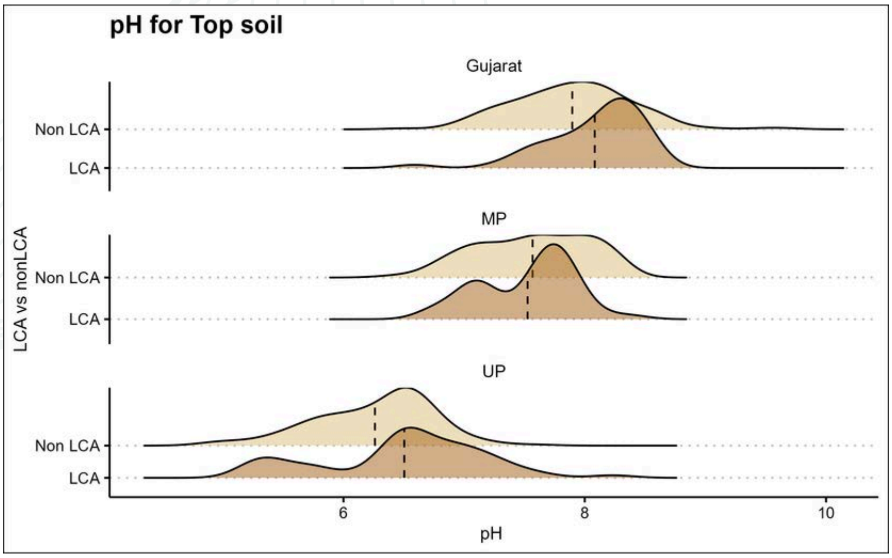
[2] R Core Team. (2020). R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. Retrieved from https://www.R-project.org/

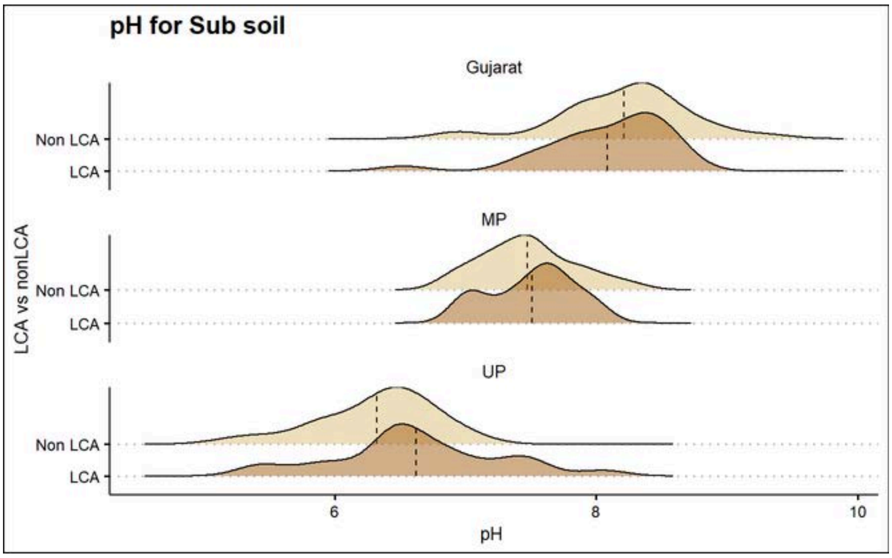
3. Results and discussion from Land Degradation Surveillance Framework (LDSF) survey

The results and discussion for soil properties and LDSF observations are mentioned below with the help of density plots and statistical analysis. A density plot shows frequency or repeated occurrence of a value with respect to its spread. A more width of the plot indicates more spread of the value while height indicates larger occurrence of the corresponding value. The dotted vertical line shown in the plot denotes the weighted average value.

3.1 Soil *pH*:

Soil pH has a significant influence on the availability of nutrients to plants. The optimal *pH* range for nutrient availability is between 6.0 and 7.0 and is called neutral. Below this range the soil is acidic while above the range refers to alkaline soil and leads to unavailability of various nutrients. The density plot below shows the average pH value in LCA and non-LCA plots as well as in Top and Subsoil at three locations namely Sayla (Gujarat), Jhirnya (Madhya Pradesh) and Risia, Bharich (Uttar Pradesh).





From the figures above, the pH overall status was observed as 'moderately alkaline' along with slight depth-wise variation at Sayla. We recorded higher pH in Topsoil of LCA plot than non LCA while Higher *pH* in Sub-soil of LCA plot than non-LCA plot. Observing the soil data from Jhirnya, the pH overall status was seen to be 'nearly neutral to alkaline' along with slight depth-wise and plot-wise variation while at third site that is UP, pH was 'slightly acidic to nearly neutral'.

Table no. 3: The *pH* trends are summarized

Gujarat	Madhya Pradesh	Uttar Pradesh
'Moderately alkaline'	'Nearly neutral to alkaline'	'Slightly acidic to nearly neutral'
No depth-wise variation in LCA plots	Slight depth-wise variation in LCA plots	Depth-wise variation in LCA plots
Depth-wise variation in non-LCA plots	Depth wise variation in non LCA plots	Depth-wise variation in non LCA plots
Higher pH in Topsoil of LCA plot than non-LCA	Lower *pH* in Topsoil of LCA plot than non-LCA	Higher *pH* in Topsoil of LCA plot than non-LCA
Lower *pH* in Subsoil of LCA plot than non-LCA	Higher *pH* in Subsoil of LCA plot than non-LCA	Higher *pH* in Subsoil of LCA plot than non-LCA

Further, we tried to see whether the changes in soil properties of LCA and non-LCA plots are statistically significant, by using 't' test at significance level of 5%.

Statistical Analysis

Sayla LDSF Site, Gujarat

pH (Top)	*LCA*	*Non LCA*
Mean	8.082609	7.896076
Variance	0.159424	0.243727
Observations	46	158
Hypothesized Mean Difference	0	
df	89	
t Stat	2.635779	
P(T<=t) one-tail	0.004951	
t Critical one-tail	1.662155	
P(T<=t) two-tail	**0.009903**	
t Critical two-tail	1.986979	

pH (Sub)	*LCA*	*Non LCA*
Mean	8.0819231	8.2142857
Variance	0.2259202	0.246984
Observations	26	35
Hypothesized Mean Difference	0	
df	55	
t Stat	-1.054827	
P(T<=t) one-tail	0.1480581	
t Critical one-tail	1.673034	
P(T<=t) two-tail	**0.2961161**	
t Critical two-tail	2.0040448	

Jhirnya LDSF site, Madhya Pradesh (MP)

pH (Top)	*LCA*	*Non LCA*
Mean	7.525952381	7.567650602
Variance	0.149658827	0.213408386
Observations	42	166
Hypothesized Mean Difference	0	
df	74	
t Stat	-0.59881959	
P(T<=t) one-tail	0.275560974	
t Critical one-tail	1.665706893	
P(T<=t) two-tail	**0.551121949**	
t Critical two-tail	1.992543495	

pH (Sub)	*LCA*	*Non LCA*
Mean	7.506666667	7.474489796
Variance	0.104611765	0.126646088
Observations	18	49
Hypothesized Mean Difference	0	
df	33	
t Stat	0.351154142	
P(T<=t) one-tail	0.363852403	
t Critical one-tail	1.692360309	
P(T<=t) two-tail	**0.727704805**	
t Critical two-tail	2.034515297	

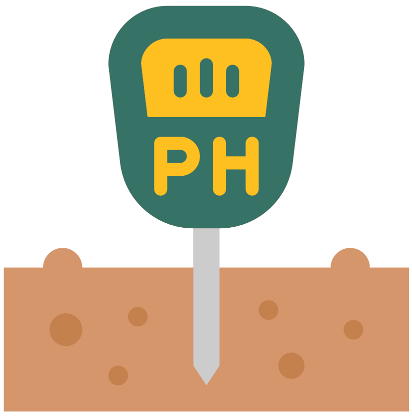
Bahraich (Risia) LDSF site, Uttar Pradesh (UP)

pH (Top)	*LCA*	*Non LCA*
Mean	6.503928571	6.260844156
Variance	0.459613377	0.238526734
Observations	56	154
Hypothesized Mean Difference	0	
df	77	
t Stat	2.461022074	
P(T<=t) one-tail	0.008046284	
t Critical one-tail	1.664884537	
P(T<=t) two-tail	**0.016092568**	
t Critical two-tail	1.991254395	

pH (Sub)	*LCA*	*Non LCA*
Mean	6.62375	6.319552
Variance	0.410824	0.202635
Observations	24	67
Hypothesized Mean Difference	0	
df	32	
t Stat	2.143403	
P(T<=t) one-tail	0.019892	
t Critical one-tail	1.693889	
P(T<=t) two-tail	**0.039783**	
t Critical two-tail	2.036933	

The above tables show significant and slightly higher pH in Topsoil of LCA plots over non-LCA and non-significant but higher *pH* in Subsoil of LCA plots over non-LCA plots. Overall, not much variation in soil *pH* was observed at Sayla. At Jhirnya, slight depth-wise variation and plot-wise variation was noted but the change was not significant.

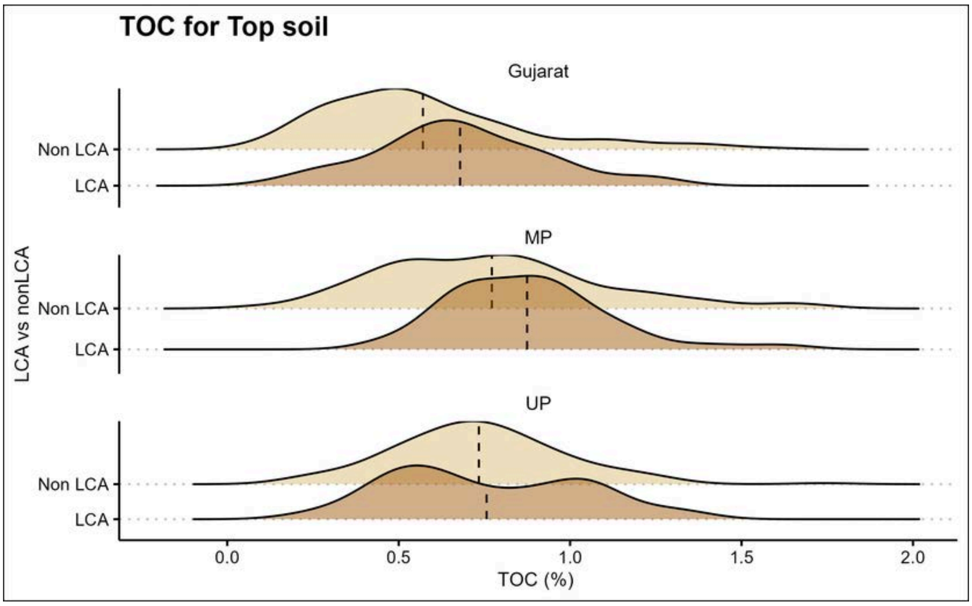
Significant increase in of *pH* in Topsoil and Subsoil of LCA plot over non-LCA at Bahraich possible shows positive impact as the increase in pH of both Topsoil and Subsoil of LCA plots are towards neutral class.



3.2 Soil Organic Carbon:

Soil organic carbon is a basic indicator of soil health. Organic carbon is basis of soil fertility and serves like a nutrient store house. Therefore, it is crucial to increase its content in soil.

At Sayla, focusing on soil organic carbon content, the samples were categorized as 'low to medium'. Soil organic carbon found to be higher in Topsoil than Subsoil in LCA plots and non-LCA plots and higher in Topsoil and sub soil of LCA plots than non-LCA plots.
At Jhirnya, it was categorized as 'medium'. Soil organic carbon was higher in Topsoil than Subsoil in LCA plots and non-LCA plots and higher in Topsoil and Subsoil of LCA plot than non-LCA plots.
In case of soil organic carbon content at Bahraich, the overall status was 'medium' and it was higher in Topsoil than Subsoil in LCA plots and non-LCA plots and also higher in Topsoil and Subsoil of LCA plots than non-LCA plots.



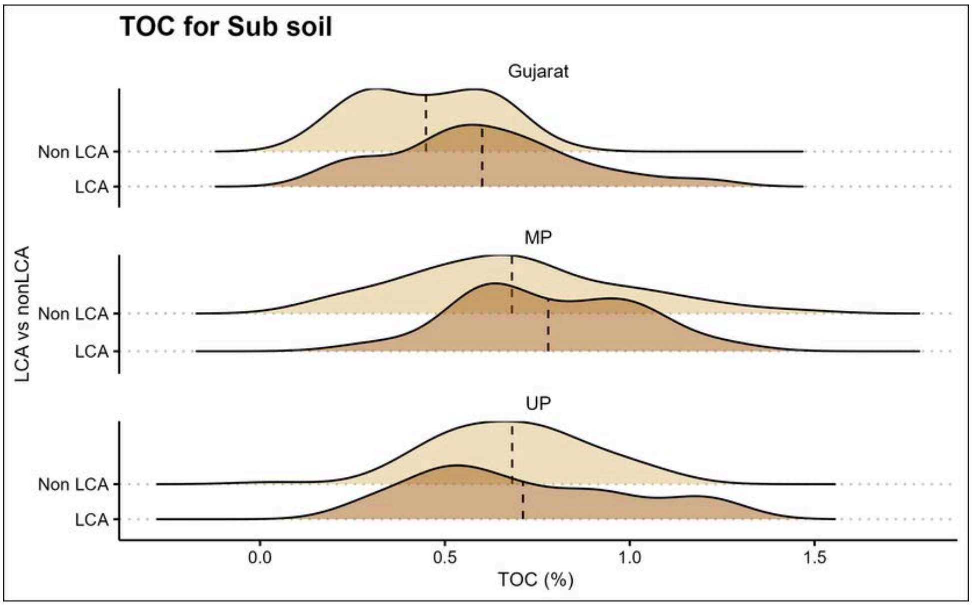


Table no. 4: Summarizes the plot-wise and location-wise variation and content of soil organic carbon

Gujarat	Madhya Pradesh	Uttar Pradesh
‘Low to medium’	‘Medium’	‘Medium’
Higher in Topsoil than Subsoil in LCA plots	Higher in Topsoil than Subsoil in LCA plots	Higher in Topsoil than Subsoil in LCA plots
Higher in Topsoil than Subsoil in non-LCA plots	Higher in Topsoil than Subsoil in non-LCA plots	Higher in Topsoil than Subsoil in non-LCA plots
Higher in Topsoil of LCA plot than non-LCA	Higher in Topsoil of LCA plot than non-LCA	Higher in Topsoil of LCA plot than non-LCA
Higher in Subsoil of LCA plot than non-LCA	Higher in Subsoil of LCA plot than non-LCA	Higher in Subsoil of LCA plot than non-LCA

Further, from statistical analysis, it was reported that the increase in soil organic carbon content in Top and Subsoil of LCA plots over non-LCA plots was statistically significant and that may be attributed to positive impact of LCA practices at Sayla.

Statistical Analysis

Sayla LDSF Site, Gujarat

Soil organic carbon (%) (Top)	*LCA*	*Non LCA*
Mean	0.678988	0.570723
Variance	0.06199	0.089332
Observations	46	158
Hypothesized Mean Difference	0	
df	86	
t Stat	2.475321	
P(T<=t) one-tail	0.007637	
t Critical one-tail	1.662765	
P(T<=t) two-tail	**0.015273**	
t Critical two-tail	1.987934	

Soil organic carbon (%) (Sub)	*LCA*	*Non LCA*
Mean	0.600838	0.448874
Variance	0.062894	0.030669
Observations	26	35
Hypothesized Mean Difference	0	
df	42	
t Stat	2.647259	
P(T<=t) one-tail	0.005688	
t Critical one-tail	1.681952	
P(T<=t) two-tail	**0.011377**	
t Critical two-tail	2.018082	

Jhirnya LDSF site, Madhya Pradesh (MP)

Soil organic carbon (%) (Top)	*LCA*	*Non LCA*
Mean	0.8745819	0.7717437
Variance	0.05313155	0.1050254
Observations	42	166
Hypothesized Mean Difference	0	
df	87	
t Stat	2.36068678	
P(T<=t) one-tail	0.01023808	
t Critical one-tail	1.66255735	
P(T<=t) two-tail	**0.02047616**	
t Critical two-tail	1.98760828	

Soil organic carbon (%) (Sub)	*LCA*	*Non LCA*
Mean	0.77945927	0.68131101
Variance	0.05275149	0.08424685
Observations	18	49
Hypothesized Mean Difference	0	
df	38	
t Stat	1.43932185	
P(T<=t) one-tail	0.07912329	
t Critical one-tail	1.68595446	
P(T<=t) two-tail	**0.15824659**	
t Critical two-tail	2.02439416	

At Jhirnya, in Topsoil, the increase was statistically significant denoting overall improvement in the content of organic carbon. Though statically non-significant increase was observed at Bahraich (Risia) but still slight increase also can be taken into consideration as a good sign as to change soil organic carbon in such a short period of time is difficult.

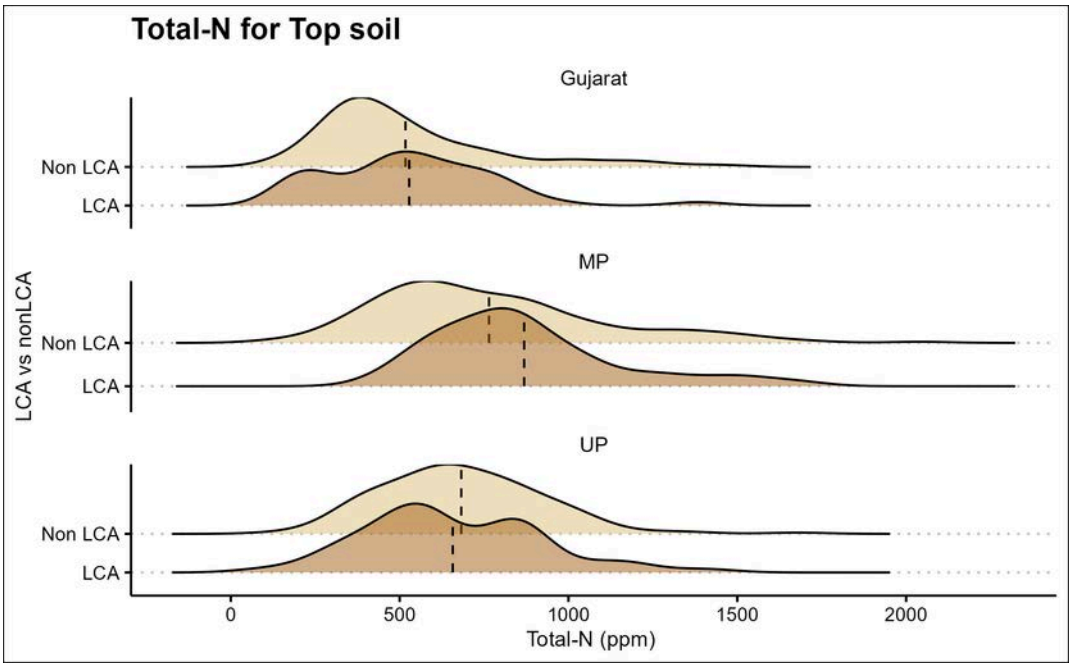
Bahraich (Risia) LDSF site, Uttar Pradesh (UP)

Soil organic carbon (%) (Top)	*LCA*	*Non LCA*
Mean	0.756426385	0.733926129
Variance	0.079917791	0.060998066
Observations	56	154
Hypothesized Mean Difference	0	
df	87	
t Stat	0.526951859	
P(T<=t) one-tail	0.299784053	
t Critical one-tail	1.662557349	
P(T<=t) two-tail	**0.599568106**	
t Critical two-tail	1.987608282	

Soil organic carbon (%) (Sub)	*LCA*	*Non LCA*
Mean	0.711262789	0.68192714
Variance	0.085249718	0.04190398
Observations	24	67
Hypothesized Mean Difference	0	
df	31	
t Stat	0.453875967	
P(T<=t) one-tail	0.326539917	
t Critical one-tail	1.695518783	
P(T<=t) two-tail	**0.653079835**	
t Critical two-tail	2.039513446	

3.3 Nitrogen content (ppm):

Coming to nitrogen content, higher content in Topsoil of LCA plots was noticed than non-LCA plots at Sayla while nitrogen content was found to be higher in Topsoil and Subsoil of LCA plot than non-LCA plot at Jhirnya. Bahraich site showed improvement in LCA plots over non-LCA plots.



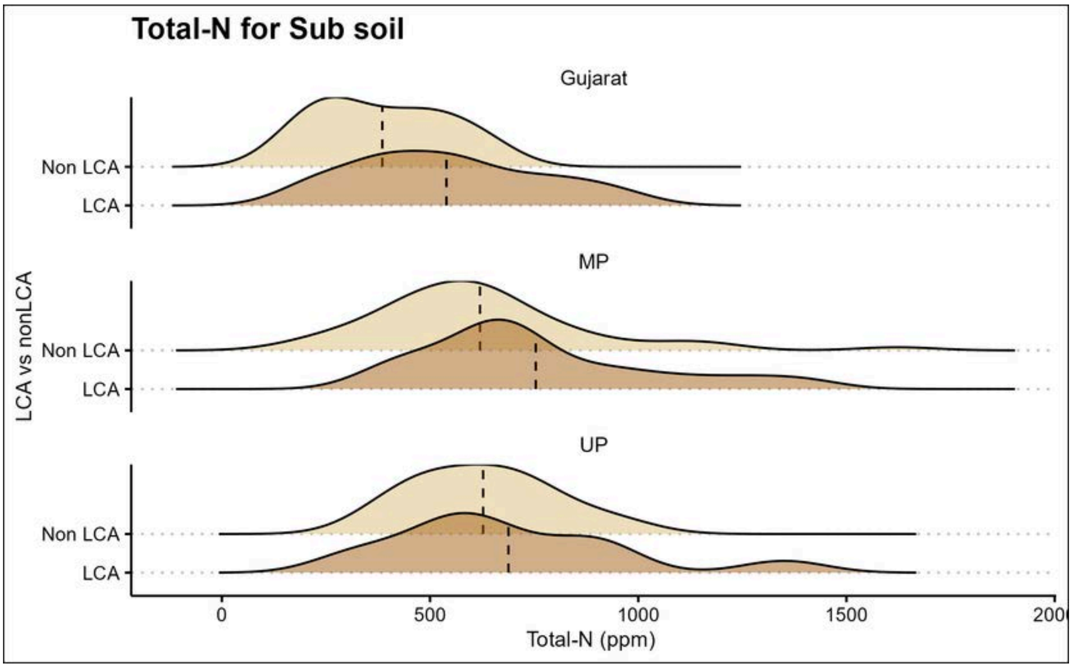


Table no. 5: The scenario of soil nitrogen content

Gujarat	Madhya Pradesh	Uttar Pradesh
Higher content in Subsoil than Topsoil in LCA Plots	Higher content in Subsoil than Topsoil in LCA Plots	Higher content in Subsoil than Topsoil in LCA Plots
Higher content in Topsoil than Subsoil in non-LCA plots	Higher content in Topsoil than Subsoil in non-LCA plots	Higher content in Topsoil than Subsoil in non-LCA plots
Higher content in Topsoil of LCA plot than non-LCA plot	Higher content in Topsoil of LCA plot than non-LCA plot	Higher content in Topsoil of non-LCA plot than LCA plot
Higher content in Subsoil of LCA plot than non-LCA plot	Higher content in Subsoil of LCA plot than non-LCA plot	Higher content in Subsoil of LCA plot than non-LCA plot

With respect to statical analysis showed below, non-significant increase in nitrogen content of LCA plots over non-LCA plots at Sayla may indicate focused and continued implementation of LCA practices along with monitoring the changes.
Statistically significant and higher content of soil nitrogen in Topsoil, showed overall improvement in nitrogen content at Jhirnya. At Bharaich, the observations of soil nitrogen content were like that of Jhirnya.

Statistical Analysis

Sayla LDSF Site, Gujarat

Total N (ppm) (Top)	*LCA*	*Non LCA*
Mean	528.3587	517.3642
Variance	60437.42	70732.47
Observations	46	158
Hypothesized Mean Difference	0	
df	78	
t Stat	0.261956	
P(T<=t) one-tail	0.397023	
t Critical one-tail	1.664625	
P(T<=t) two-tail	**0.794046**	
t Critical two-tail	1.990847	

Total N (ppm) (Sub)	*LCA*	*Non LCA*
Mean	539.38462	385.364286
Variance	50272.086	23405.8285
Observations	26	35
Hypothesized Mean Difference	0	
df	42	
t Stat	3.0192638	
P(T<=t) one-tail	0.0021484	
t Critical one-tail	1.6819524	
P(T<=t) two-tail	**0.0042968**	
t Critical two-tail	2.0180817	

Jhirnya LDSF site, Madhya Pradesh (MP)

Total N (ppm) (Top)	*LCA*	*Non LCA*
Mean	868.7142857	764.80271
Variance	77322.08101	113658.97
Observations	42	166
Hypothesized Mean Difference	0	
df	75	
t Stat	2.067633297	
P(T<=t) one-tail	0.02106209	
t Critical one-tail	1.665425373	
P(T<=t) two-tail	**0.042124181**	
t Critical two-tail	1.992102154	

Total N (ppm) (Sub)	*LCA*	*Non LCA*
Mean	753.902222	620.02041
Variance	76655.3486	68714.653
Observations	18	49
Hypothesized Mean Difference	0	
df	29	
t Stat	1.7794105	
P(T<=t) one-tail	0.04282808	
t Critical one-tail	1.69912703	
P(T<=t) two-tail	**0.08565616**	
t Critical two-tail	2.04522964	

Bahraich (Risia) LDSF site, Uttar Pradesh (UP)

Total N (ppm) (Top)	*LCA*	*Non LCA*
Mean	657.3482	682.4838
Variance	67628.7	55331
Observations	56	154
Hypothesized Mean Difference	0	
df	90	
t Stat	-0.63498	
P(T<=t) one-tail	0.263526	
t Critical one-tail	1.661961	
P(T<=t) two-tail	**0.527051**	
t Critical two-tail	1.986675	

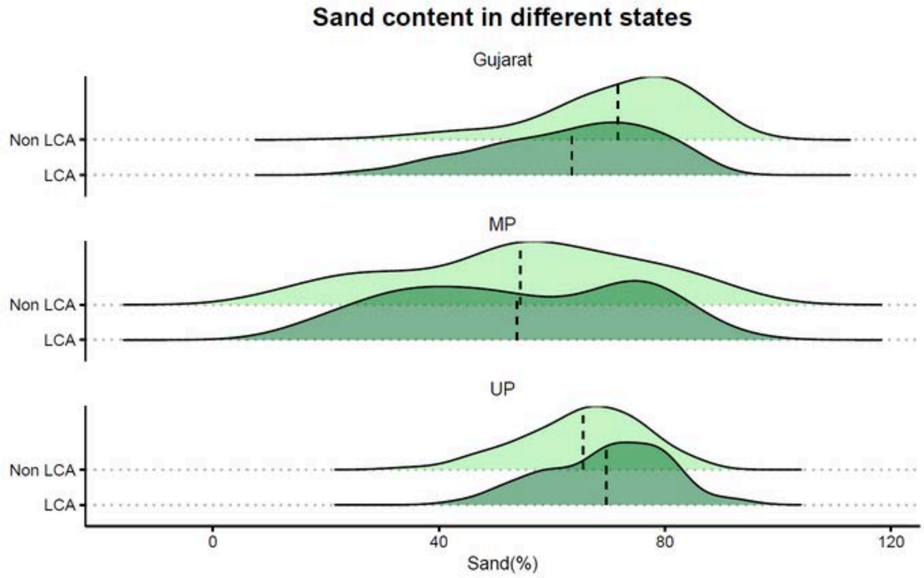
Total N (ppm) (Sub)	*LCA*	*Non LCA*
Mean	688.25	627.365672
Variance	78102.71739	27172.7317
Observations	24	67
Hypothesized Mean Difference	0	
df	29	
t Stat	1.006408483	
P(T<=t) one-tail	0.161271568	
t Critical one-tail	1.699127027	
P(T<=t) two-tail	**0.322543135**	
t Critical two-tail	2.045229642	

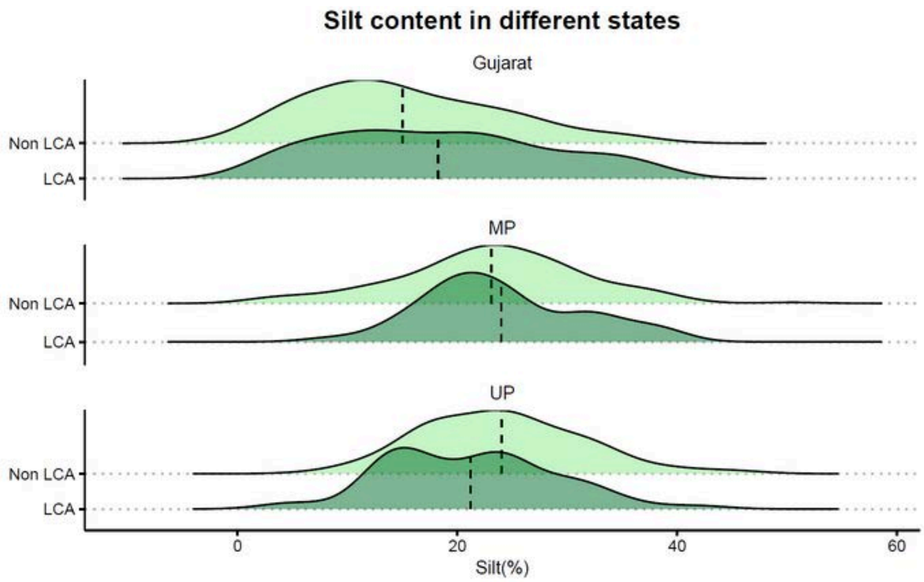
3.4 Texture (sand, silt and clay contents in %)

Soil texture refers to the proportion of sand, silt and clay. An appropriate proportion improves aeration in soil, water movement and storage and nutrient holding capacity of soil.

From density plots and statistical analysis related to texture soil texture, following conclusions can be drawn. The Sayla site showed dominance of sand content and textural class as 'Sandy loam'.
Further, improvement in clay and silt percentage in Topsoil of LCA plots over non-LCA plots was seen along with decline in sand content at Sayla. These changes were statistically significant.
At Jhirnya site, overall textural class was observed as 'Sandy clay loam' along with non-significant depth-wise and plot-wise variation.
Looking to texture at Bahraich, it was classified as 'Sandy loam' along with no significant variation.

Below are the figures and tables which shows the density plots, plot wise trends and statistical analysis of soil texture at all three locations.





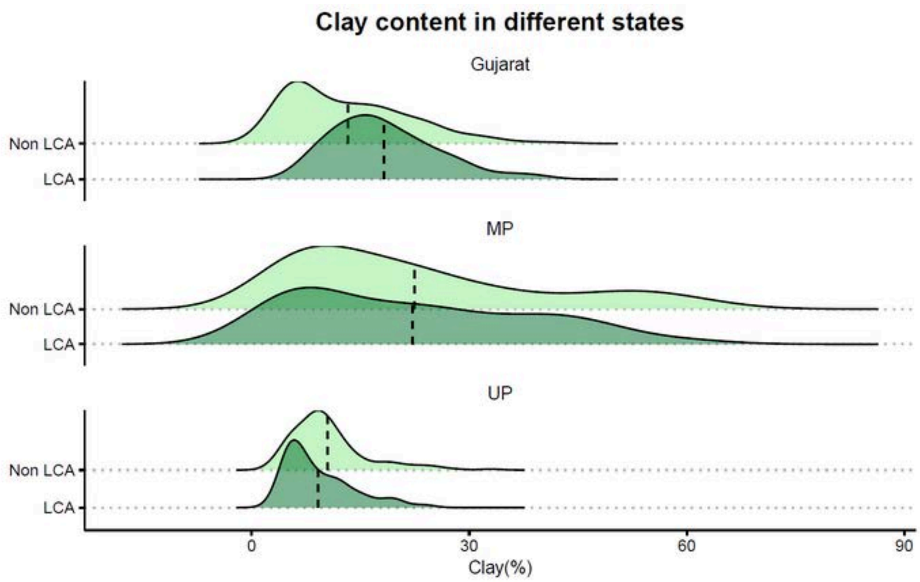


Table no. 6: The scenario of texture (sand, silt and clay contents in %)

Gujarat
Dominance of sand content
Overall textural class ‘Sandy loam’
Improvement in clay percentage in Topsoil of LCA plot over non-LCA plot
Improvement in silt percentage in Topsoil of LCA plot over non-LCA plot
Decline in sand content in LCA plot than non LCA-plot

Madhya Pradesh
Overall textural class ‘Sandy clay loam’

Uttar Pradesh
Overall textural class ‘Sandy loam’
Slight plot-wise change in sand, silt and clay content

Statistical Analysis

Sayla LDSF Site, Gujarat

Clay (%) (Top)	LCA	Non LCA
Mean	18.2498716	13.2675
Variance	51.2564956	70.6344
Observations	46	158
Hypothesized Mean Difference	0	
df	84	
t Stat	3.98741373	
P(T<=t) one-tail	7.0977E-05	
t Critical one-tail	1.66319668	
P(T<=t) two-tail	**0.00014195**	
t Critical two-tail	1.98860967	

Silt (%) (Top)	LCA	Non LCA
Mean	18.2271599	15.01134
Variance	99.0153922	73.40339
Observations	46	158
Hypothesized Mean Difference	0	
df	66	
t Stat	1.9878456	
P(T<=t) one-tail	0.02548993	
t Critical one-tail	1.66827051	
P(T<=t) two-tail	**0.05097986**	
t Critical two-tail	1.99656442	

Fine sand (%) (Top)	LCA	Non LCA
Mean	19.570187	21.8975326
Variance	31.378339	69.2998772
Observations	46	158
Hypothesized Mean Difference	0	
df	109	
t Stat	-2.198404	
P(T<=t) one-tail	0.0150171	
t Critical one-tail	1.6589535	
P(T<=t) two-tail	**0.0300341**	
t Critical two-tail	1.9819675	

Coarse sand (%) (Top)	LCA	Non LCA
Mean	43.952781	49.823638
Variance	191.03763	227.75256
Observations	46	158
Hypothesized Mean Difference	0	
df	79	
t Stat	-2.482117	
P(T<=t) one-tail	0.0075907	
t Critical one-tail	1.6643714	
P(T<=t) two-tail	**0.0151815**	
t Critical two-tail	1.9904502	

Jhirnya LDSF site, Madhya Pradesh (MP)

Fine sand (%) (Top)	LCA	Non LCA
Mean	28.99792403	31.421636
Variance	123.0774485	169.59462
Observations	42	166
Hypothesized Mean Difference	0	
df	72	
t Stat	-1.219182513	
P(T<=t) one-tail	0.113377047	
t Critical one-tail	1.666293696	
P(T<=t) two-tail	**0.226754094**	
t Critical two-tail	1.993463567	

Fine sand (%) (Sub)	LCA	Non LCA
Mean	23.3454312	27.22698114
Variance	95.5479128	139.313359
Observations	18	49
Hypothesized Mean Difference	0	
df	36	
t Stat	-1.3595353	
P(T<=t) one-tail	0.09121616	
t Critical one-tail	1.68829771	
P(T<=t) two-tail	**0.18243231**	
t Critical two-tail	2.028094	

Bahraich (Risia) LDSF site, Uttar Pradesh (UP)

Silt (%) (Top)	LCA	Non LCA
Mean	21.19302	24.02757
Variance	58.36678	53.65067
Observations	56	154
Hypothesized Mean Difference	0	
df	94	
t Stat	-2.40368	
P(T<=t) one-tail	0.009097	
t Critical one-tail	1.661226	
P(T<=t) two-tail	**0.018193**	
t Critical two-tail	1.985523	

Coarse sand (%) (Top)	LCA	Non LCA
Mean	9.4752357	6.995867
Variance	48.641489	23.784
Observations	56	154
Hypothesized Mean Difference	0	
df	75	
t Stat	2.4512912	
P(T<=t) one-tail	0.0082815	
t Critical one-tail	1.6654254	
P(T<=t) two-tail	**0.016563**	
t Critical two-tail	1.9921022	

3.5 Soil infiltration

Soil infiltration capacity measurements are the most time-consuming aspect of the field measurements. Three infiltration measurements through random allocation were conducted per cluster. Repeated measurements across the landscape enabled to assess the effects of land management and vegetation types. The single-ring infiltration test, which is a robust method, was used for calculating infiltration rates.

The analysed data of soil infiltration measurements was showcased through box plot, density plot and infiltration curves (Figure 14). This allowed to see the variation of soil infiltration rate within LCA and non- LCA plot as well as with respect to three project locations. From the results, we observed no significant variation plot-wise and also location-wise.

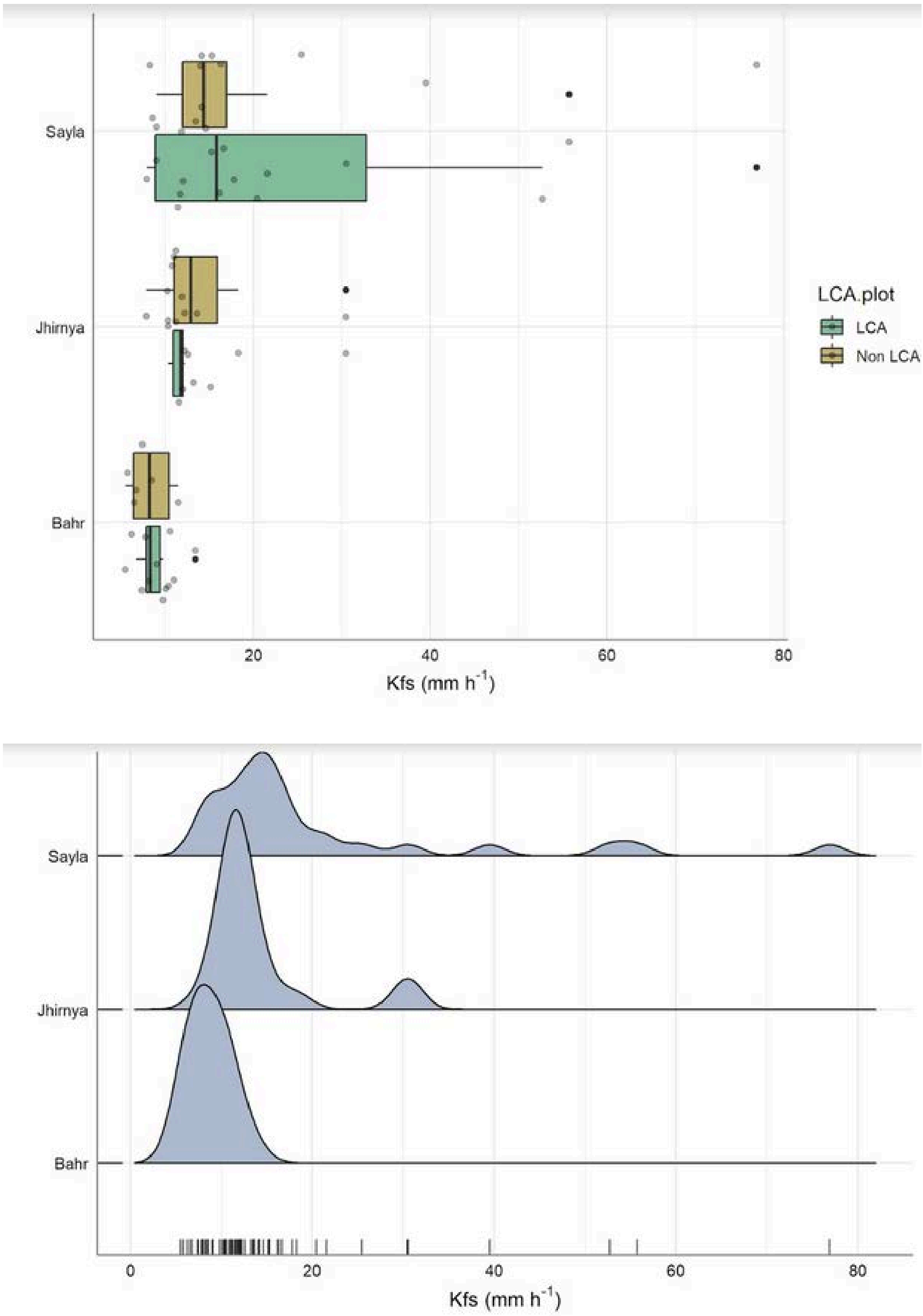
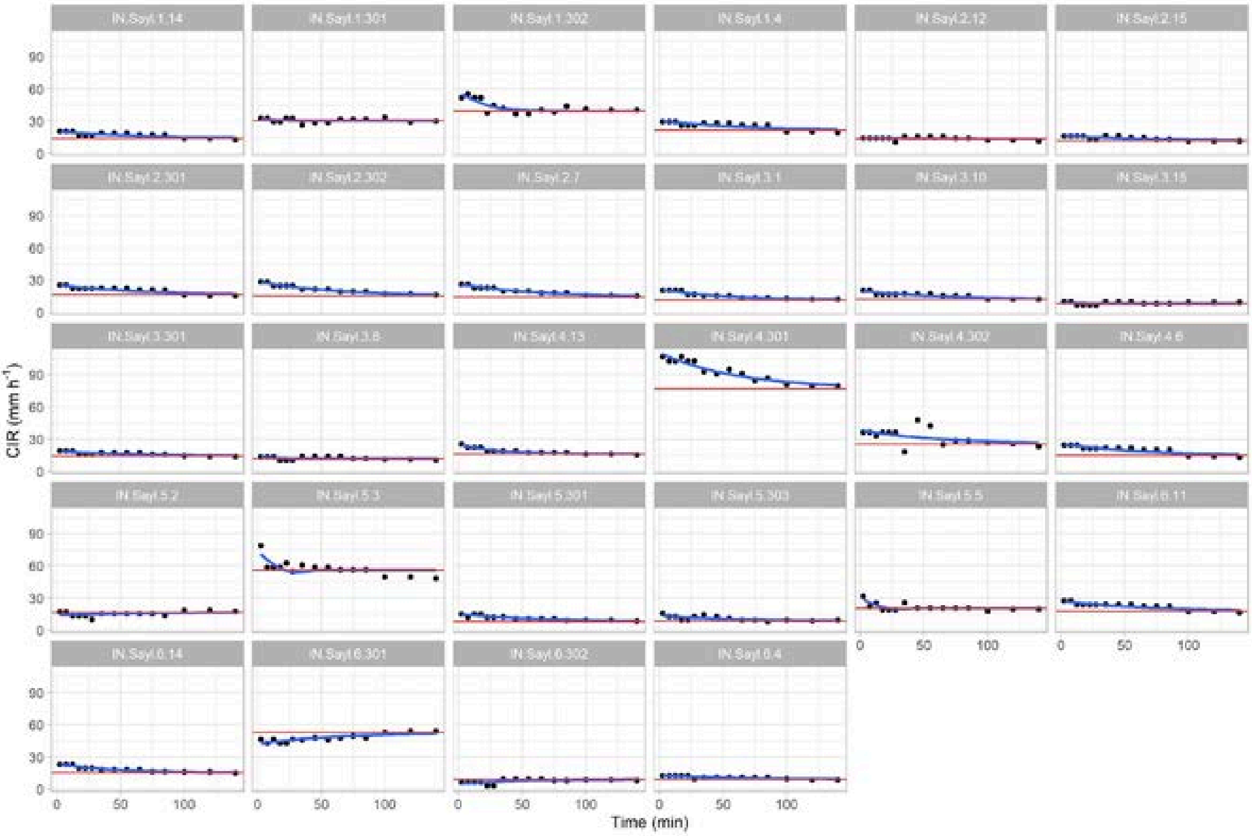
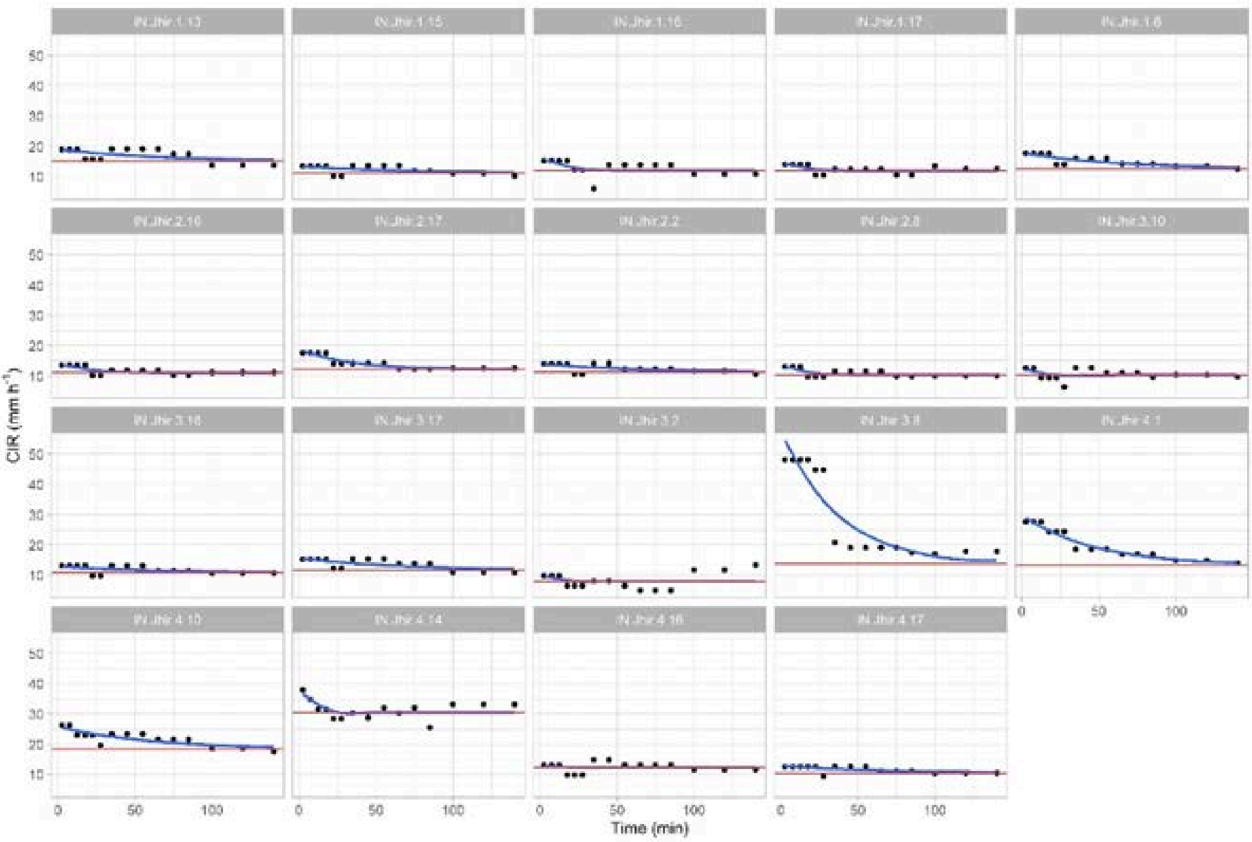


Figure 14: Box plots showing soil infiltration property for LCA and Non-LCA site plots and density plot showing soil infiltration property for the whole sample

(a)



(b)



(c)

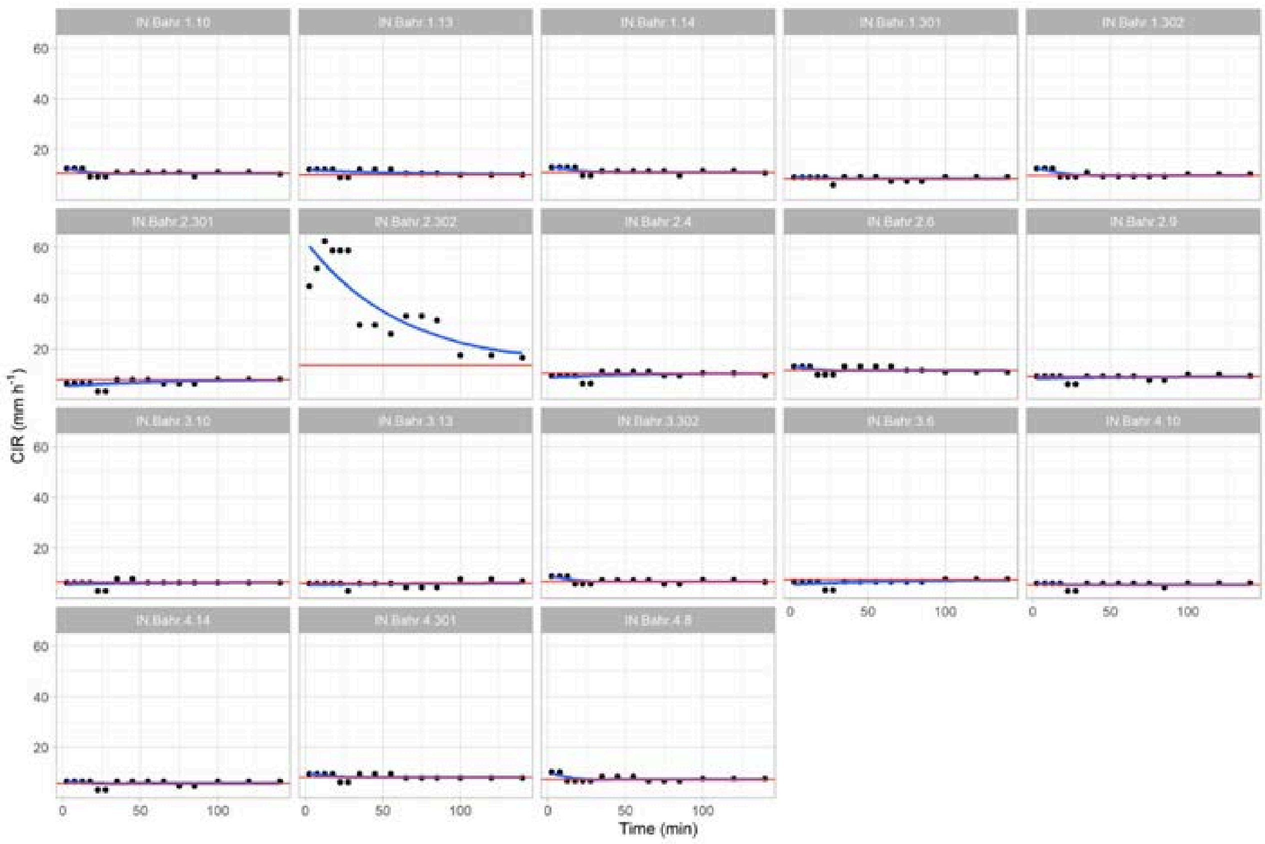


Figure 15: Infiltration curves for Sayla, Gujarat site (a), Jhirnya, Madhya Pradesh (b) and Bahraich (Risia), Uttar Pradesh (c)

3.6 Land cover/use classification

Land degradation surveillance framework (LDSF) covers recording of observations related to land cover system, which speak undoubtfully about soil health.

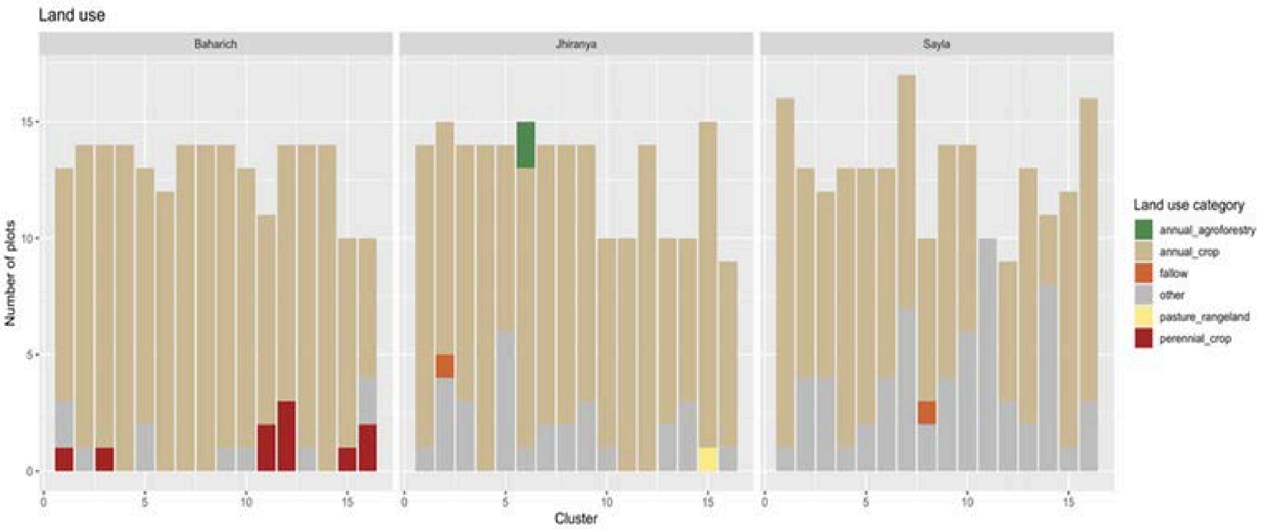
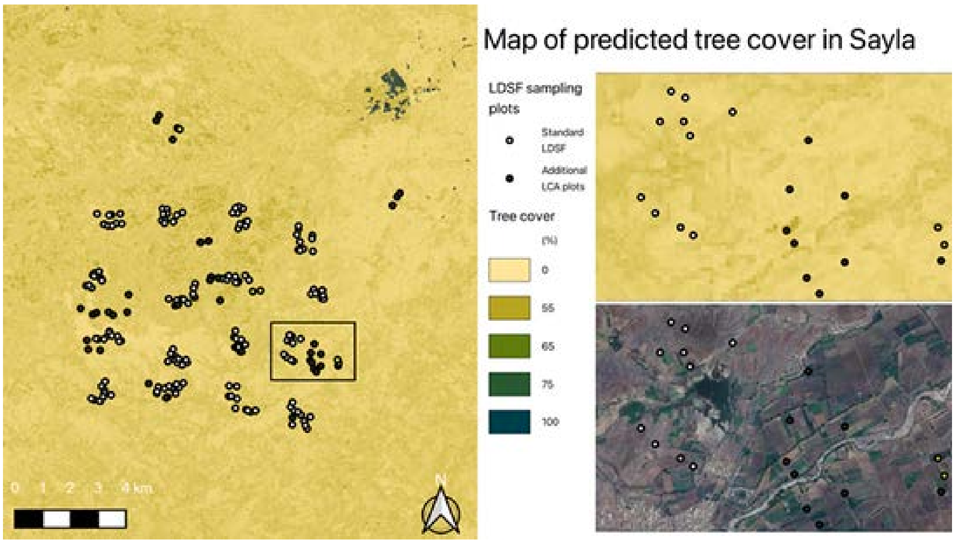


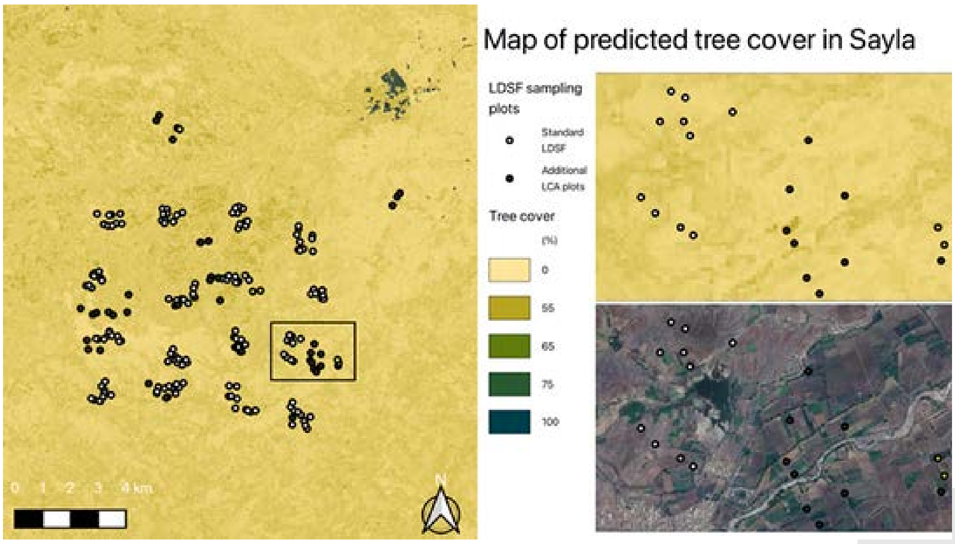
Figure 16: The land use classification by site

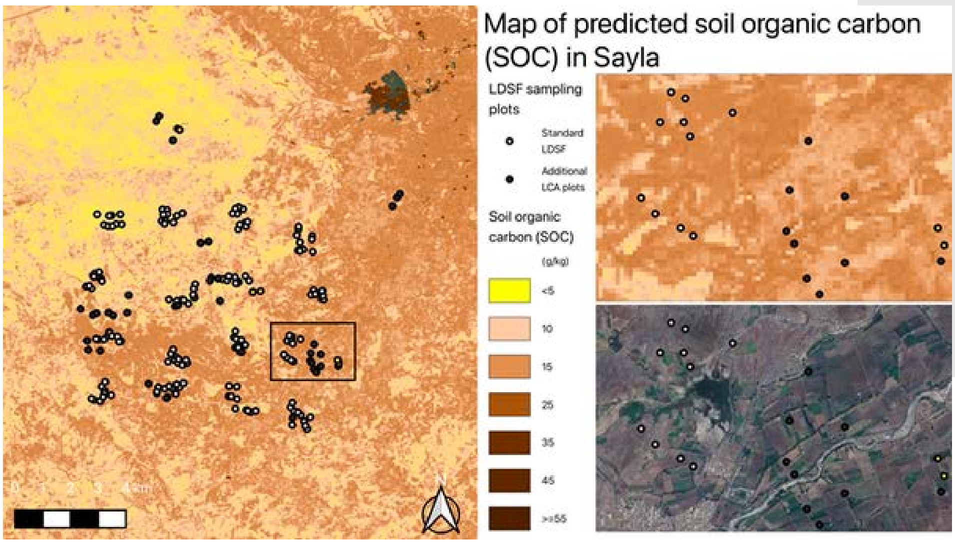
In all three project locations, agroforestry systems were less common, with annual crops prevailing over trees. This highlights the need to increase tree cover as well as pasture, which could ultimately lead to improvements in soil and ecosystem health.

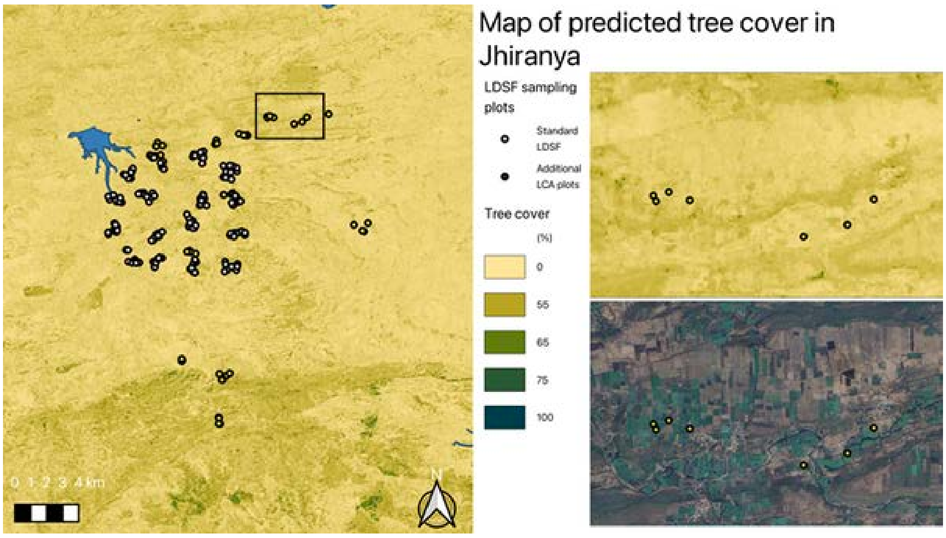
3.7 Predictive mapping

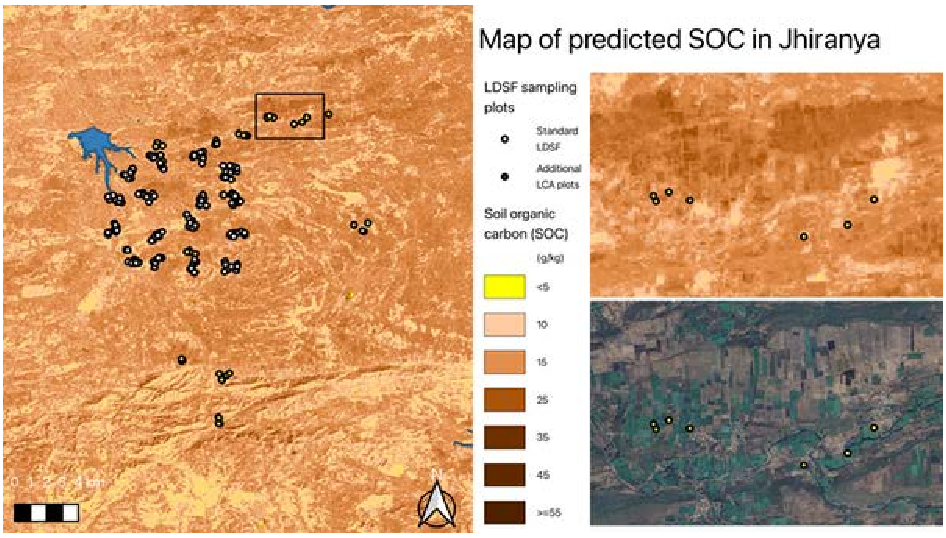
By using the data collected through Land degradation surveillance framework (LDSF), location- wise predictive maps of soil organic carbon, tree cover and predicted cropland were generated. The results discussed above relate to these parameters and are effectively exhibited through these maps. The maps also enable to zoom in to a specific area of the site and assess the possible parameters therein.








Map of predicted tree cover in Jhiranya
LDSF sampling plots
Standard LDSF
Additional LCA plots
Tree cover (%)
0
55
65
75
100
0 1 2 3 4 km
N


Map of predicted SOC in Jhiranya
LDSF sampling plots
Standard LDSF
Additional LCA plots
Soil organic carbon (SOC) (g/kg)
<5
10
15
25
35
45
>=55
N

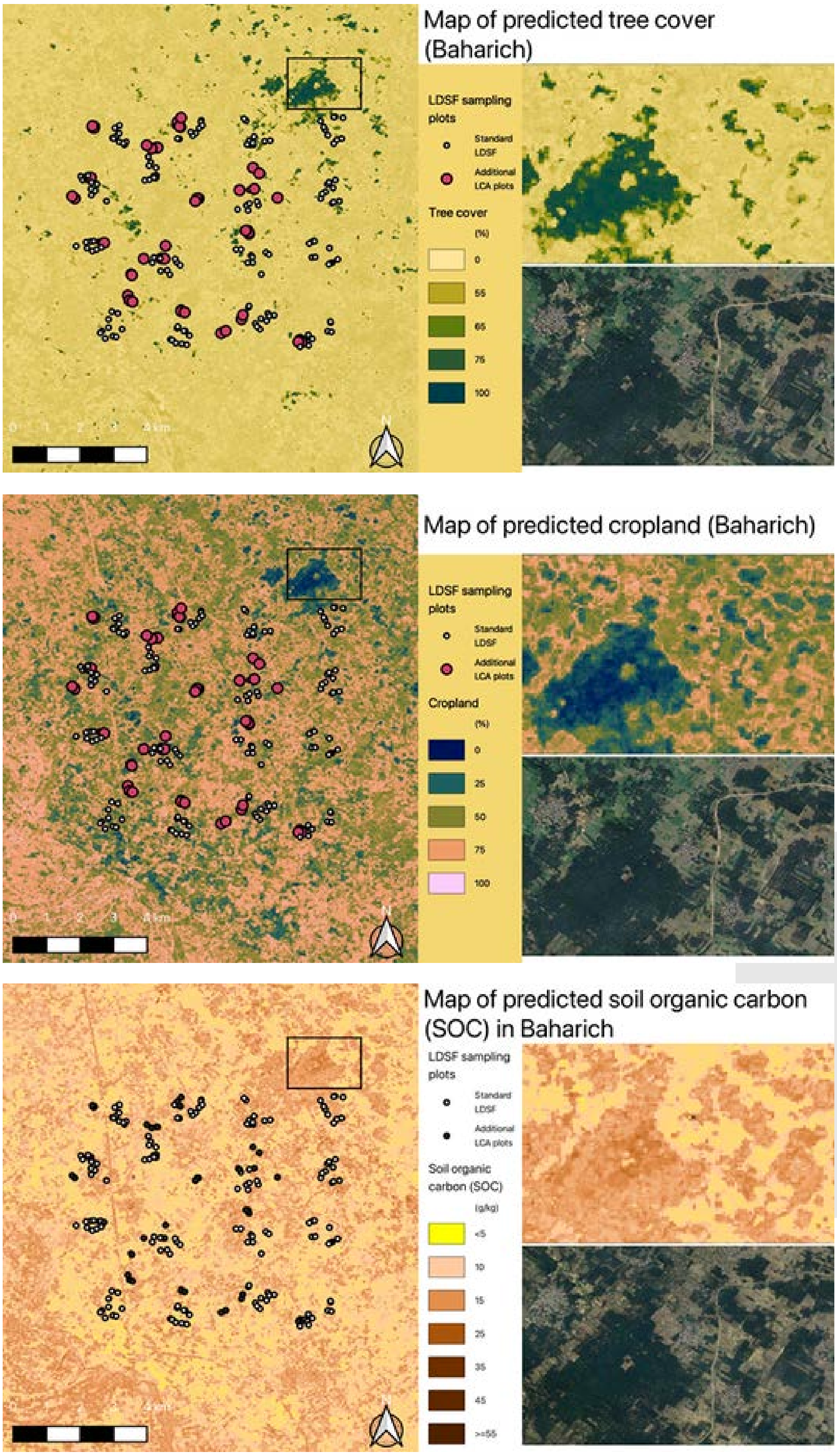


Figure 17: Location-wise maps exhibiting tree cover, predicted cropland and soil organic carbon content

4. Assessment of changes in LCA adoption and impacts on socio-economic outcomes

The two important indicators dimension from the farm family survey and highlighted in this report are:

Adoption

Adoption of the key LCA practices and dis-adoption of the HCA practices

- Land preparation tillage methods
- Soil amendments and Soil and Water Conservation (SWC)
- Resilient crop cultivation
- Irrigation types and renewable energy use

Socio-economic Indicators

Change in socio-economic outcomes

- Farm expense
- Farm income and crop values
- Food security status using FIES
- Asset wealth
- Adoption of in maladaptive coping behaviors using LCSI

4.1 Adoption of Low carbon agricultural practices (LCA)

The adoption of LCA practices is measured by the number of households that have implemented various LCA techniques or discontinued the use of HCA techniques on their farm during the cropping seasons. In both the baseline and endline surveys, respondents provided details about their cultivated fields, including whether they used one or more LCA and HCA practices. For simplicity, households that discontinued HCA practices are categorized as adopters of LCA practices in this report. Thus, for the adoption indicator, households are considered to be practicing LCA if they engaged in any of the following activities:

- Tillage Practices: Implementing zero or minimum tillage and direct sowing of wheat or rice.
- Organic Soil Amendments: Utilizing farmyard manure (FYM), compost, green manure, natural farming inputs such as jivamrita/jeevamrutham, and incorporating crop residues.
- Bio Inputs: Using biological inputs for crop growth and protection and reducing the use of chemical fertilizers, herbicides and pesticides.
- Soil Cover: Integrating trees into farming fields, mulching, intercropping, and other pre-planting activities that promote soil health.
- Water and Energy Efficient Irrigation Systems: The use of drip irrigation and solar power to pump water for irrigation.
- Soil and Water Conservation Practices: Terracing, contour farming, check dam, farm bund and other methods to conserve soil and water resources.

The adoption of Low Carbon Agriculture (LCA) practices among surveyed households showed significant changes between 2021 and 2024. Table 7 shows that at the baseline in 2021, 13% of households did not adopt any LCA practices, with most households adopting between one to three practices. By the endline (Kharif 2023), this percentage of non-adopters of LCA practices reduced to 2.9%, while a notable increase was observed in households adopting two to four practices, highlighting increased intensification of LCA and dis-adoption of HCA practices. Specifically, the percentage of households adopting two practices increased from 27% to 34%, three practices from 18% to 24%, and four practices from 11% to 13%. Overall, the results indicate a positive trend in the adoption of LCA practices, reflecting increased engagement in sustainable agricultural practices among the surveyed households over the three-year period. The significant decrease in the percentage of households not adopting any practices and the corresponding increase in those adopting multiple practices underscore the growing commitment to low-carbon farming methods.

Table 7: Summary statistics of farm characteristics and adoption of LCA practices by survey wave

Characteristic	**2021** (N = 1,046)	**2024** (N = 1,046)	**p-value**
Farm size (Acre)	2.95 (2.82)	2.85 (3.84)	0.014
Female decides on land use	317 (30%)	367 (35%)	0.020
Male decides on land use	985 (94%)	541 (52%)	<0.001
Joint decision on land use	256 (24%)	118 (11%)	<0.001
Change in soil quality			<0.001
No change	301 (29%)	469 (45%)	
Declined	108 (10%)	94 (9.0%)	
Improved	637 (61%)	483 (46%)	
Number of LCA practices adopted			
0	132 (13%)	30 (2.9%)	
1	275 (26%)	222 (21%)	
2	283 (27%)	358 (34%)	
3	192 (18%)	250 (24%)	
4	113 (11%)	137 (13%)	
5	37 (3.5%)	32 (3.1%)	
6	10 (1.0%)	11 (1.1%)	
7	2 (0.2%)	5 (0.5%)	
8	2 (0.2%)	1 (<0.1%)	
LCA practice index (0-1 scale)	0.13 (0.09)	0.15 (0.08)	<0.001
Crop production value (INR)	70,065 (117,642)	86,658 (186,896)	0.092
Variable farm input cost (INR)	31,480 (44,277)	17,027 (32,555)	<0.001
Net farm return (INR)	38,619 (102,060)	69,535 (170,274)	<0.001

Note: Values reported are Mean with SD in the parenthesis for continuous; number with percentage in the parenthesis for categorical variables. Two-sided t-tests were used for statistical testing, and the corresponding p-values are presented in the last column. The tests performed are Pearsons Chi-squared test for categorical variables and the Wilcoxon rank sum test for continuous variables

However, we observe some variations in the number of LCA practices across the three states. As shown in the supplementary tables SM1-SM3, while all three states recorded a considerable increase in the percentage of households adopting multiple practices and a significant decrease in non-adopters, the extent of adoption varies.

In Gujarat, the highest percentage of households adopted three or more LCA practices compared to the baseline, demonstrating comprehensive adoption of multiple practices. Similarly, Uttar Pradesh saw a significant increase in the percentage of households adopting two or more LCA practices, reflecting growing engagement. In contrast, Madhya Pradesh showed more households adopting one or two practices compared to the baseline, but the percentage of households adopting more than three practices decreased.

These differences highlight the varying levels of engagement and intensity in adopting LCA practices across states. Gujarat demonstrated a broad and intensive uptake of multiple practices, while Madhya Pradesh and Uttar Pradesh exhibited more moderate but still positive trends. Tailored strategies to address local contexts and barriers could further enhance the adoption and impact of LCA practices.

LCA intensification index

As indicated above, the project intervention promoted various types of LCA practices in the targeted pilot villages over the project period. We identified 16 LCA practices promoted across the three states and constructed a weighted LCA index to understand the level of intensification. The LCA practice index comprises four categories of practices (Figure 18), with four binary (yes-no) indicators, each practice assigned equal weight. The more a household adopts multiple LCA practices, the higher its score on the 0-to-1 index. Although the total possible combination of LCA practices is 16, the maximum number of LCA practices adopted by households was 8. This resulted in a lower overall LCA index, with the overall average value at the endline being 0.15 out of 1, and the maximum value observed being 0.5.

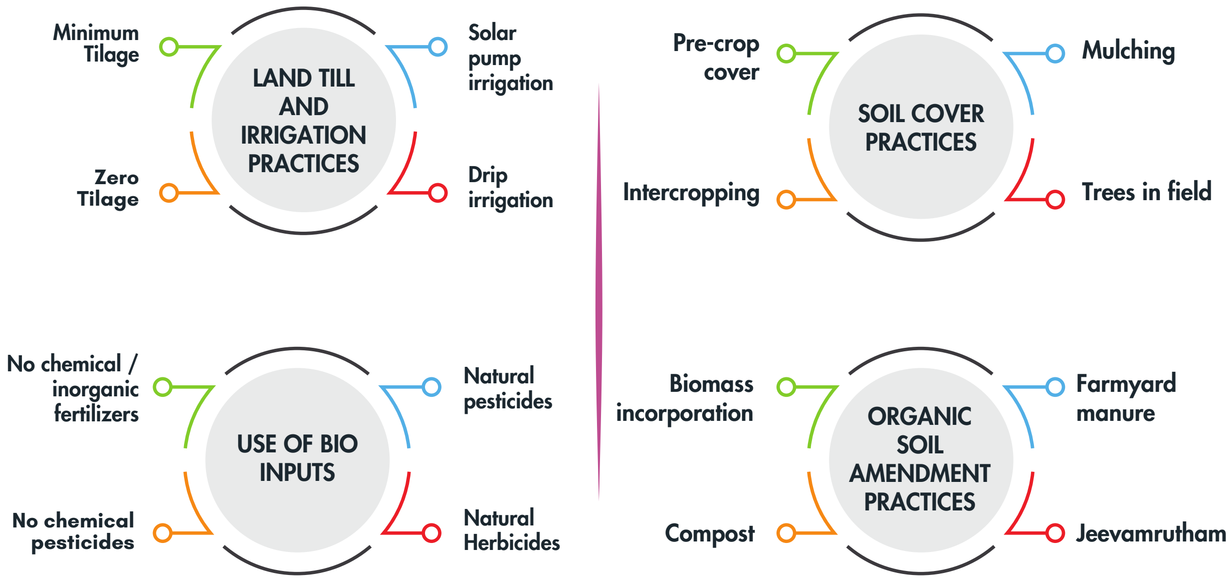


Fig 18: LCA intensification index: categories and indicators

The overall index showed a slight improvement across the surveyed households, with the average score increasing from 0. 13 to 0.15 at the endline (Table 7). This indicates a gradual but positive shift towards more sustainable low-carbon agricultural practices, although the index remained relatively low due to the limited number of practices adopted.

Similar to the number of practices adopted, we observe some variations in the gains of the LCA index across the three states (Figure 19). In Gujarat, the LCA practice index demonstrated significant progress. The index increased from 0.16 at baseline to 0.20 at endline with, the mean difference statistically significant ($p < 0.001$). Despite the overall average index being only 0.2, Gujarat's households showed a broad and intensive engagement with sustainable agriculture.

Similarly, in Uttar Pradesh, the LCA practice index improved from 0.09 at baseline to 0.13 at the endline and the difference is statistically significant ($p < 0.001$). This increase, though modest, indicates a growing engagement among households in adopting sustainable LCA practices. Madhya Pradesh exhibited a different trend compared to Gujarat and Uttar Pradesh. The LCA practice index decreased from 0.14 to 0.11, which is statistically significant ($p = 0.001$). Although there was an increase in the number of households adopting one or two LCA practices, the overall intensity and diversity of practices per household did not increase, leading to a slight decline in the LCA practice index. The overall average index remained low, reflecting limited practice adoption.

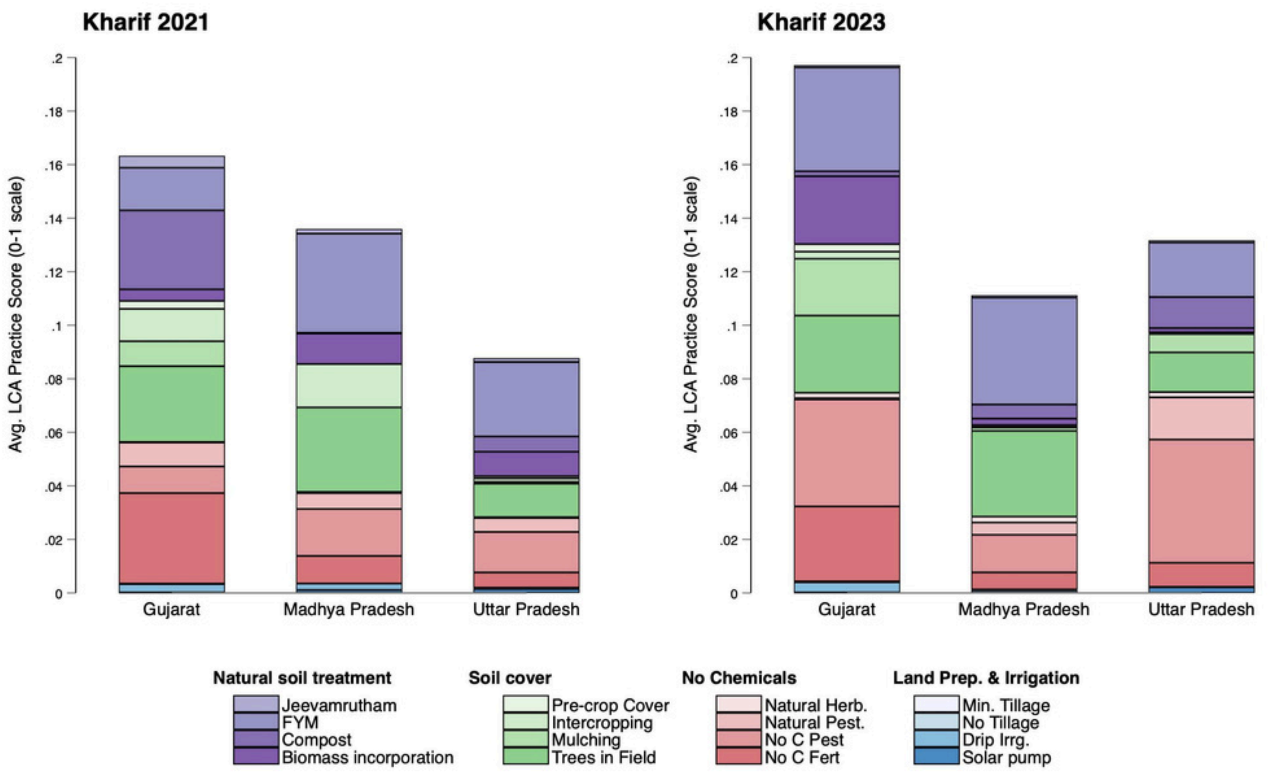


Figure 19: Low Carbon Agricultural Index, with components and contribution at the overall index at baseline and endline

Focusing only on changes at the state level can mask variation across sites within the states and even more among households in specific geographies. We therefore graphically present the distribution of household-level scores by district as density plots (Figure 20). The LCA practice index across the three states reveals varying levels of improvement in adoption at the district level.

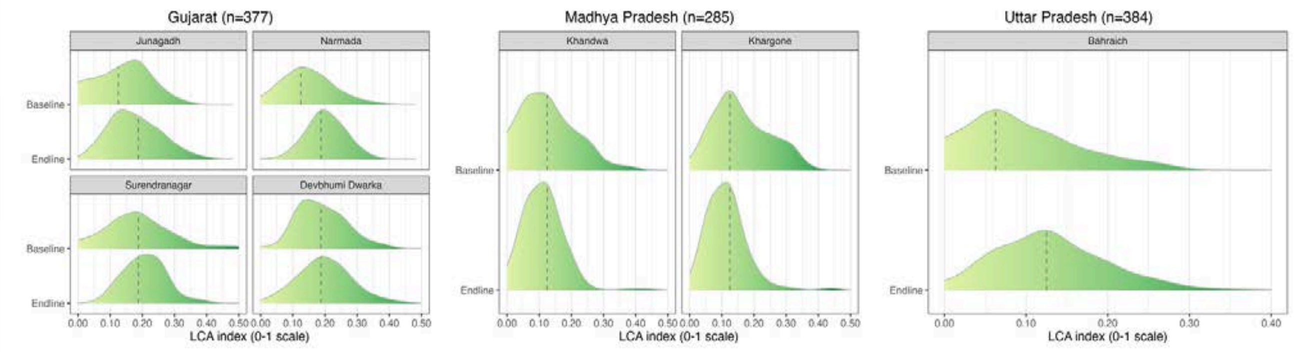


Figure 20: Density plots depicting changes in the statistical distribution of the LCA index between the baseline (top plots) and endline (bottom plots) periods at the district level. The vertical dotted lines represent the median values.

In Gujarat the most substantial improvement, with a significant increase in the median LCA index is observed for Junagadh and Narmada districts reflecting a broad and intensive adoption of multiple practices in these districts. Although the median index stayed about the same in the districts of Surendranagar and Devbhumi Dwarka, the distribution at endline is more spread out compared to baseline. There is a slight increase in higher index values, suggesting varied adoption levels across households. Similarly, the density plot for Bahraich district of Uttar Pradesh shows a substantial improvement with clear shift towards higher LCA practice index values at endline, indicating a moderate improvement in the LCA practice index. Although the adoption is growing, it is less intensive compared to Gujarat. Madhya Pradesh exhibits a decline in LCA practice adoption. Both districts show a shift towards lower LCA practice index values at endline indicating a reduction in the uptake of LCA practices.

These differences underscore the importance of tailored strategies to address local contexts and barriers, further enhancing the adoption and impact of LCA practices in each state.

LCA practices upscaling

Using the difference in the LCA practice index between the endline and baseline, we assessed the extent to which households upscaled or scaled back their use of LCA practices. This difference provides a clear indication of changes in LCA practice adoption at the household level:

- Difference = 0: Indicates that the household maintained the same level of LCA practice adoption.
- Difference > 0: Indicates that the household upscaled, adopting more LCA practices compared to the baseline.
- Difference < 0: Indicates that the household scaled back, dis-adopting or adopting fewer LCA practices compared to the baseline.

We then constructed a binary indicator for the up-scaler, taking the value 1 if the difference is > 0 and 0 for non-up-scaler if the difference is <=0.

The results show that, overall, 48% of the sampled households upscaled their use of Low LCA practices. This indicates that nearly half of the households adopted more LCA practices at the endline compared to the baseline. In Gujarat, 51% of the sampled households upscaled suggesting a strong positive trend in the adoption of LCA practices. The significant percentage of upscalers may reflect the effectiveness of interventions and support systems in encouraging households to integrate more LCA practices on their farm. Uttar Pradesh demonstrated the highest proportion of up-scalers, with 58% of households increasing their LCA practice adoption. Again, this substantial improvement is likely driven by successful program implementation and favourable local conditions that support sustainable and low-carbon farming practices. In contrast, Madhya Pradesh had only 30% of household's upscaling their LCA practices. This lower percentage suggests challenges in the adoption of LCA practices, possibly due to local barriers, limited access to resources, or less effective dissemination of the LCA practices. The results indicate a need for more focused and tailored strategies to support and encourage LCA adoption among the targeted villages in this state.

In summary, 48% of sampled households upscaled their use of LCA practices, with significant variation across states. The findings emphasize the importance of understanding local contexts and tailoring interventions to enhance the adoption and impact of LCA practices. By addressing the specific needs and challenges of each state, especially those with lower adoption rates like Madhya Pradesh, it is possible to support broader and more intensive engagement with sustainable agricultural practices.

4.2 Adoption by types of practices

The LCA intervention promoted a range of contextually relevant LCA practices and provided support to enhance their adoption. In this section, we examine the adoption of these practices to identify which LCA practices were most effective in different contexts.

4.2.1 Soil treatment practices

The bar graphs in Figure 21 illustrate the changes in the use of soil treatment inputs, including inorganic and bio fertilizers, across the three states. The data span four seasons: Kharif 2020 and 2021 (Baseline) and Kharif 2023 and Rabi 2024 (Endline). We observe that chemical fertilizers are widely used across the three states, with a slight reduction compared to the baseline in Uttar Pradesh. Compared to Kharif 2021, the baseline, 146 (14%) discontinued the use of inorganic fertilizer at the endline – 73 (19%) in Gujarat, 25 (9%) in Madhya Pradesh, and 48 (12%) in Uttar Pradesh.

Although chemical fertilizers remain prevalent, some farmers are switching to biofertilizers or organic soil amendment practices. Specifically, a significant proportion of farmers in Gujarat reported using FYM and crop residue, while the use of compost has decreased compared to the baseline. A similar trend in the use of FYM was observed in Madhya Pradesh for the Kharif season 2023, compared to the baseline. Except for compost use, there is no significant change in the use of organic soil amendments in Uttar Pradesh. Overall, 324 (31%) of sampled households used FYM; 155 (15%) incorporated crop residues into their crop fields, and 156 (15%) used mulching at the endline (Kharif 2023) compared to the baseline (Kharif 2021).

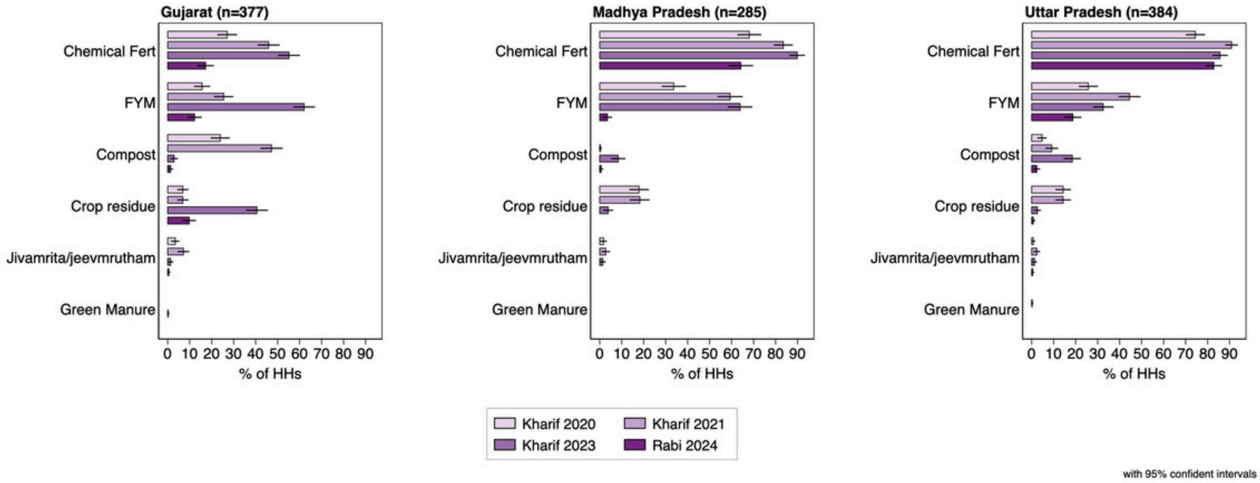


Figure 21: Changes in the use of organic and inorganic soil amendment practices

In conclusion, while there are some shifts towards biofertilizers and organic soil amendments, specifically in Gujarat, the overall reliance on chemical fertilizers and the lack of adoption of natural farming practices persist across the three states. Furthermore, the rates of natural farming, such as the use of Jeevmrutham, showed no changes across the seasons in the three states.

4.2.2 Crop protection practices

The use of chemical pesticides has considerably dropped in both Gujarat and Uttar Pradesh. However, the use of natural pesticides has significantly increased only in Uttar Pradesh.

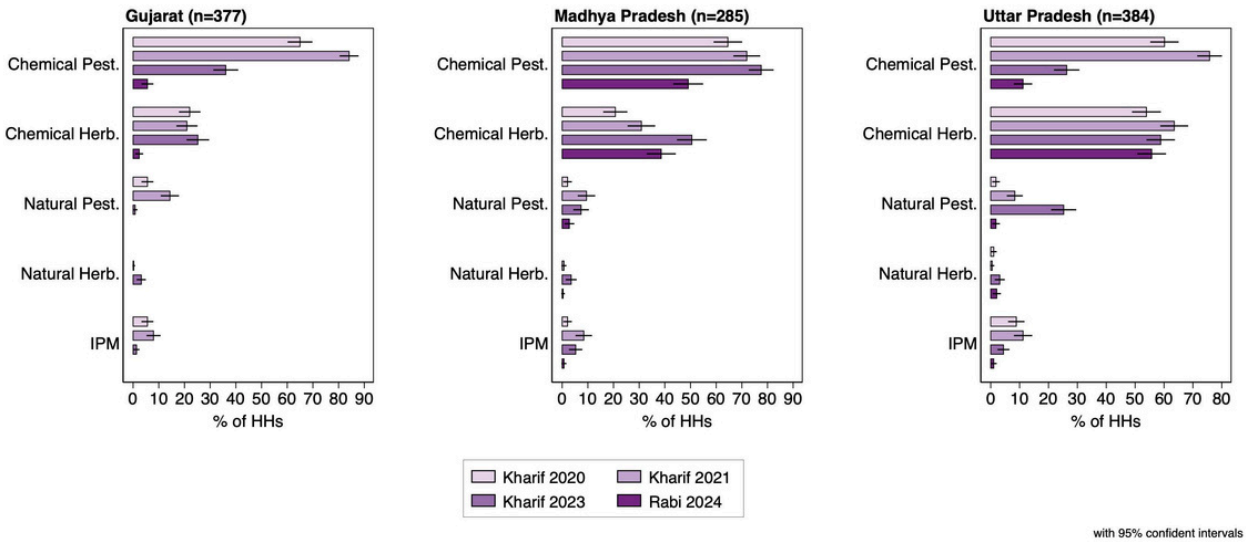


Figure 22: Change in the use of organic (natural) and inorganic crop protection practices

Regarding the use of crop protection and growth stimulant inputs, Figure 22 shows a significant decrease in the proportion of farmers in Gujarat and Uttar Pradesh using chemical pesticides compared to the baseline. In Uttar Pradesh, there was a notable increase in the proportion of farmers using natural pesticides.

Overall, our findings show that 447 (43%) of the sampled households across the three states discontinued the use of chemical pesticides by the endline survey, and 178 (17%) stopped using chemical herbicides. Of the households that discontinued pesticides, 201 (45%) are in Gujarat, 207 (46%) in Uttar Pradesh, and 39 (8%) in Madhya Pradesh. Among those that discontinued herbicides, 85 (48%) are in Uttar Pradesh, 57 (32%) in Gujarat, and 36 (20%) in Madhya Pradesh.

Although the shift towards natural alternatives is not as pronounced as the discontinuation of inorganic inputs, 129 households (12%) reported adopting natural herbicides and pesticides by the endline survey, with 92 of these (71%) located in Uttar Pradesh. Additionally, there were no significant changes observed in the use of Integrated Pest Management (IPM) practices.

The observed reductions in the use of chemical pesticides and the increased adoption of natural pesticides, particularly in Uttar Pradesh, align with the results from the follow-up survey and the support provided through the project. The project encouraged the use of bio-inputs, promoted IPM practices, and established bio-input centers, particularly in Uttar Pradesh and Gujarat.

4.2.3 Tillage Practices

Regarding tillage practices for soil preparation, the results indicate that conventional HCA tillage methods, such as tractor and animal ploughing, which cause significant soil disturbances, continue to be widely used across the three states (Figure 23). There has been no significant change in these practices compared to the baseline.

Despite intervention efforts promoting minimum tillage and direct sowing of rice or wheat in Uttar Pradesh and Gujarat, these more sustainable practices have not seen any substantial adoption among farmers. The persistence of traditional tillage methods suggests that additional efforts and incentives may be necessary to encourage a behavioural shift towards less disruptive and more environmentally friendly tillage practices.

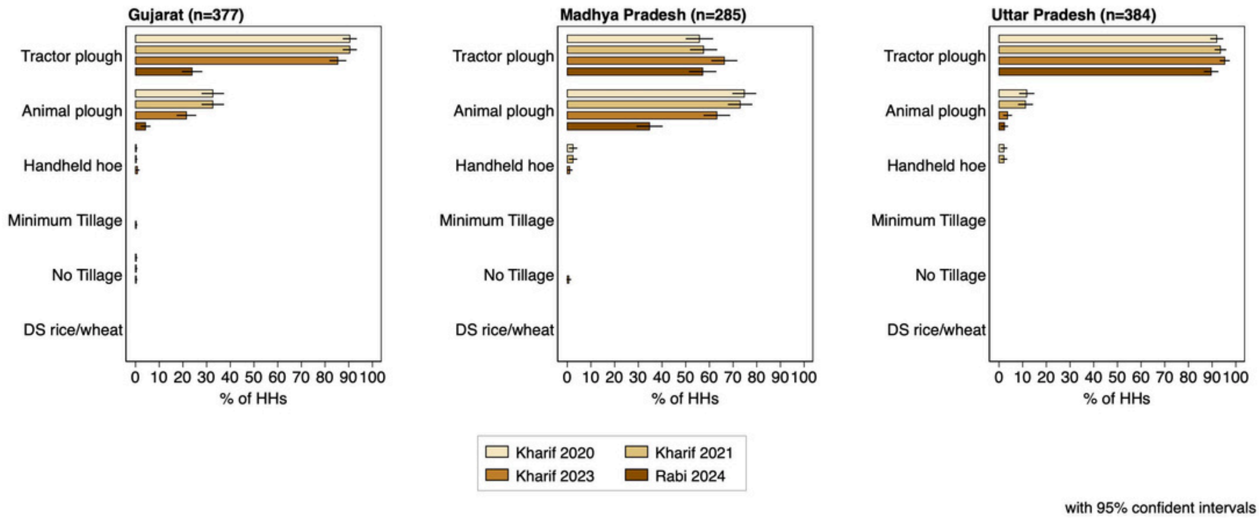


Figure 23: Change in the use of tillage practices

4.2.4 Soil cover practices

Figure 24 shows a significant increase in the proportion of farmers reporting the use of pre-crop soil cover in Gujarat in Kharif 2023 (endline) compared to Kharif 2021 (baseline). Boundary trees, which are widely practiced across the three states, saw a slight increase only in Madhya Pradesh and Uttar Pradesh compared to the baseline. The proportion of farmers using sustainable organic amendment practices, such as bio-mulching and pre-crop cover in Gujarat and Uttar Pradesh, and integrating trees in the field in Gujarat, has increased compared to the baseline. This trend is particularly strong in Gujarat and is consistent with project support promoting bio-mulching and the planting of fruit trees on farm bunds or private lands. While these practices have seen increased adoption in Gujarat, the trend in Uttar Pradesh is less pronounced, with only a small increase in bio-mulching.

Overall, our results indicate that 156 farmers (15%) employed mulching, 166(16%) used pre-planting soil cover, 208 (20%) planted boundary trees and only 31(3%) engaged in agroforestry by integrating trees into crop fields. Planting boundary trees, which serves multiple functions including acting as windbreaks, providing shade, and potentially contributing to biodiversity conservation, is common across the three states. In contrast, agroforestry, which is the integration of trees into crop fields to create a more diversified, productive, and sustainable land-use system, was less common. This relatively low adoption rate might reflect the greater complexity and longer-term commitment required by agroforestry compared to other practices such as boundary tree, as well as possible constraints related to land size, initial investment, and the need for specific knowledge and skills.

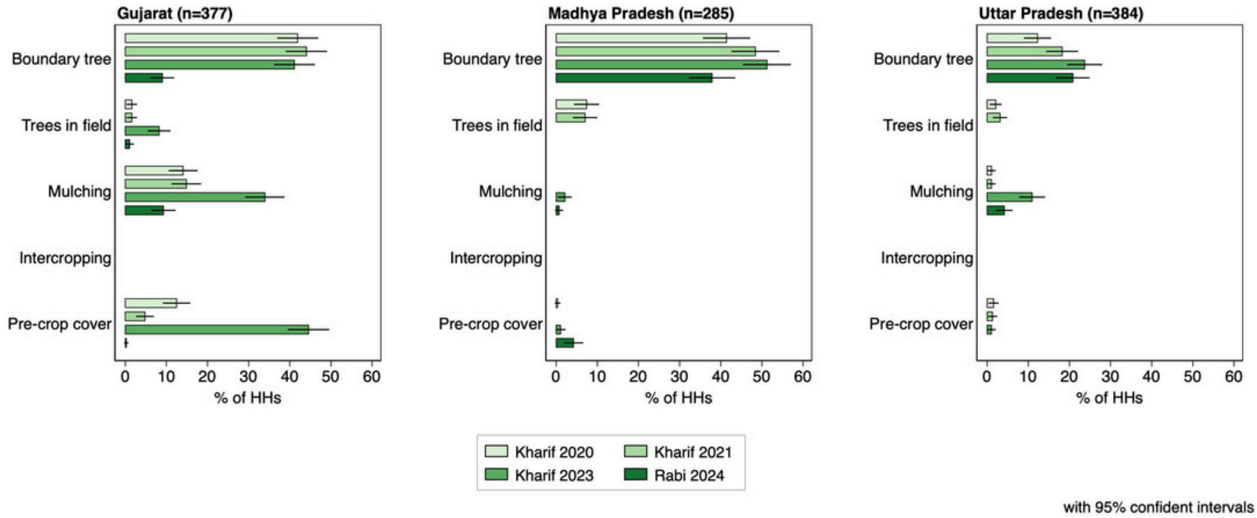


Figure 24: Change in soil cover practices

4.2.5. Soil and water conservation (SWC) practices

Figure 25 shows a decrease in the adoption of SWC practices compared to the baseline. A follow-up survey revealed that some farmers began using contour farming to prevent soil degradation, but this practice appears to have been discontinued by the endline. Farm bunding remains widely used across the three states, although its use also showed a slight decline in the latter seasons, as indicated in the endline survey. These findings are consistent with the follow-up survey results.

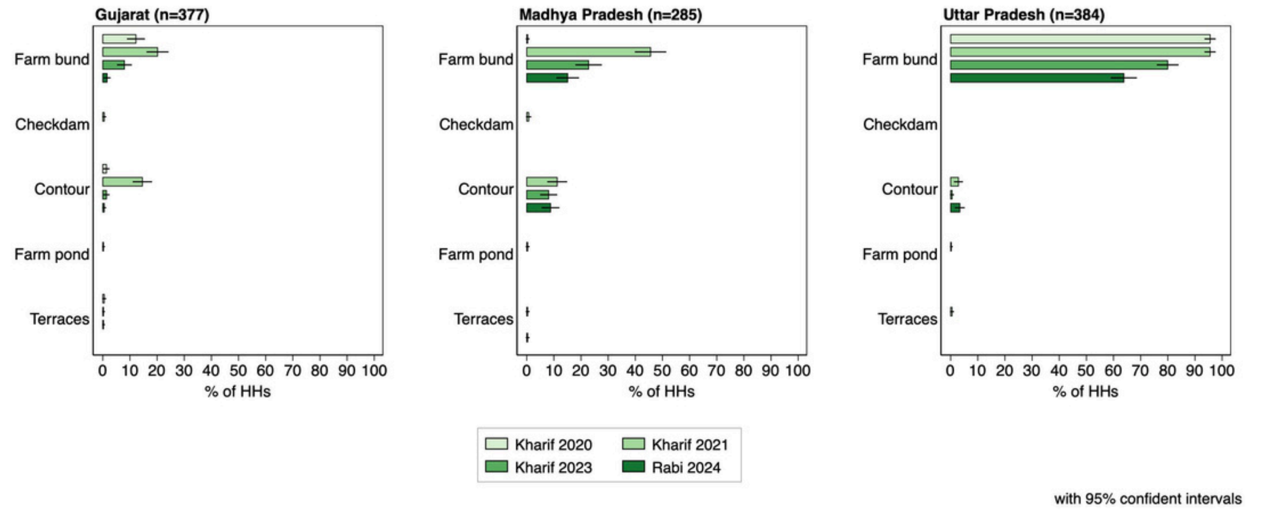


Figure 25: Change in SWC practices

4.2.6 Cultivation of resilient, high nutrition and nitrogen fixing crops

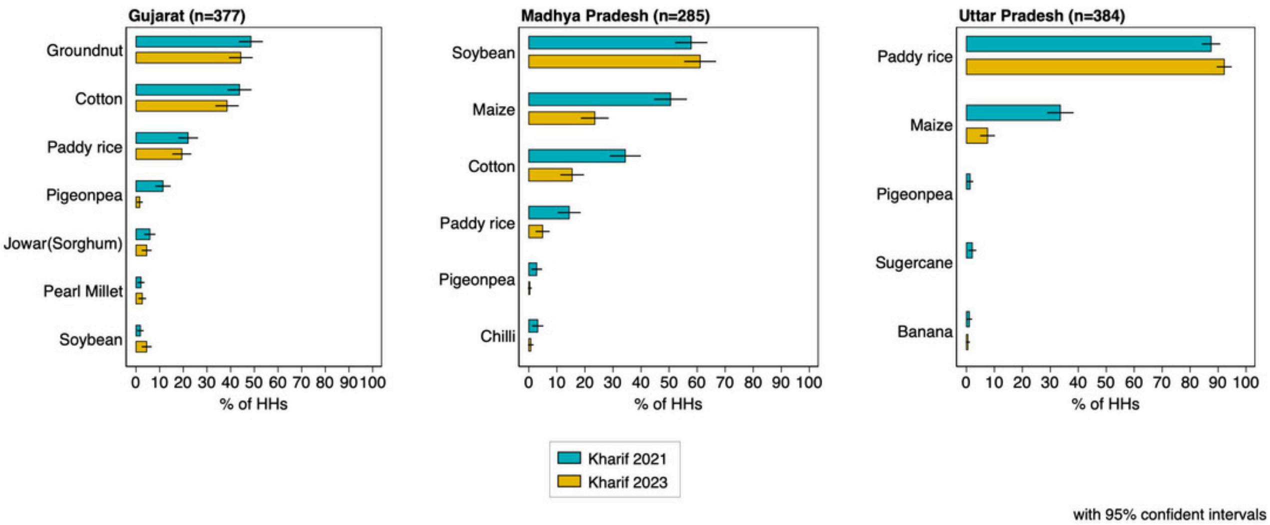


Figure 26: Changes in major crop cultivated during the Kharif season 2021 and 2023

The project provided support to encourage farmers to cultivate resilient, high-nutrition value, and nitrogen-fixing crops on a small scale as a trial. However, Figure 26 shows that the major crops cultivated across the three states during the two Kharif seasons at baseline and endline did not change significantly. Paddy rice remains a common crop grown across the three states, and it is the dominant crop in Uttar Pradesh, cultivated by nearly 90% of households. In contrast, Gujarat and Madhya Pradesh have more diversified production systems compared to Uttar Pradesh.

No significant changes in production patterns were observed across the two Kharif seasons, although a few more farmers in Gujarat and Madhya Pradesh began cultivating crops like soybeans.

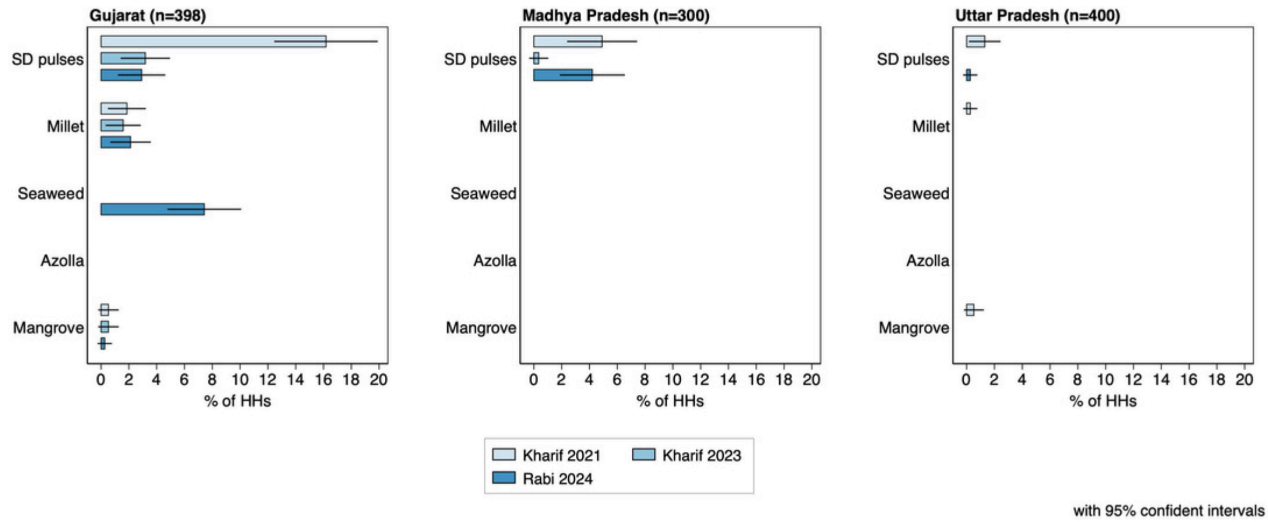


Figure 27: Changes in the cultivation of crops promoted by the intervention

Overall, as shown in Figure 27, there were no substantial changes in the cultivation of crops supported by the project, such as short-duration pulses, millet, seaweed, Azolla plantation, and mangrove. The lack of adoption of these crops may be due to limited exposure, as the support was provided on a small-scale pilot basis.

4.2.7 Irrigation types

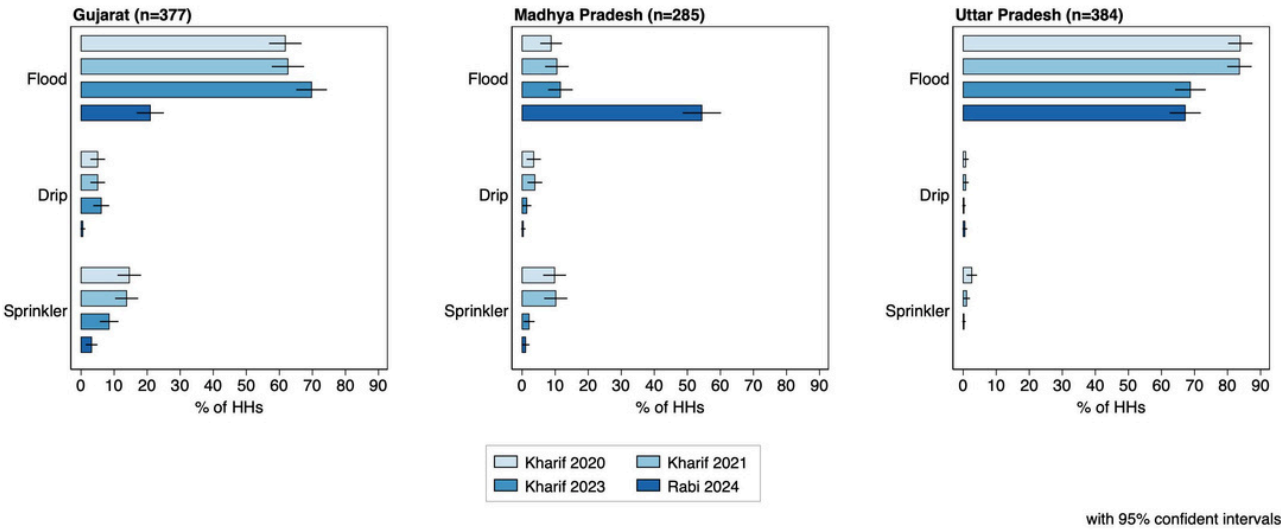


Figure 28: Changes in irrigation types used

Regarding irrigation practices, less water-efficient and unsustainable methods like flood irrigation are widely practiced across the three states, especially in Uttar Pradesh and Gujarat (Figure 28). Although a few households in Gujarat and Madhya Pradesh reported using drip irrigation at the baseline, this practice declined by the endline. These findings are consistent with the results from a follow-up survey indicating a continued reliance on traditional methods that lead to water wastage and reduced agricultural sustainability. Encouraging efficient irrigation techniques and providing necessary incentives and resources are crucial for promoting sustainable agriculture and ensuring water conservation in these regions.

4.2.8 Energy sources for irrigation

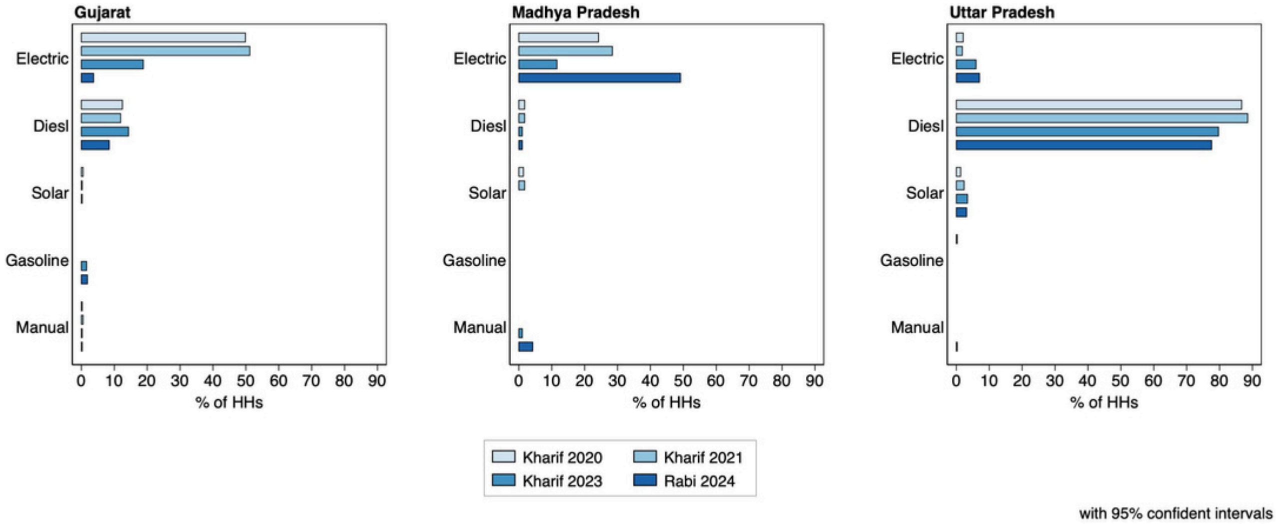


Figure 29: Changes in types of energy use for pumping water for irrigation

In Uttar Pradesh, diesel is a common energy source for irrigation, while electricity is more prevalent in Madhya Pradesh and Gujarat. By the endline (Kharif 2023), some farmers in MP and Gujarat reduced their use of electricity compared to the baseline (Kharif 2021), while a few more farmers in UP began using electricity (Figure 29). The use of energy-efficient and low-carbon sources, such as solar pumps, showed a slight increase in UP, consistent with follow-up survey results. This indicates that farmers are beginning to diversify their energy sources for irrigation from diesel to electric and solar. However, the project's support to increase the use of energy-efficient irrigation systems did not lead to significant uptake.

Overall, the project has led to some positive changes in specific practices, notably the shift towards biofertilizers and the increased use of natural pesticides in Uttar Pradesh and Gujarat. Despite these successes, traditional practices like chemical fertilizers, flood irrigation, and conventional tillage remain prevalent, indicating limited adoption of more sustainable methods. Additional efforts are needed to encourage the widespread uptake of energy-efficient irrigation systems, soil and water conservation practices, and the cultivation of resilient crops across the three states.

4.2.9. Livestock feed

One of the livestock production practices promoted by the program is ration balancing, specifically in Gujarat and Uttar Pradesh. During the baseline and endline surveys, respondents provided details on the primary feed sources for their large livestock. As illustrated in Figure 1 in Appendix I, grazing and the cut-and-carry method of local grass are the prevalent feeding methods for large livestock in Gujarat and Madhya Pradesh. In Uttar Pradesh, the majority of farmers reported using wheat, cut-and-carry local grass, and berseem. Although the overall composition of feed sources remained largely unchanged across the two survey periods, there was a notable increase in the proportion of households in Gujarat reporting the use of plant/tree leaves and stems as livestock feed, rising from less than 1% to over 12% by the endline survey.

4.3 Impact of LCA practices adoption

4.3.1 Socioeconomic outcomes

Was there an improvement in the state of household's welfare who adopted LCA practices?

To determine if households that adopted LCA practices experienced an improvement in welfare, we employed the first difference estimation method. This approach estimates the project's impact by using the change in the LCA index as the predictor variable and the changes in socioeconomic indicators as the outcome variables.

$$\Delta yi = \Delta \; xi\beta + \varphi d + \Delta ei$$

Where:

Δyi represents the changes in outcome variables (Asset index, LCSI, FIES, Production expense, and Farm return); Δxi represents changes in key variable of interest – the LCA index; β is estimated effect of LCA index on the socioeconomic indicators, ϕd is district fixed effects which we use to control heterogeneity across the districts and it is the idiosyncratic error term.

First difference estimation for a two-period panel involves calculating the difference between observations in the two time periods for both the dependent and independent variables. This approach removes time-invariant unobserved heterogeneity by differencing the variables, allowing us to estimate the causal effect of the independent variable—in this case, the LCA index—on the socio-economic outcome variables. By focusing on changes within the units over time, we can more accurately assess the impact of the LCA practices.

In addition to examining changes in the LCA index, we use the LCA up-scaler—a binary variable that equals 1 if the change in the LCA index is greater than 0, and 0 otherwise, as defined in the previous section. By comparing households that upscaled their LCA practices with those that did not change or reduced their use, we can gain deeper insights into the project's impact on household well-being. We hypothesize that increasing the use of low-carbon and less capital-intensive practices will lead to improvements in socioeconomic outcomes.
Key assumptions:

- LCA project made a significant contribution on the improvement of LCA index and LCA up-scaler
- Improvements in the socioeconomic indicators were caused by improvements in the uptake of LCA practices not by some other confounding factors

4.3.2 Household Asset Wealth

First, we examined whether households that a) intensified their LCA practices overall (as measured by the LCA index) and b) upscaled LCA practices accumulated more assets between the baseline and endline periods. The asset gain index was constructed using Principal Component Analysis (PCA) based on data on households' ownership of livestock, nondurable farm assets, other durable assets, and housing characteristics collected at both baseline and endline surveys[3].

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[3] Woldeyohanes, T., Kegode, H., Hughes, K., Outtara, I., Vågen, T.-G., Winowiecki, L. A., Kleinsmann, J., Prabhu, R., & Bourne, M. (2023). Regreening Africa Consolidated Endline Survey Report. World Agroforestry. Nairobi, Kenya. Retrieved from https://regreeningafrica.org/wp-content/uploads/2023/08/Endline-Report_21_08_23_Online.pdf

We observed a significant gain in the overall asset index for the sampled households compared to the baseline. As shown by the density plot in Figure 30, the overall asset index for the endline (blue) is more spread to the right, with the median asset index increasing from 1.4 to 1.8 across the three states.

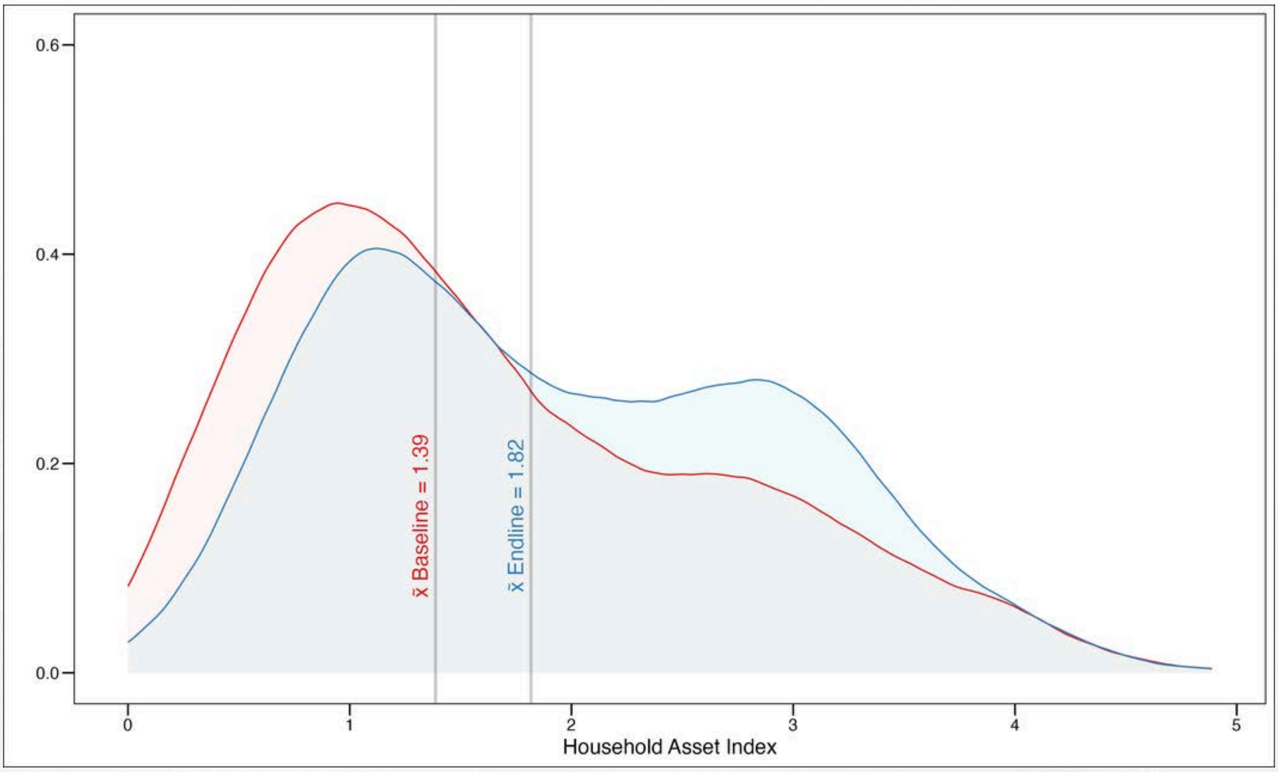


Figure 30: Distribution of asset wealth at baseline (red) and endline (blue) for the whole sample. The vertical line represents the median value for the corresponding survey years

Similar trends are observed in each state (Figure 31), with the largest asset gains experienced by households in Gujarat, followed by Uttar Pradesh, while the change is smaller in Madhya Pradesh. This pattern aligns with the increased adoption of LCA practices in Gujarat and Uttar Pradesh.

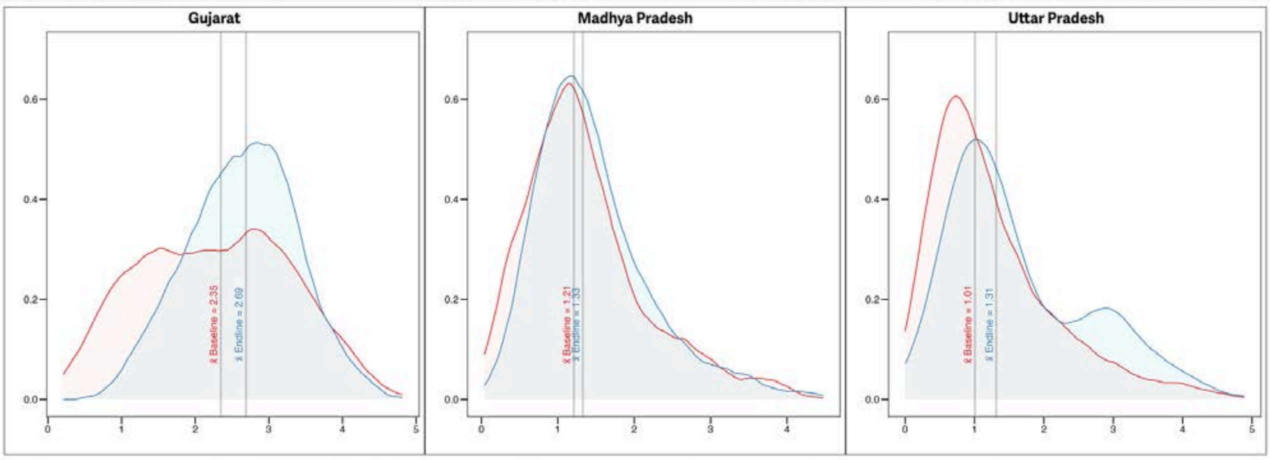
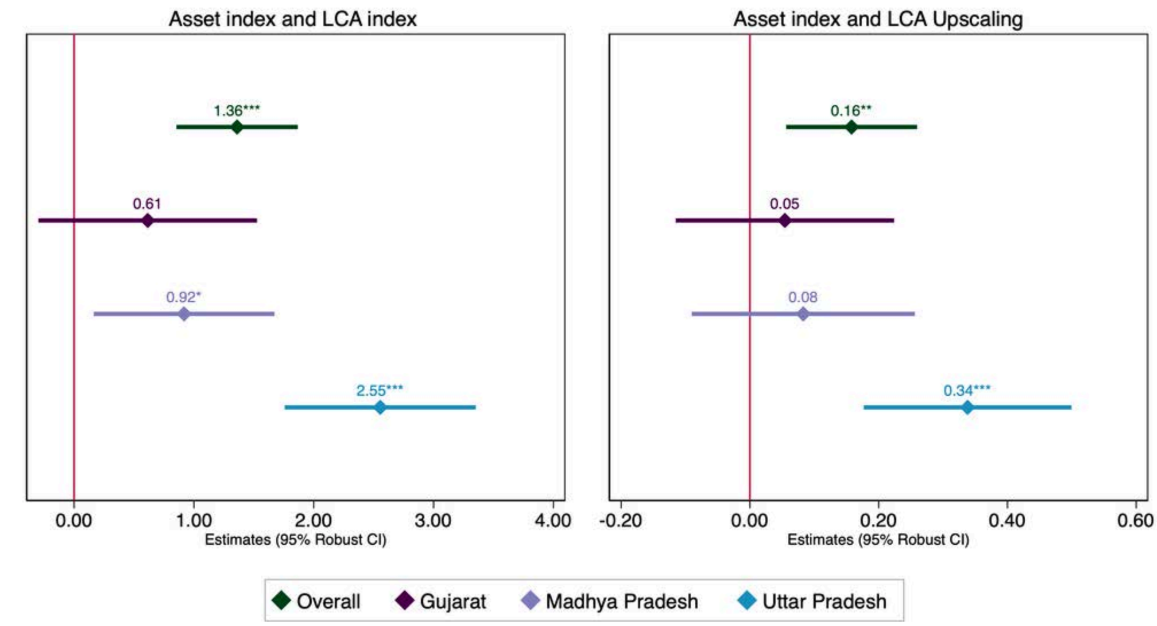


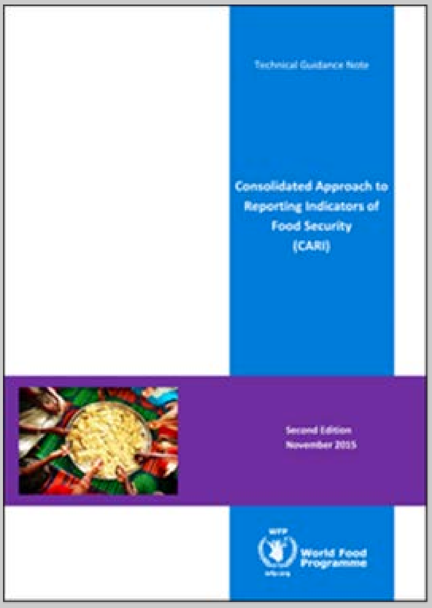
Figure 31: Distribution of asset wealth at baseline (red) and endline (blue) across the three states. The vertical line represents the median value for the corresponding survey years

First difference estimation results reveal a positive and statistically significant link between changes in the LCA index, increased adoption of LCA practices and asset gains overall and in the state of Uttar Pradesh.
This suggests that households that increased their LCA practices generally saw asset growth, with a notable impact in Uttar Pradesh. As shown in Figure 32, in Gujrat, households that upscaled their LCA practices experienced a 34 percent increase in asset gains compared to non-upscalers. This is understandable, as farmers in Uttar Pradesh are relatively poor, and modest savings on inputs or productivity improvements from adopting LCA can lead to substantial increases in asset wealth.



Note: Coefficients derived from regressing change in asset index on change in LCA index (0-1 scale) adoption of LCA practices.

Figure 32: Association between household's asset gain index and changes in LCA index (left) and LCA up scaling (right)



4.3.3 Livelihood Coping Strategies Index (LCSI)

The other socioeconomic indicator we examine is the proportion of households reporting the adoption of maladaptive coping behaviours. This indicator measures resilience indirectly by assessing the uptake of maladaptive coping strategies when faced with shocks; more resilient households are presumed to be less likely to resort to such strategies. To measure this, we adapted the World Food Programme's Livelihood Coping Strategies Index (LCSI).
During the baseline and endline surveys, respondents were asked if they had adopted any of the following coping strategies in the past 12 months due to a lack of resources to meet household needs:

"In the last 12 months (past year), did anyone in your household do any of the following due to a lack of resources to meet household needs?"

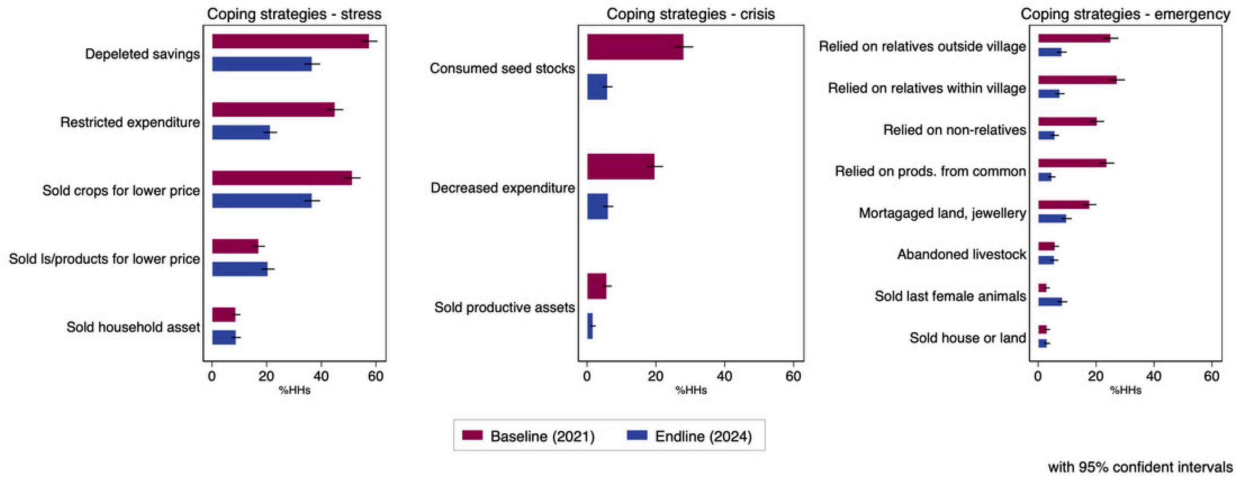


Figure 33: Changes in the use of maladaptive coping strategy items

Based on responses to this question, we observed that a high percentage of households at the baseline reported resorting to various maladaptive coping strategies, which are grouped into three categories based on their severity (Table 7). However, at the endline, these percentages were reduced across all three categories, implying that households became more resilient compared to the baseline.

To aid in interpretation and analysis, the coping strategy items are aggregated into an index. The World Food Programme's approach involves selecting the 10 most relevant strategies for the local context: 4 in the Stress, 3 in the Crisis, and 3 in the Emergency category. Each coping strategy is weighted based on the severity of its category: stress strategies are weighted at 2, crisis strategies at 3, and emergency strategies at 4. The index is then computed as a percentage of the maximum possible score of 29 (as shown in Table 7).

Table no. 8: Coping strategy items with respective weight used to construct the Weighted Livelihood Coping Strategy Index (LCSI)

STRESS (x2)	CRISIS (x3)	EMERGENCY (x4)
1. Sold HH asset	1. Sold productive assets or means of transport	1. Sold last female animals or abandoned livestock
2. Sold crops or livestock for lower price than usual	2. Consumed seed stocks that were to be saved for the next season	2. Mortgaged assets
3. Restricted HH expenditure to only essential items like food and other essentials	3. Decreased expenditures on fertilizer, pesticide, fodder, animal feed, veterinary care, etc.	3. Had family member migrate permanently or temporarily in search of work
4. Depleted savings		

The results show a decrease in households' use of maladaptive coping strategies compared to the baseline across all states, as illustrated by the LCSI density plot in Figure 34. Overall, At the endline, 706 of sampled households (67 %) reported less need to engage in maladaptive coping behaviours compared to the baseline, as measured by the change in LCSI.

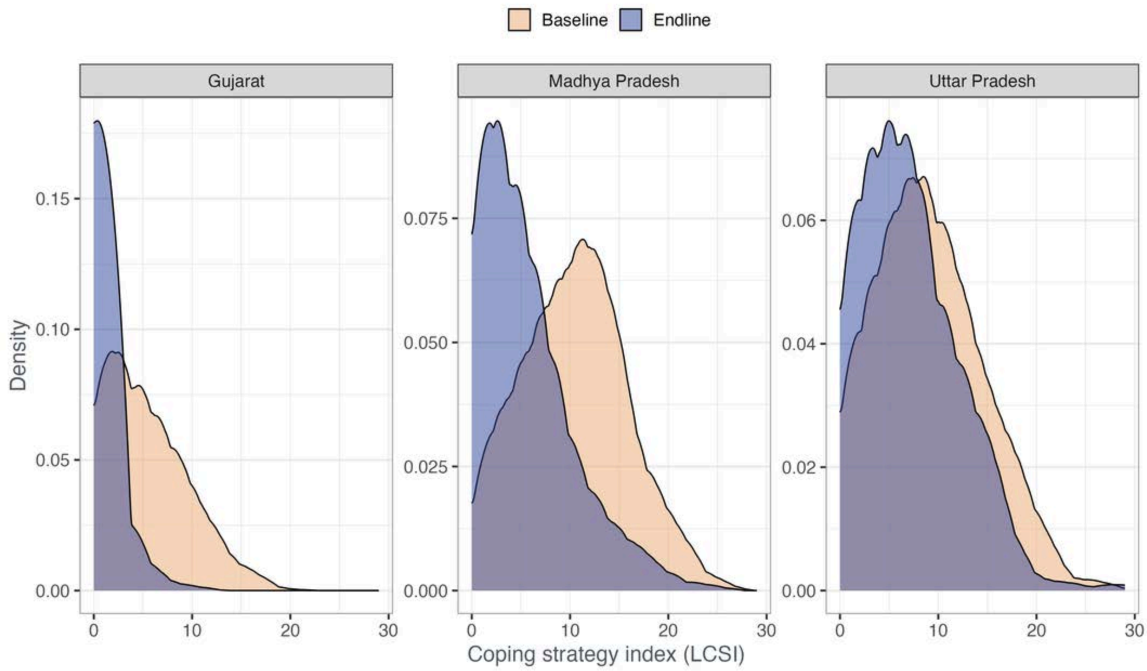
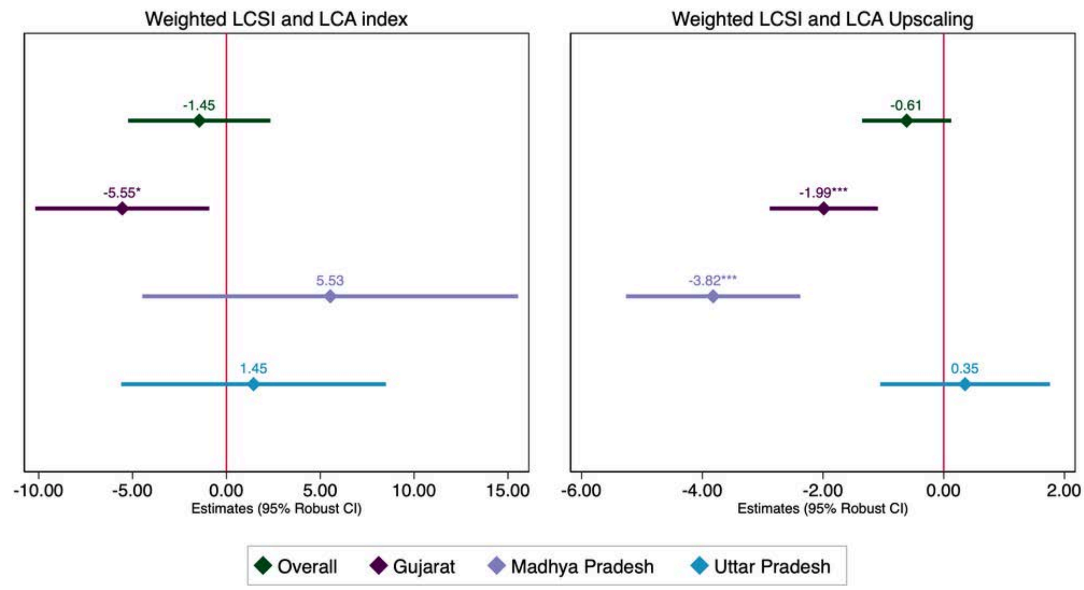


Figure 34: Distribution of weighted LCSI for the baseline and endline

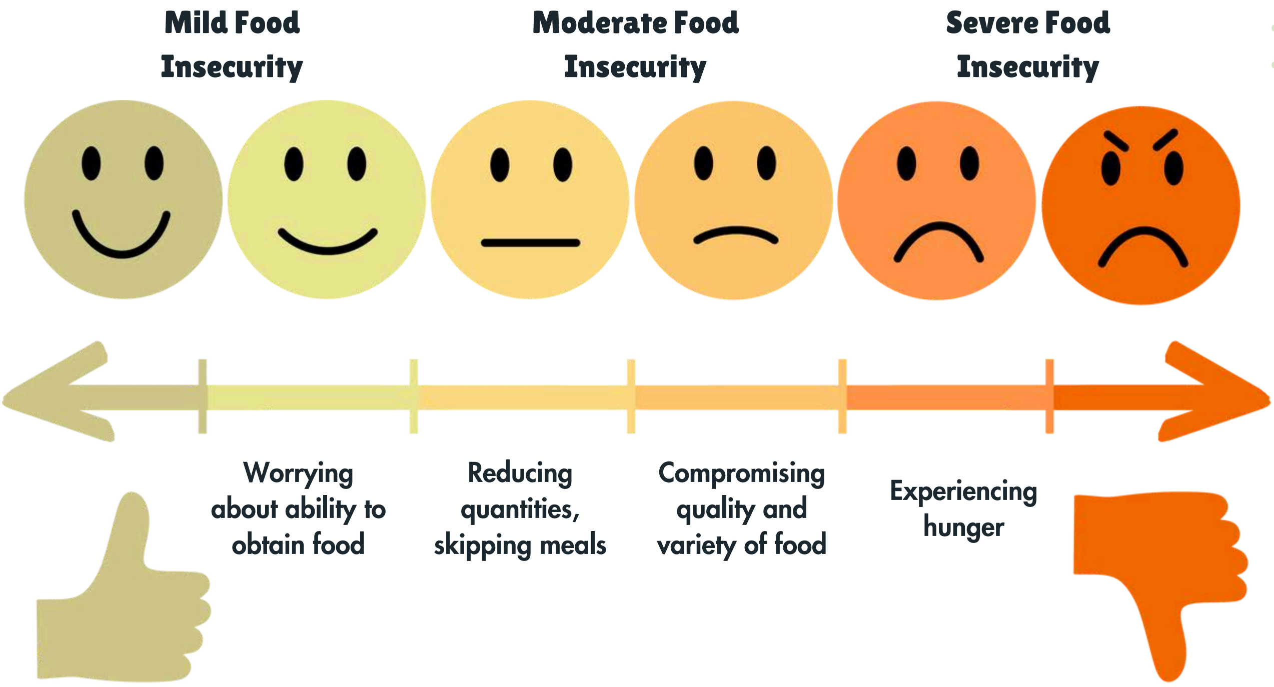
The first difference estimation results also show that households that intensify their use of LCA practices (as indicated by the LCA index) and those that upscale LCA practices are less likely to engage in maladaptive coping strategies. As shown in Figure 35, the upscaling of LCA practices has a negative and statistically significant effect on the use of maladaptive coping strategies, particularly in the states of Gujarat and Madhya Pradesh.



Note: Coefficients derived from regressing change in LCSI
on change in LCA index (0-1 scale) adoption of LCA practices.

Figure 35: Association between change in households weighted LCSI and change in LCA index (Left) and LCA upscaling (right)

4.3.4 Food insecurity Experience Scale (FIES) – 8 points score



We then looked at Food insecurity status using the food insecurity experience score (FIES). FIES is being used to measure SDG Indicator 2.1.2: Prevalence of moderate or severe food insecurity in the population.

Data for the FIES was gathered by asking eight questions about self-reported behaviours and experiences related to challenges in accessing food due to resource constraints.

Over the last 12 months:

1. Were you worried you would run out of food?

2. Were you unable to eat healthy and nutritious foods because you did not have enough money or resources?

3. Did you only eat a few kinds of foods because you did not have enough money or resources?

4. Did you skip a meal because you did not have enough money or resources?

5. Did you eat less than you thought you should because you did not have enough money or resources?

6. Did your household run out of food?

7. Were you hungry but did not eat because of a lack of money and resources?

8. Did you not eat for a whole day because you did not have enough money or resources?

If the households indicate experiencing most of these difficulties, that implies that they are at severe food insecurity and experiencing hunger.

Over the project, the overall FIES score showed a notable improvement, with the median score dropping from 2 to 0 out of a possible 8 points. This indicates a significant reduction in food insecurity (Figure 36). Compared to baseline, 531 of the sampled farming families (51%) reported improvement in their food security as indicated by the change in FIES.

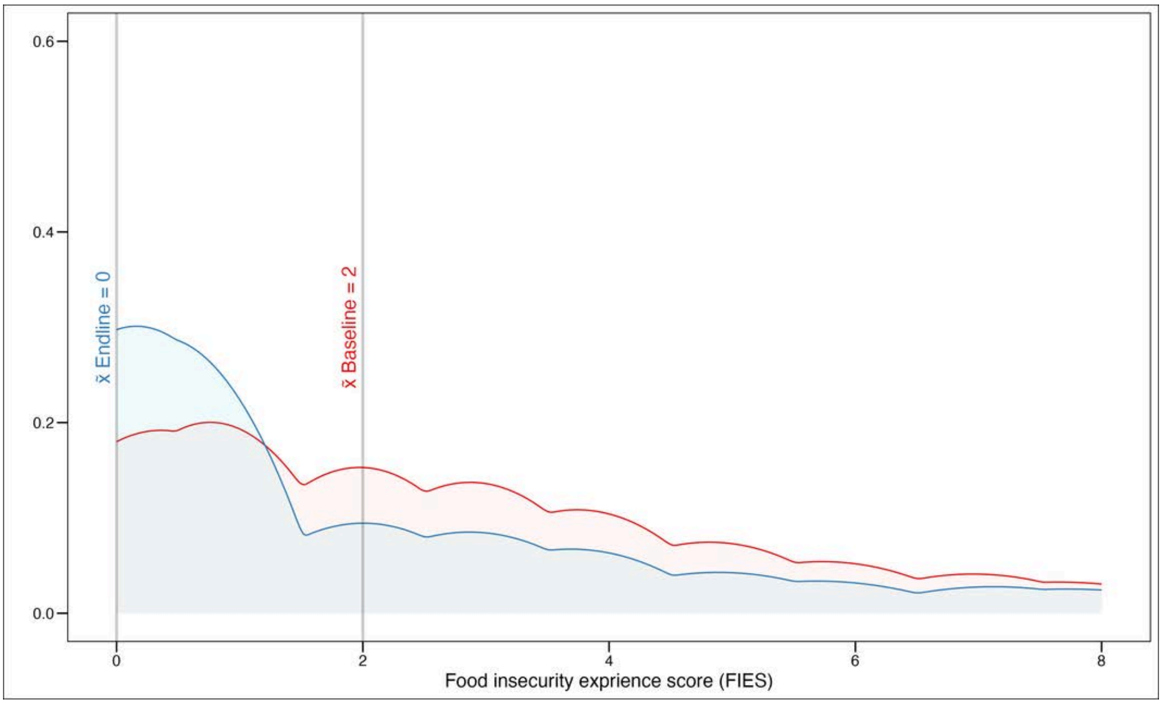


Figure 36: Change in food insecurity status – The vertical line represents the median value for the corresponding survey years

The results across the three states also show a similar trend, with household food security status improving compared to the baseline, as illustrated by the FIES density plot in Figure 37. In Gujarat, food insecurity was not a significant issue even at the baseline, with only a few respondents expressing concern about their ability to obtain food. In Madhya Pradesh and Uttar Pradesh, respondents initially reported mild and moderate food insecurity at the baseline respectively. By the endline, this had decreased to mild food insecurity, with only a few households still worried about their ability to obtain food.

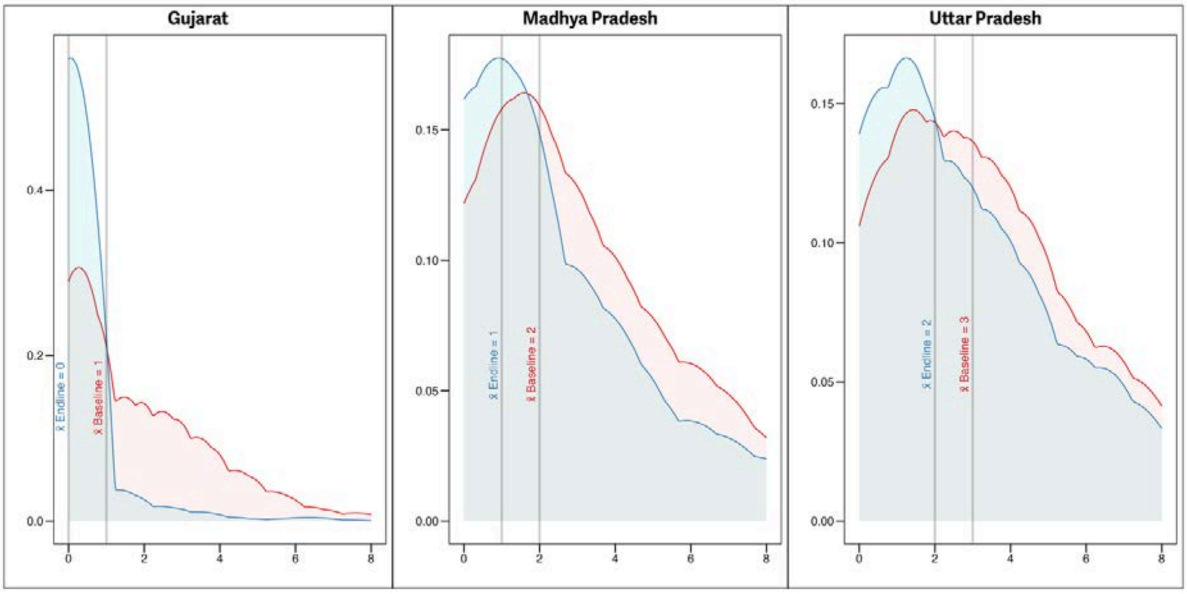


Figure 37: Distribution of FIES at baseline (red) and endline (blue) across the three states. The vertical line represents the median value for the corresponding survey years

Our estimation results also points in a positive direction for FIES, indicating that households that intensified the use of LCA practices or scaling up LCA practice compared to baseline experiencing improvement in food security status. As shown in Figure 38, households in Uttar Pradesh who intensify LCA practices and adopt at least two LCA practices are less likely to experience food insecurity which is significant at 5% level. Up-scaler of LCA practices experiences similar effect on food security in Gujarat but no significant impact is observed for Madhya Pradesh.

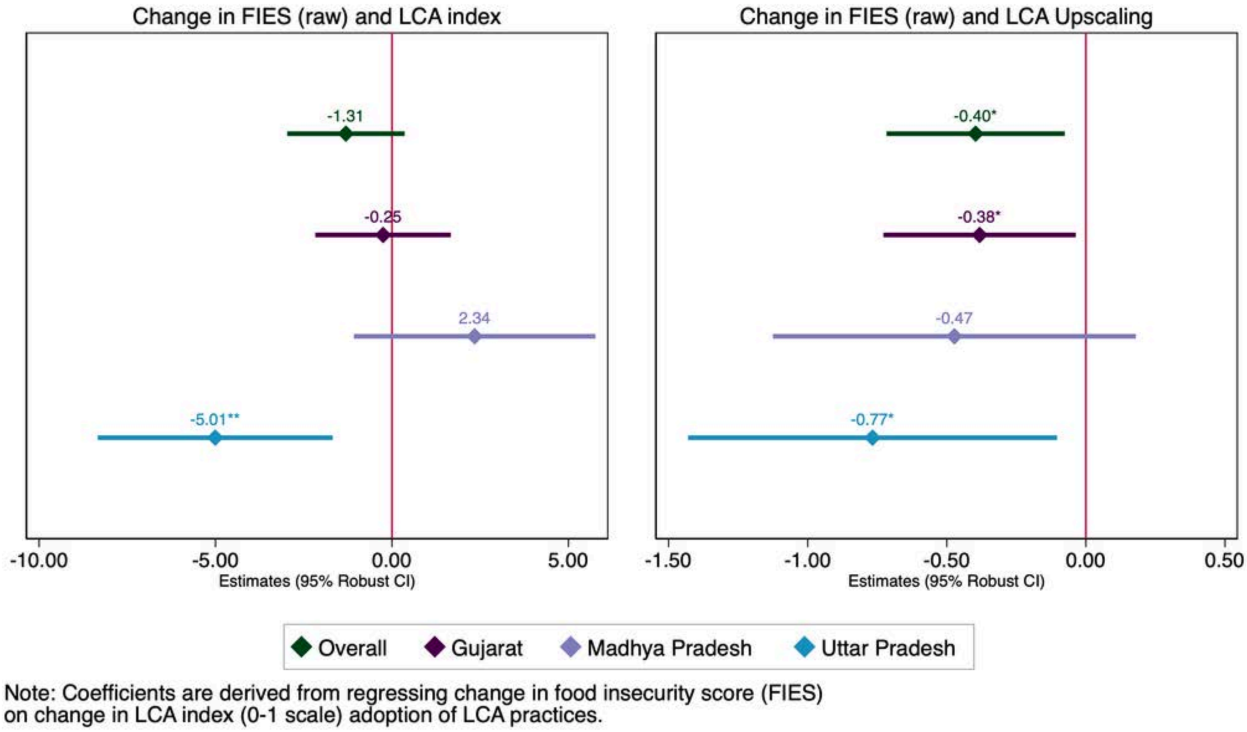


Figure 38: Association between change in FIES and change in LCA index (Left) and LCA upscaling (right)

We employed field-based data on input use, crop yields, and village-level average prices, enabling us to compute average farm expenses for variable input costs and the value of crops produced, with adjustments of baseline values for inflation. Our data collection spanned three agricultural seasons: Kharif 2021 (baseline), Kharif 2023, and Rabi 2024 (endline). However, this report primarily contrasts the two Kharif seasons of 2021 (baseline) and 2023 (endline) as value of these economic indicators likely fluctuates over the seasonal calendar.

The violin plots presented in Figure 39 illustrate a notable reduction in the average variable input costs for crop production (000 INR) across the study states. Specifically, these costs decreased significantly in Gujarat, with modest declines in Madhya Pradesh and Uttar Pradesh compared to the baseline. These reductions, all statistically significant ($p < 0.001$) across the three states, correlate positively with the increased adoption of Low Carbon Agriculture (LCA) practices. These practices included a shift towards biofertilizers and enhanced use of natural pesticides, particularly noted in Uttar Pradesh and Gujarat.

Overall, our result shows that 703 farmers (67%) reported at least 10% net reduction in farm expenses at the endline, after adjusting for inflation for the baseline period. Of these, 278 farmers (40 %) are in Gujarat, 262 (37 %) are in Uttar Pradesh and 163 (23 %) are in Madhya Pradesh.

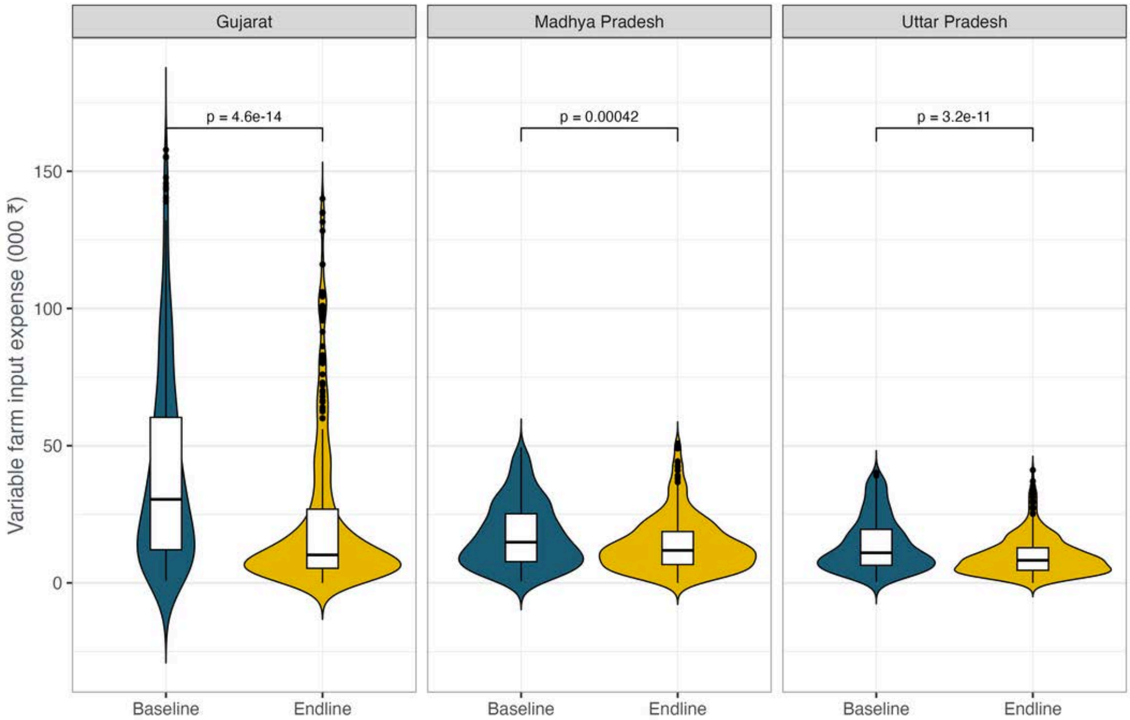


Figure 39: Violin plots showing the distribution of farm input expenses for the baseline and endline survey.

Similarly, as shown in Figure 33, the average value of crops produced show a significant increase in Gujarat and a moderate rise in Uttar Pradesh. Both increases are statistically significant. Conversely, in Madhya Pradesh, the value of crops produced exhibited a marginal decline when compared to the baseline figures.

The trends in average net farm return—which deducts variable input costs from the cash value of crops produced—echoed those observed in crop production values across the three states (Figure 40). The increases in net farm returns were statistically significant in Gujarat and Uttar Pradesh, pointing to the economic benefits of adopting LCA practices. In contrast, Madhya Pradesh saw a slight decrease in net farm returns.

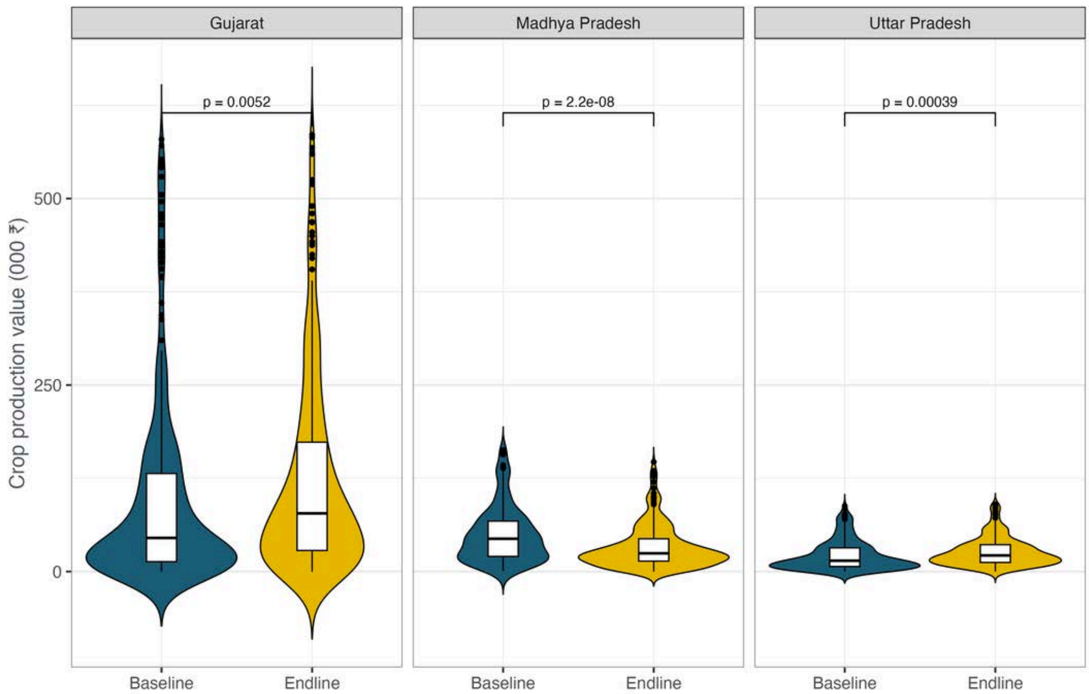


Figure 40: Violin plots showing the distribution of cash value of crop produced at the baseline and endline survey.

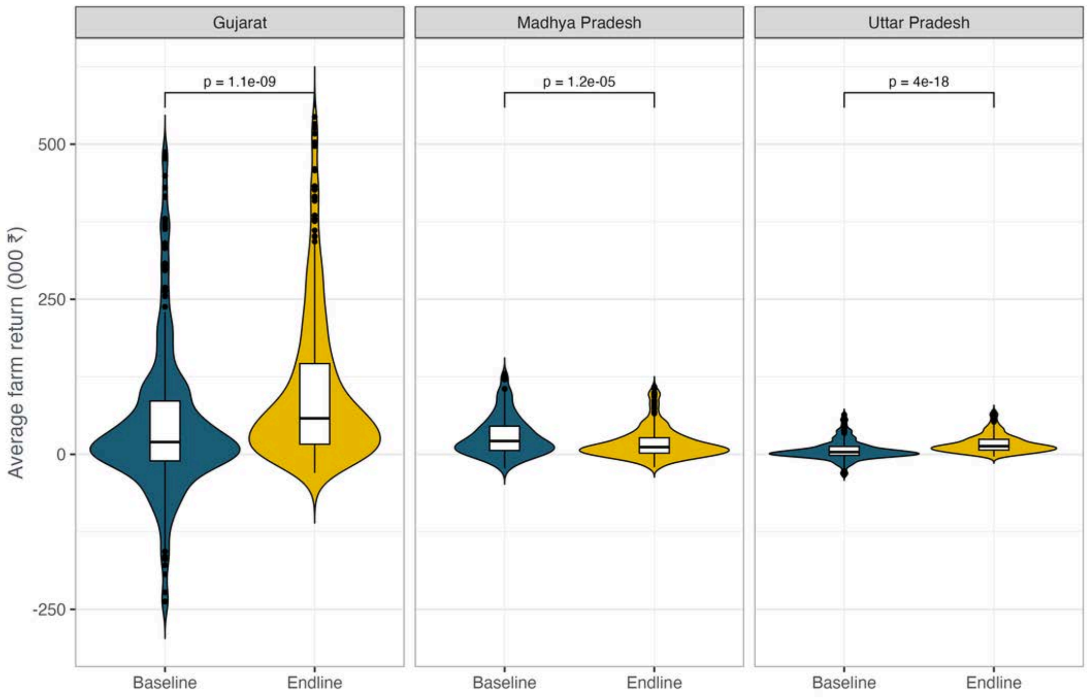


Figure 41: Violin plots showing the distribution of average farm return at the baseline and endline survey.

Our first difference estimation results align with this. As shown in Figure 42, households intensifying LCA practices (measured by LCA index) compared to the baseline are more likely to experience saving on farm input cost which is statistically significant at 10% only for Gujarat. However, households that scaled up the use of LCA practices compared to the baseline are more likely to benefit from cost saving which is statistically significant in Gujarat and Uttar Pradesh. Interestingly, our data does not support a similar effect for households in Uttar Pradesh which contradicts significant uptake of natural pesticides.

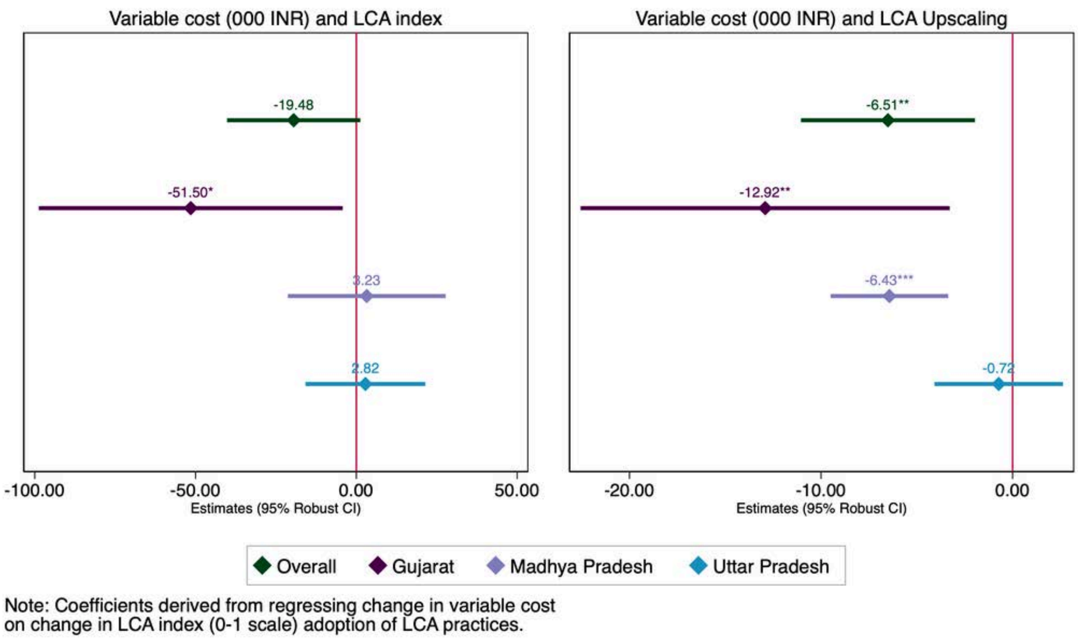


Figure 42: Association between change farm expense and change in LCA index (Left) and LCA upscaling (right)

On the other hand, the association between average farm return and LCA intensification (LCA index) is positive for Madhya Pradesh and Uttar Pradesh but statistically not significant. the association between average farm return and upscaling of LCA practices is positive for Gujarat and Uttar Pradesh. However, this positive association is statistically significant for farmers in Uttar Pradesh at 10% level, as shown in Figure 43. The association is negative for Madhya Pradesh.

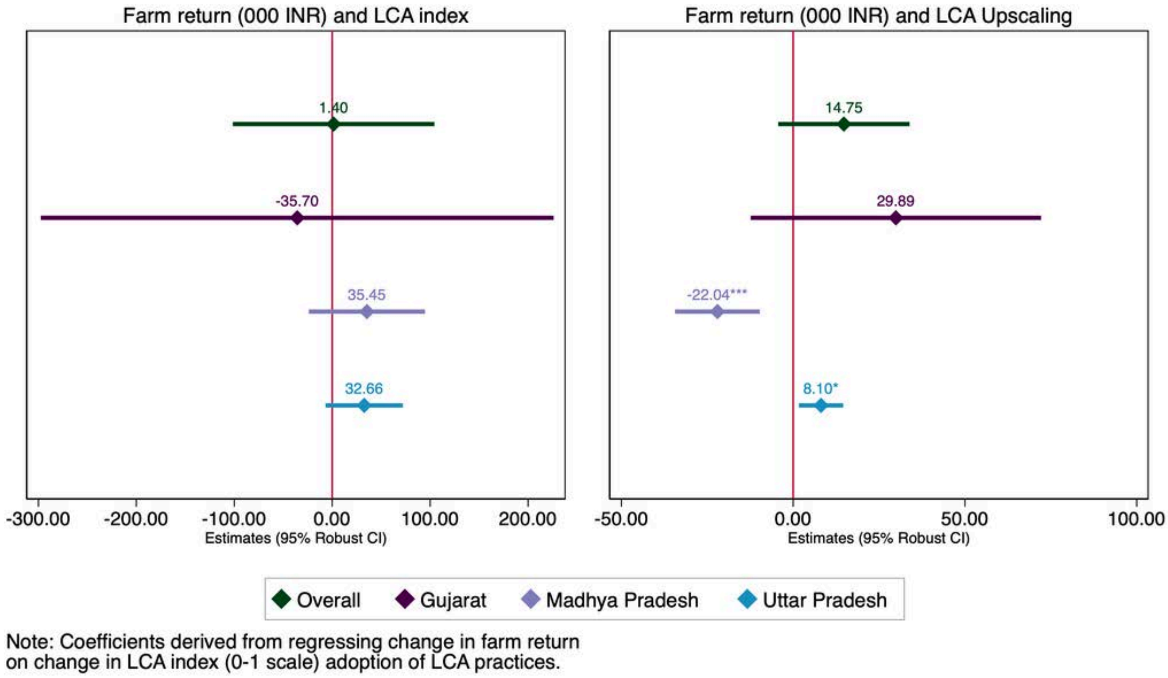


Fig 43: Association between average farm return and LCA intensification (LCA index) (left) and upscaling of LCA practices (right)

In conclusion, our result also indicates, 347 famers (33%) of the sampled farming families reported at least 10% improvement in their crop income, after adjusting for inflation. This economic benefit varies significantly across the three states but aligns with the changes in the adoption rates of LCA practices.

In Gujarat, where 123 farmers (35% of those who reported increases) experienced income gains, likely due to adopting biofertilizers and reducing chemical inputs making sustainable LCA practices both environmentally and economically viable. Uttar Pradesh saw most notable change, with 174 farmers (50% of those reporting improvements) noting income gains. This region's pronounced shift towards natural pesticides and biofertilizers, part of the LCA strategies, may have improved soil health and crop resilience, leading to better yields and higher profitability.

Conversely, only 50 farmers in Madhya Pradesh (14%) saw income gains, potentially reflecting lower adoption or effectiveness of LCA practices due to factors like insufficient local support and training. For example, while bio-input centers were established in Gujarat and Uttar Pradesh, similar LCA intervention strategy was not implemented in Madhya Pradesh.

These outcomes underline the economic potential of LCA practices, demonstrating that sustainable agriculture can increase profitability through enhanced yields and reduced costs. The variation in results across states highlights the need for tailored support and capacity building to maximize the adoption and impact of LCA practices.

Land and soil health outcomes based on representative cropping fields

During the endline surveys, one cropping field from each sampled household was randomly selected and digitally mapped to create geo-tagged field polygons. These polygons were then overlaid onto land health maps, and data were extracted for the periods 2021-2022. Our goal was to compare changes in these indicators against changes in the LCA intensification score (LCA index) and the adoption of LCA practices over the project duration. We hypothesized that improvements in the former would coincide with increases in the latter, providing evidence of the program's impact. However, since the measurements of soil and land health indicators we have are only for the baseline situation and not for changes from the baseline, we are unable to assess the impact. Therefore, in this section, we present the baseline situation of soil and land health indicators for the representative cropping fields of the sampled households.

The soil organic carbon, expressed as the grams of organic carbon per kilogram of soil (gC /kg), was estimated based on soil data from a global network of LDSF sites and Landsat remote sensing data. Machine learning algorithms (models) were trained to predict SOC based on a satellite image reflectance value. There are large variations (Figure 44) between project sites, as expected, given the wide range of climate zones, altitudes, and management systems represented. Narmada and Junagadh districts of Gujarat have highest SOC overall while the SOC in the remaining two districts is lower. We do not see large variations across the two districts in Madhya Pradesh where the SOC is in the range of 10 to 20 gC/kg.

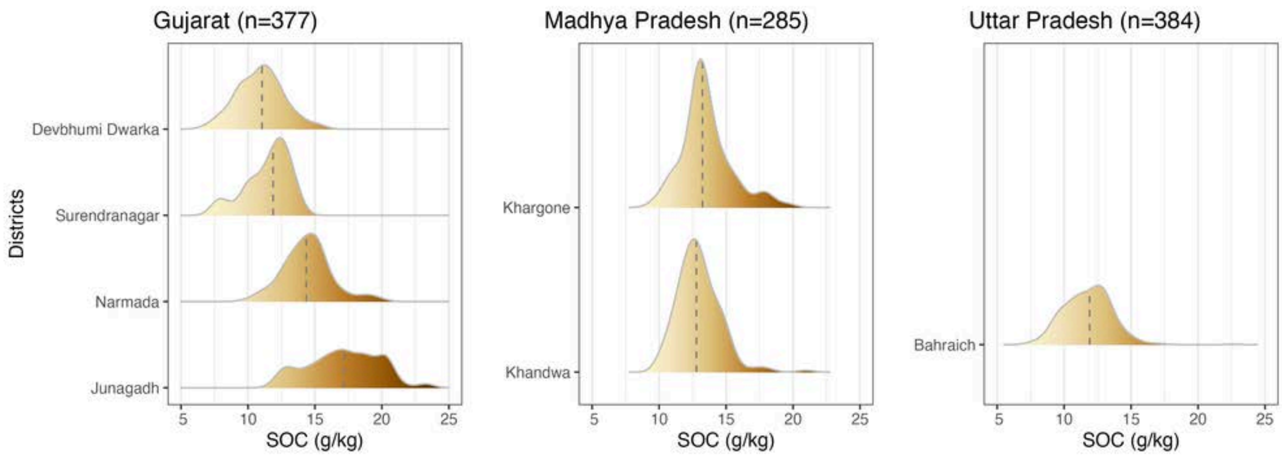


Figure 44: Distributions of SOC at baseline across seven of the districts. The dashed line represents the median and the colour shows the level of SOC, with browner representing more SOC

Similarly, the soil erosion prevalence (%), expressed as the weighted mean probability of severe erosion within each farmer field, was estimated using field data on different types of erosion from the global network of LDSF sites and Landsat remote sensing data. The number of fields with higher levels of erosion prevalence is relatively higher in the districts of Junagadh and Narmada in Gujarat and the two districts in Madhya Pradesh, as shown in Figure 45.

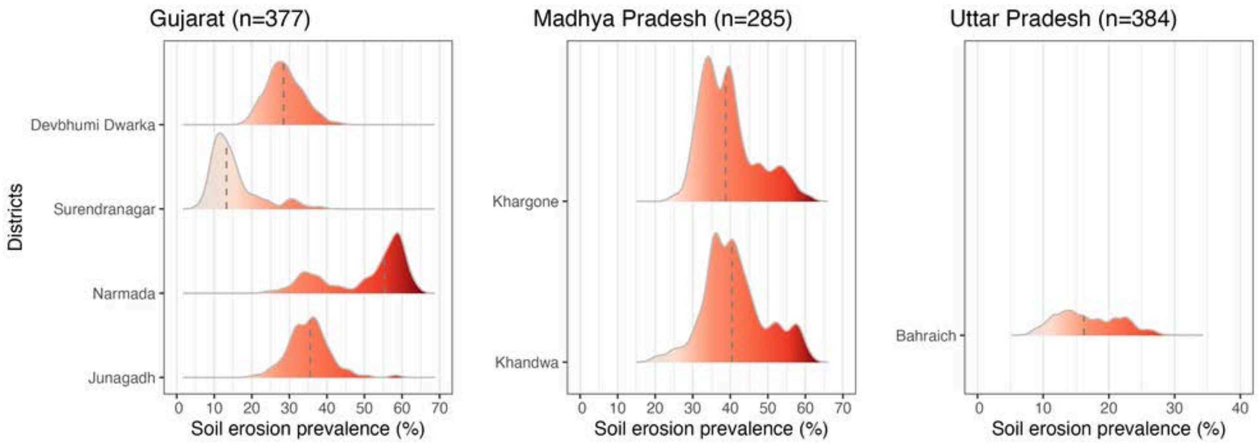


Figure 45: The density plots show the distribution of soil erosion prevalence (%) across the districts of the three LCA programme States. The dashed line shows the median and the colour shows the severity of erosion prevalence, with reddish representing serious erosion

5. Conclusions

5.1

The analysis of soil health data from the LDSF survey revealed significant improvements in soil organic carbon and nitrogen content in LCA intervention plots compared to non-intervention plots in a relatively short period. This probably indicates extended adoption of LCA practices on long term basis to achieve sustainable positive change. Despite these gains, there is still a need to enhance soil organic carbon and nitrogen content further. In addition, proper selection and long term implementation of ecosystem specific LCA practices can add to the organic carbon and nitrogen content substantially. In Sayla, Gujarat, slight replacement of high values of sand content by clay content may add to improvement in soil water holding capacity. However, longer interventions are recommended to achieve significant improvements in the physical properties of the soil.

Additionally, a shift toward a neutral soil pH in the LCA plots compared to non-intervention plots in Risia, Bahraich (Uttar Pradesh), suggests a potential increase in nutrient availability. In all three project areas, agroforestry systems were less common, with annual crops predominating over trees. This underscores the need for increased tree cover, which could ultimately lead to enhanced soil and ecosystem health.

5.2

Using baseline and endline surveys, we tracked the adoption of Low Carbon Agriculture (LCA) practices and the discontinuation of conventional High Carbon Agriculture (HCA) practices. We noted a considerable increase in the use of bio-inputs and a reduction in capital-intensive chemical inputs, particularly in Gujarat and Uttar Pradesh. In contrast, Madhya Pradesh did not show a significant change in the adoption of LCA practices. By comparing the changes in the LCA intensification index, we found that 504 households (48%) up-scaled LCA practices adopting at least one new LCA practice or dis-adopted at least one HCA practice compared to the baseline, as measured by LCA up scaling, i.e. positive change in LCA index.

Despite these successes, the adoption of multiple LCA practices remains limited, as indicated by the low LCA index. Traditional practices like the use of chemical fertilizers, flood irrigation, and conventional tillage are still widespread, underscoring a slow transition to more sustainable methods. Additionally, the adoption of agroforestry—integrating trees into crop fields—was less common, a trend also observed in the Land Degradation Surveillance Framework (LDSF) results. Enhanced and tailored efforts are needed to promote the broader implementation of energy-efficient irrigation systems, soil and water conservation practices, agroforestry, and the cultivation of resilient crop varieties across the three states.

5.3

Using first difference estimation and accounting for district fixed effects we assess the impact of the intensification of LCA practices on various socio-economic outcomes. Our assessment shows that there is strong and positive association between changes in socio-economic outcomes and the adoption of LCA practices.
The average variable cost significantly decreased in Gujrat and modestly in Uttar Pradesh compared to the baseline resulting in increased farm income gains. This change is consistent with the dis-adoption of capital-intensive chemical inputs and increased use of bio-inputs in Gujarat and Uttar Pradesh. Our model estimates also point in a similar direction where adoption of LCA practices or scaling up the use is associated with a decline in input cost in Gujarat which is statistically significant.

Similarly, we show that households that adopt LCA practices or scaled up the use are more likely to see asset wealth growth, engage less in maladaptive coping strategies, and less likely to experience food insecurity.

APPENDIX I

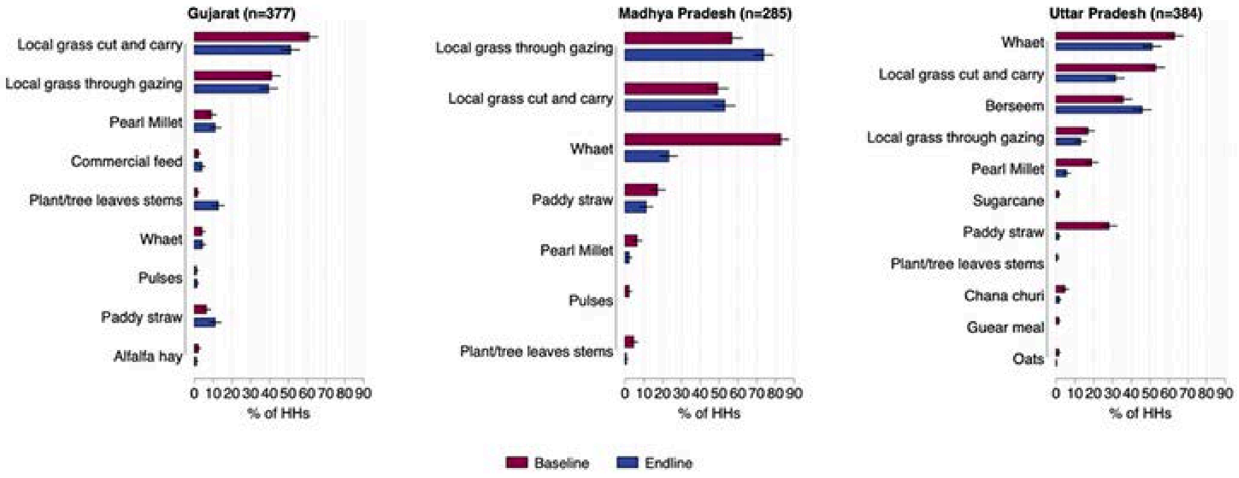


Fig 46: Proportion of farmers reporting primary sources of feed for large live stock at the baseline and endline

I. Supplementary Materials:

Table SM2: Summary statistics of farm characteristics and adoption of LCA practices - Madhya Pradesh

Characteristic	2021 (n = 285)	2024 (n = 285)	p-value
Farm size (Acre)	3.46 (2.61)	2.98 (2.22)	0.090
Female decides on land use	72 (25%)	122 (43%)	<0.001
Male decides on land use	263 (92%)	149 (52%)	<0.001
Joint decision on land use	50 (18%)	51 (18%)	>0.9
Change in soil quality			<0.001
No change	107 (38%)	93 (33%)	
Declined	45 (16%)	83 (29%)	
Improved	133 (47%)	109 (38%)	
Number of LCA practices adopted			
0	28 (9.8%)	13 (4.6%)	
1	71 (25%)	102 (36%)	
2	86 (30%)	122 (43%)	
3	46 (16%)	40 (14%)	
4	35 (12%)	4 (1.4%)	
5	15 (5.3%)	1 (0.4%)	
6	4 (1.4%)	1 (0.4%)	
7	0 (0%)	2 (0.7%)	
LCA practice index (0-1 scale)	0.14 (0.09)	0.11 (0.06)	0.001
Change in LCA practice index	-0.02 (0.10)	-0.02 (0.10)	>0.9
Change in number of LCA practices adopted	-0.40 (1.63)	-0.40 (1.63)	>0.9
Crop production value (INR)	66,445 (69,848)	34,607 (33,478)	<0.001
Variable farm input cost (INR)	21,283 (19,329)	15,105 (12,009)	<0.001
Net farm return (INR)	44,993 (61,496)	19,493 (27,904)	<0.001

Note: Values reported are Mean with SD in the parenthesis for continuous; number with percentage in the parenthesis for categorical variables. Two-sided t-tests were used for statistical testing, and the corresponding p-values are presented in the last column. The tests performed are Pearsons Chi-squared test for categorical variables and the Wilcoxon rank sum test for continuous variables.

I. Supplementary Materials:

Table SM2: Summary statistics of farm characteristics and adoption of LCA practices - Madhya Pradesh

Characteristic	2021 (n = 285)	2024 (n = 285)	p-value
Farm size (Acre)	3.46 (2.61)	2.98 (2.22)	0.090
Female decides on land use	72 (25%)	122 (43%)	<0.001
Male decides on land use	263 (92%)	149 (52%)	<0.001
Joint decision on land use	50 (18%)	51 (18%)	>0.9
Change in soil quality			<0.001
No change	107 (38%)	93 (33%)	
Declined	45 (16%)	83 (29%)	
Improved	133 (47%)	109 (38%)	
Number of LCA practices adopted			
0	28 (9.8%)	13 (4.6%)	
1	71 (25%)	102 (36%)	
2	86 (30%)	122 (43%)	
3	46 (16%)	40 (14%)	
4	35 (12%)	4 (1.4%)	
5	15 (5.3%)	1 (0.4%)	
6	4 (1.4%)	1 (0.4%)	
7	0 (0%)	2 (0.7%)	
LCA practice index (0-1 scale)	0.14 (0.09)	0.11 (0.06)	0.001
Change in LCA practice index	-0.02 (0.10)	-0.02 (0.10)	>0.9
Change in number of LCA practices adopted	-0.40 (1.63)	-0.40 (1.63)	>0.9
Crop production value (INR)	66,445 (69,848)	34,607 (33,478)	<0.001
Variable farm input cost (INR)	21,283 (19,329)	15,105 (12,009)	<0.001
Net farm return (INR)	44,993 (61,496)	19,493 (27,904)	<0.001

Note: Values reported are Mean with SD in the parenthesis for continuous; number with percentage in the parenthesis for categorical variables. Two-sided t-tests were used for statistical testing, and the corresponding p-values are presented in the last column. The tests performed are Pearsons Chi-squared test for categorical variables and the Wilcoxon rank sum test for continuous variables.

I. Supplementary Materials:

Table SM3: Summary statistics of farm characteristics and adoption of LCA practices - Uttar Pradesh

Characteristic	2021 (n = 384)	2024 (n = 384)	p-value
Farm size (Acre)	1.39 (1.58)	1.09 (0.98)	0.7
Female decides on land use	126 (33%)	97 (25%)	0.021
Male decides on land use	362 (94%)	184 (48%)	<0.001
Joint decision on land use	104 (27%)	19 (4.9%)	<0.001
Change in soil quality			<0.001
No change	143 (37%)	155 (40%)	
Declined	38 (9.9%)	1 (0.3%)	
Improved	203 (53%)	228 (59%)	
Number of LCA practices adopted			
0	77 (20%)	16 (4.2%)	
1	157 (41%)	100 (26%)	
2	89 (23%)	153 (40%)	
3	40 (10%)	76 (20%)	
4	21 (5.5%)	29 (7.6%)	
5	0 (0%)	5 (1.3%)	
6	0 (0%)	2 (0.5%)	
7	0 (0%)	2 (0.5%)	
8	0 (0%)	1 (0.3%)	
LCA practice index (0-1 scale)	0.09 (0.07)	0.13 (0.07)	<0.001
Change in LCA practice index	0.04 (0.10)	0.04 (0.10)	>0.9
Change in number of LCA practices adopted	0.70 (1.52)	0.70 (1.52)	>0.9
Crop production value (INR)	27,764 (33,601)	31,714 (30,492)	<0.001
Variable farm input cost (INR)	17,588 (17,217)	9,880 (7,452)	<0.001
Net farm return (INR)	10,484 (26,785)	21,816 (25,329)	<0.001

Note: Values reported are Mean with SD in the parenthesis for continuous; number with percentage in the parenthesis for categorical variables. Two-sided t-tests were used for statistical testing, and the corresponding p-values are presented in the last column. The tests performed are Pearsons Chi-squared test for categorical variables and the Wilcoxon rank sum test for continuous variables.

II. Materials related to the Land Degradation Surveillance Framework (LDSF):

LDSF Webpage: *https://ldsf.thegrit.earth/*

LDSF Field Manual: *https://www.cifor-icraf.org/knowledge/publication/25533/*

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World Agroforestry

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MRV support to CIFF's investment towards Low Carbon Agriculture

PROJECT TECHNICAL REPORT

(JANUARY 2022 - AUGUST 2024)

https://www.cifor-icraf.org