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Impact of climate services on farm-level operational decisions: Evidence from Andhra Pradesh, India

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Abstract

The frequency and intensity of extreme weather and climate phenomena are increasing globally due to ongoing climate change, posing serious risks and challenges for farming communities. In this context, climate services have emerged as a critical decision support tool to assist farmers in managing production risks. This study examined the impact of climate services, particularly short-term weather forecast information, on farm level operational decisions among groundnut farmers in Anantapur district of Andhra Pradesh, India. Primary data were collected from 160 farmers, comprising 80 users and 80 non-users of climate services, using a structured interview schedule. To address potential selection bias arising from non-random utilization, the study employed the Propensity Score Matching (PSM) approach. Multiple matching algorithms, including Kernel Matching, Nearest Neighbour Matching, and Radius Matching, were applied to estimate the Average Treatment Effect on the Treated (ATT). The results indicated that the utilization of climate services had a positive and statistically significant impact on key farm level decisions, including land preparation, sowing time, irrigation scheduling, and input management. The effects were found to be consistent across different matching methods, demonstrating the robustness of the findings. However, the impact on harvesting decisions was relatively weaker and statistically insignificant. The findings highlighted the importance of timely and location specific climate information in enhancing farmers' decision-making capacity under climatic uncertainty. The study also emphasized the need to strengthen the dissemination of climate services through digital platforms and extension systems to improve accessibility and effective utilization. Such interventions could contribute to improved resilience, productivity, and livelihood security among smallholder farmers in climate vulnerable regions.

Keywords: Agricultural impact, Climate services, Operational decision making, Propensity Score Matching, Weather forecasts

Introduction

In India, where agriculture is largely dependent on monsoon rainfall, the increasing adverse impacts of climate change and weather variability pose significant risks to agricultural productivity and farmers' livelihoods at both local and regional levels ^[1] (Nesheim, Barkved and Bharti, 2017). Although farmers have traditionally managed climatic variability, the rising uncertainty and intensity of climate-related events are reducing their adaptive capacity. In this context, climate services play a critical role in supporting both adaptation and mitigation by providing relevant climate information and knowledge to guide decision-making processes ^[2] (Hewitt and Stone, 2021), thus serving as an important tool for the agricultural sector to anticipate and effectively respond to climatic changes.

Climate services are conceptualized as decision-support mechanisms derived from the systematic transformation of climate information into context-specific advisory outputs that inform decision-making processes among individuals and institutions. These services generate tailored, relevant, and actionable advisories for diverse stakeholders, including policymakers and vulnerable populations, based on available climate data (e.g., forecasts of extreme rainfall events or anticipated dry spells). Effective climate services require

sustained stakeholder engagement to ensure that advisories are aligned with user needs, thereby supporting decision-making under conditions of uncertainty and enabling timely preparedness and response actions. Furthermore, such services depend on efficient access and dissemination mechanisms. Fundamentally, the design and delivery of climate services must be user-centric, prioritizing responsiveness to the specific requirements of end users ^[3] (Tall and Njinga, 2013).

Climate services provide information on key climatic variables, including temperature, precipitation, wind speed, humidity, as well as extreme events such as droughts and floods. This information is disseminated at temporal scales ranging from daily to seasonal through diverse institutional channels, including mobile phones (SMS, voice calls, and digital platforms), mass media such as radio and television, printed materials, extension services (through demonstrations, trainings, and field visits), and participatory approaches such as public meetings and farmer-to-farmer exchanges ^[4] (Yegbemey and Janvier Egah, 2021). In particular, mobile-based platforms, including SMS and applications such as WhatsApp, have emerged as effective tools for delivering timely and location-specific climate advisories, thereby enhancing accessibility, user engagement,

and responsiveness to climate variability ^[5, 6] (Mittal, 2016; Mittal and Hariharan, 2018).

Farmers predominantly rely on two main categories of climate services: seasonal climate forecasts and short-term weather forecasts. Seasonal forecasts provide probabilistic projections of rainfall and temperature patterns over forthcoming months, supporting strategic decisions related to crop selection, planting schedules, and resource allocation, whereas short-term weather forecasts offer near-term atmospheric information at daily to weekly timescales, enabling timely operational decisions such as irrigation scheduling, pest and disease management, and harvesting activities ^[7] (Hansen *et al.*, 2019). Such climate services are particularly critical in regions that are highly vulnerable to climatic variability.

Andhra Pradesh, one of the major agrarian states in southern India, is particularly susceptible to such climatic fluctuations. The Anantapur district, located in the semi-arid Rayalaseema region, is one of the most drought-prone areas in the country, characterized by low and uneven rainfall distribution, frequent dry spells, and severe water scarcity. These climatic constraints, combined with limited irrigation facilities and declining groundwater resources, render agriculture in Anantapur highly risk-prone and vulnerable to crop failures ^[8, 9] (Rao *et al.*, 2017; Bohidar and Senapati, 2024).

Despite the well-recognized potential of climate services in enhancing agricultural resilience, their adoption among smallholder farmers in India remains limited and uneven. Empirical evidence suggested that constraints such as inadequate access to timely and location-specific climate information, low levels of awareness, and socio-economic barriers significantly hinder the effective utilization of such services. Furthermore, disparities in access to information and communication technologies (ICTs), along with concerns regarding the reliability and usability of climate advisories, continue to influence farmers' adoption decisions. For instance, mobile-based climate advisory services in India have been shown to improve awareness and decision-making ^[10] (Manjunath *et al.*, 2024). However, their effectiveness is often mediated by enabling factors such as institutional support, accessibility, and user trust ^[6, 11] (Mittal and Hariharan, 2018; Anshul *et al.*, 2022). Similarly, research highlighted that farmers' intention to use climate information is strongly influenced by perceived usefulness, behavioural factors, and access to information systems ^[12] (Ritu and Kaur, 2025).

Numerous studies in the agricultural domain have examined the potential benefits of climate services; however, only a limited number of studies have systematically evaluated implemented services and rigorously assessed their linkage to measurable outcomes, such as changes in decision making, and impacts on household and farm level well-being within rural contexts ^[13] (Tall *et al.*, 2018). This gap is particularly evident in region-specific contexts such as Anantapur, where empirical evidence on the adoption and practical effectiveness of climate services remains scarce.

Building on this context, the present study aims to assess the impact of climate services on farmers' decision-making processes, with particular emphasis on how the use of short-term weather forecast information influence critical farm-level operational decisions, including land preparation, sowing schedules, irrigation management, input application,

and harvesting practices.

2. Materials and methods

2.1 Study Area

The study was conducted in Anantapur district of Andhra Pradesh, India, which was purposively selected due to its high vulnerability to climate variability, semi-arid agro-climatic conditions, and the presence of climate information services delivered through Automated Weather Station (AWS) based information systems. The district experiences a hot semi-arid climate, characterized by a mean annual temperature ranging between 27 °C and 28 °C, with summer temperatures frequently exceeding 40 °C and relatively mild winters averaging 22 °C to 24 °C. The region receives an average annual rainfall of approximately 550- 600 mm, the majority of which is concentrated during the southwest monsoon season ^[14] (Parapurath and Veluswamy, 2025). Agriculture in the district is predominantly rainfed, with groundnut as the principal crop, making farming systems highly sensitive to climatic fluctuations.

In recent years, AWS based climate information services have been introduced in the region to provide real-time, location-specific weather information and advisories to farmers through digital platforms, thereby supporting informed decision making under conditions of climatic uncertainty. Particularly, agritech startups and service providers are increasingly delivering these advisories at the community level and disseminating short term weather forecast information through mobile based channels, such as SMS and WhatsApp groups, thus enhancing accessibility and collective learning. These combined climatic and institutional characteristics make the district particularly suitable for examining the role of climate services in influencing farm level decision making.

2.2 Sample size

Primary data were collected from groundnut farmers through structured interviews using a pre-tested interview schedule. To ensure balanced representation, the sample was stratified into two groups: users (adopters) and non-users (non-adopters). Users were randomly selected from lists provided by the respective technology or service providers, while non-users were purposively selected from geographically proximate farms to ensure similarity in agro-climatic and socio-economic conditions, thereby enabling a reliable comparison between the two groups. A total sample of 160 respondents was considered for the analysis of climate information services, comprising 80 users and 80 non-users.

2.3 Tools and techniques used

Propensity Score Matching

In a scenario where technological innovations were randomly disseminated among farmers, the causal effect of their use on farm level outcomes could be evaluated through comparisons between users and non-users. However, in reality, adoption was not a random process but subject to self-selection, as farmers' adoption decisions were systematically influenced by various socio-economic characteristics.

These socio-economic characteristics not only influence farmers' decisions to access and utilize innovations but also affect their farm-level outcomes and performance. Consequently, the observed relationship between technology

use and farm level outcomes may be confounded by endogeneity, thereby introducing potential selection bias in estimating the true causal effect. To address this issue, Propensity Score Matching (PSM) was employed in this study to estimate the impact of climate services on farm level operational decisions. The PSM approach utilized a set of observed explanatory variables to construct a counterfactual comparison group, matching users of climate services with non-users based on their probability of utilizing such services^[15] (Khandker *et al.*, 2010). The estimated probability, or propensity score, served as the basis for matching farmers using different matching algorithms. The average treatment effect of climate service utilization was then calculated as the mean difference in outcome variables between users and the matched non-users.

The treatment variable was defined as the use of climate services, particularly short-term weather forecasts information. It is specified as a binary variable, taking the value 1 if the farmer utilizes climate services and 0 otherwise. The outcome variables were farm level operational decisions, which reflects whether farmers perceived an improvement in their ability to make climate informed cropping decisions. This includes decisions related to land preparation, sowing time, irrigation scheduling, fertilizer and pesticide application, and harvesting. These variables were measured as a binary indicator, where a value of 1 denotes that the farmer reported improvement in operation decisions in response to climatic risks, and 0 otherwise.

Considering the rational behaviour of a household, a farmer

is expected to utilize a particular climate service if the anticipated benefit of usage (D_1) exceeds that of non-usage (D_0).

$$D^*_i = D^*_1 - D^*_0 > 0 \quad (\text{Equation 1})$$

Let D^*_i represents the unobserved difference in utility between using and not using climate services. Although this difference cannot be directly observed, it can be modelled as a function of measurable farmer characteristics, forming the basis of a latent variable approach:

$$D^*_i = \beta X_i + \varepsilon_i \text{ with } D_i = 1 \text{ if } D^*_i > 0, \text{ otherwise } 0 \quad (\text{Equation 2})$$

Here, D^*_i is a dichotomous variable that takes the value 1 if farmer i utilize climate services and 0 otherwise. The vector X_i represents the observed covariates influencing the usage behaviour, β represents the coefficients to be computed, and ε_i is the error term capturing unobserved factors.

In the preliminary stage of the Propensity Score Matching (PSM) analysis, a probit regression model was specified to estimate the likelihood of utilizing climate services. Relevant explanatory variables were included to identify the determinants of usage behaviour, and the propensity scores for each farmer in the sample were generated. The description of identified covariates is provided in the table 2.1.

Table 2.1: Description of variables used in PSM analysis

S. No	Independent Variables	Definition	Measurement / Type	A priori expectation
1	Gender	Indicates the sex of the household head.	Binary variable: 1 = Male, 0 = otherwise	+
2	Age	Age of the household head.	Continuous variable, measured in years	-
3	Education level	Number of years of formal schooling completed by the household head.	Continuous variable (years)	+
4	Household size (Adult equivalent of household)	Number of economically active individuals within the household.	Continuous variable (count)	+
5	Off-farm income	Whether the household has income from non-agricultural activities.	Binary variable: 1 = Yes, 0 = otherwise	+
6	ln (farm size)	Natural logarithm of the total cultivated land area owned/operated by the household.	Continuous variable (hectare, log-transformed)	+
7	ICT ownership	Whether the household owns information and communication technology devices (e.g., mobile phone, computer, tablet).	Binary variable: 1 = Yes, 0 = No	+
8	Access to the internet	Whether the household has access to the internet.	Binary variable: 1 = Yes, 0 = No	+
9	Access to credit	Whether the household has access to formal or informal credit sources.	Binary variable: 1 = Yes, 0 = No	+
10	Social participation	Involvement of the household head in community-based or farmers' organizations.	Binary variable: 1 = Yes, 0 = No	+
11	Training attended	Participation of the household head in ICT related training programs.	Binary variable: 1 = Yes, 0 = No	+
12	Market distance	Distance from the household's farm to the nearest market.	Continuous variable, measured in kilometres	-
13	Extension contacts	Number of contacts with agricultural extension agents	Continuous variable (frequency of contacts)	+
14	Drought exposure	Whether the household's crops are affected by adverse climatic events (e.g., droughts or extreme weather) that reduce productivity and crop quality.	Dummy variable: 1 = Yes, 0 = No	+

In the second stage of the Propensity Score Matching (PSM) procedure, three different matching algorithms including Kernel Matching, Nearest Neighbour Matching, and Radius (Caliper) Matching were used to compare outcomes between users and non-users of climate services, thus ensuring robustness of the results. Since the matching process relies on the propensity scores rather than individual variables, it was necessary to verify that the distribution of covariates was balanced between the treated and control groups. To evaluate this, Rosenbaum and Rubin, (1983)^[16] recommended the use of standardized bias along with t-tests for mean differences. Furthermore, Sianesi, (2001)^[17] recommended recalculating the propensity scores using only the treated (users) group and then matching these to the control group (non-users) to ensure matching quality. If the observed explanatory variables were randomly distributed between the treated and control groups, the associated R^2 statistic must be relatively low. A low pseudo R^2 thus indicated that systematic differences between the two groups had been minimized, reflecting improved covariate balance after matching. To further confirm the covariate balance across the groups, the Likelihood Ratio test for the combined significance of explanatory variables was also anticipated to show a significant result before matching, but this significance should be eliminated after matching.

Finally, the impact of utilizing climate services on the outcome variables was estimated by computing the Average Treatment Effect on the Treated (ATT).

$$ATT = E(Y(1) - Y(0) | D_i = 1) = E(Y(1) | D_i = 1) - E(Y(0) | D_i = 1)$$

Here, $E(Y(1) | D_i = 1)$ indicates the outcome for farmers who have chosen to utilize climate services, whereas $E(Y(0) | D_i = 1)$ represents their potential outcomes had

they not utilized such services, serving as the counterfactual for comparison.

According to Khonje *et al.* (2015)^[18], the effectiveness of Propensity Score Matching relies on two key assumptions. The first assumption, referred to as 'conditional independence,' states that, given a set of observed covariates X , which are not influenced by the treatment, the potential outcomes remain independent of the treatment assignment.

Let $Y_i(1)$ be the potential outcome of a farmer utilizing climate services, while $Y_i(0)$ be the potential outcome of non-users. The assumption of conditional independence can therefore be expressed as $(Y_i(1), Y_i(0)) \perp D_i | X_i$ (Caliendo and Kopeinig, 2008).

The second assumption is the common support or overlap condition. This condition requires that treated and control units share a comparable range of propensity scores, ensuring that each treated unit can be appropriately matched with similar control units. Propensity Score Matching (PSM) aims to estimate the average difference in outcomes between treated and control groups with similar observable characteristics. However, potential bias may still arise if unobserved factors influence both treatment assignment and the outcome variables.

3. Results and Discussion

3.1 Determinants of usage of climate services

In the preliminary stage of the propensity score matching (PSM) analysis, a probit regression model was specified to estimate the probability of using climate services. Relevant explanatory variables were included to identify the determinants of usage behaviour, and the propensity scores for each farmer in the sample were generated. The estimated coefficients and associated statistics obtained from the probit model are presented in Table 3.1

Table 3.1: Determinants of usage of climate services: Probit Model

S. No	Independent variables	Coefficient	Standard error	z	P Value
1	Gender	0.2342**	0.1048	2.23	0.023
2	Age	-0.0435**	0.0210	-2.07	0.038
3	Education level	0.3726**	0.1770	2.10	0.035
4	Household size (Adult equivalent of household)	0.8843**	0.3187	2.77	0.006
5	Off-farm income	0.4824	0.3599	1.34	0.180
6	ln (farm size)	0.0829	0.0587	1.41	0.159
7	ICT ownership	0.3907***	0.0694	5.63	0.000
8	Access to the internet	0.0997**	0.0436	2.29	0.024
9	Access to credit	0.2659	0.1761	1.51	0.131
10	Social participation	0.1935***	0.0326	5.93	0.000
11	Training attended	0.4162**	0.1970	2.11	0.035
12	Market distance	0.0568	0.0317	1.79	0.073
13	Extension contacts	0.6010**	0.2944	2.04	0.040
14	Drought exposure	0.7589**	0.3149	2.41	0.015
15	constant	1.3829***	0.3618	3.82	0.000
16	Log likelihood	-93.24			
17	LR χ^2 (14)	73.63			
18	Prob > χ^2	0.0000			
19	Pseudo R^2	0.2831			
20	Number of observations	160			

*** 1% significance level; ** 5% significance level; *10% significance level

As shown in Table 3.1 the Wald χ^2 statistic (73.63) was found to be highly significant ($p = 0.000$), indicating that the independent variables were jointly significant in the model. Out of the fourteen explanatory variables included in the

model, ten exhibited a statistically significant relationship with the usage behaviour of climate services. The findings of the study revealed that several individual attributes, such as gender, education level, household size (measured in adult

equivalents), ICT ownership, access to the internet, social participation, involvement in training programs, and contacts with extension services, were all positively and significantly associated with the usage of climate services. Similarly, climatic factors, particularly the drought exposure, exhibited a significant positive effect on usage behaviour. On the other hand, age was found to have a significant negative relationship with the likelihood of using climate services.

Gender plays a critical role in household decision making, particularly in rural areas. The study found that gender had a significant positive association with the usage of weather forecast information ($\beta = 0.2342$, $p < 0.05$), indicating that male farmers had a higher likelihood of using climate services compared to their female counterparts. This outcome was explained by men's relatively greater access to and familiarity with mobile devices, which served as the primary channel for receiving weather forecast information. In addition, men had stronger financial capacity and greater control over family income, which enabled them to independently acquire and utilize mobile phones^[19] (Sharma, 2009) for accessing climate services.

As expected, age had a statistically significant negative effect on usage of climate services ($\beta = -0.0435$, $p < 0.05$), indicating that older farmers were less inclined to use modern forecast information. This relationship may be because older farmers had relatively lower levels of digital literacy and relied more on traditional approaches to weather prediction, including indigenous knowledge and personal experience, rather than on modern forecasting technologies.

The educational attainment of farmers ($\beta = 0.3726$, $p < 0.05$) was also found to exert a significant positive effect on the usage of climate services. The positive coefficient showed that farmers with higher levels of education were more inclined to effectively access, interpret, and apply weather forecast information. This could be attributed to the fact that educated farmers possessed greater digital literacy, which enabled them to use modern communication tools and record keeping practices that facilitated the understanding and practical application of weather forecast information in agricultural decision-making. These findings were consistent with the evidence reported in previous research^[20] (Deressa *et al.*, 2011).

Furthermore, the results indicated that farmers from households with a greater proportion of economically active adult equivalents ($\beta = 0.8843$, $p = 0.006$) were more persuaded to utilize climate services, as enhanced labour and resource capacity could improve their ability to apply weather forecast information in farm decisions. Similar results were reported by^[21] Addison *et al.* (2024) within the

context of African agriculture.

It was also evident that farmers who owned ICT devices ($\beta = 0.3907$, $p = 0.000$) and had better access to internet facilities ($\beta = 0.0997$, $p < 0.05$) demonstrated a higher probability of using climate services. This might be because ownership of ICT tools facilitated easier access to digital platforms, improved the flow of information, and enhanced farmers' capacity to utilize weather forecast information in their farming decisions. These results were aligned with findings of research conducted by Mwenda *et al.* (2023)^[22] Similarly, participation in ICT related training programs also exerted a significant influence on the utilization of climate services.

Previous studies highlighted the critical role of institutional and social networks in the dissemination of climate related information. For instance, Thomas and Sanyaolu (2017)^[23] reported that farmers in rural areas placed considerable trust in extension agents, who served as reliable channels for delivering climatic information. Similarly, farm organizations were also described as important information hubs, as group interactions provided opportunities for farmers to collectively discuss the implications of climate change on agriculture and to explore potential adaptation strategies (Tarhule and Lamb, 2003)^[24]. Consistent with this evidence, the present study found that the frequency of extension contacts ($\beta = 0.6010$, $p < 0.05$) and social participation ($\beta = 0.1935$, $p = 0.000$) were both positively and significantly associated with the probability of adopting climate services.

The study further revealed that the decision to utilize climate services was significantly ($p < 0.001$) influenced by the rising occurrence of drought events and the increasing variability in rainfall patterns across the study area. With the changing climatic conditions, climate services were considered essential for supporting correct decision-making in farm operations and for minimizing crop losses. Hence, as weather conditions continue to fluctuate, the utilization of weather forecasts disseminated by climate services is likely to increase. These findings were consistent with the results reported by Partey *et al.* (2020)^[25].

Overall, the findings indicated that the usage of climate services was shaped by a combination of socio-economic characteristics, access to digital tools, institutional support, and climatic pressures.

Matching Quality

In the second stage of the propensity score matching (PSM) procedure, individuals who used climate services were paired with non-users based on their estimated propensity scores.

Table 3.2: Balancing Tests

Sample	Pseudo R ²	Lr χ^2	P> χ^2	Mean bias	Med bias
Unmatched	0.283	73.63	0.000	30.30	31.60
Kernel based Matching (KBM)	0.018	5.56	0.892	6.50	6.50
Nearest Neighbour Matching (NNM)	0.024	7.24	0.868	7.50	7.80
Radius Matching (RM)	0.022	6.16	0.886	6.50	6.50

The results of the matching procedure are summarized in Table 3.2. Before matching, the larger Pseudo R² and likelihood ratio chi-square values indicated that the PSM model was highly significant ($p = 0.000$), confirming that users and non-users differed significantly in their observable characteristics before matching. Following the matching

process, both Pseudo R² and LR Chi² values decreased significantly from 0.283 to a range of 0.018 to 0.024, and from 73.64 to a range of 5.56 to 7.24, respectively. This shows that the treatment group and the control group were comparable in terms of observed covariates after matching, thereby reducing systematic differences between the groups.

Furthermore, there was a marked reduction in both mean and median standardized biases across covariates, indicating improved balance between users and non-users in the matched sample.

Assumption of Common Support

The density distributions of propensity scores for users and

non-users of climate services after the matching process are illustrated in Figure 3.1. The significant overlap observed between the treated and control groups in the matched sample confirmed that the common support assumption was satisfied, ensuring that both groups share a comparable range of propensity scores for valid comparison.

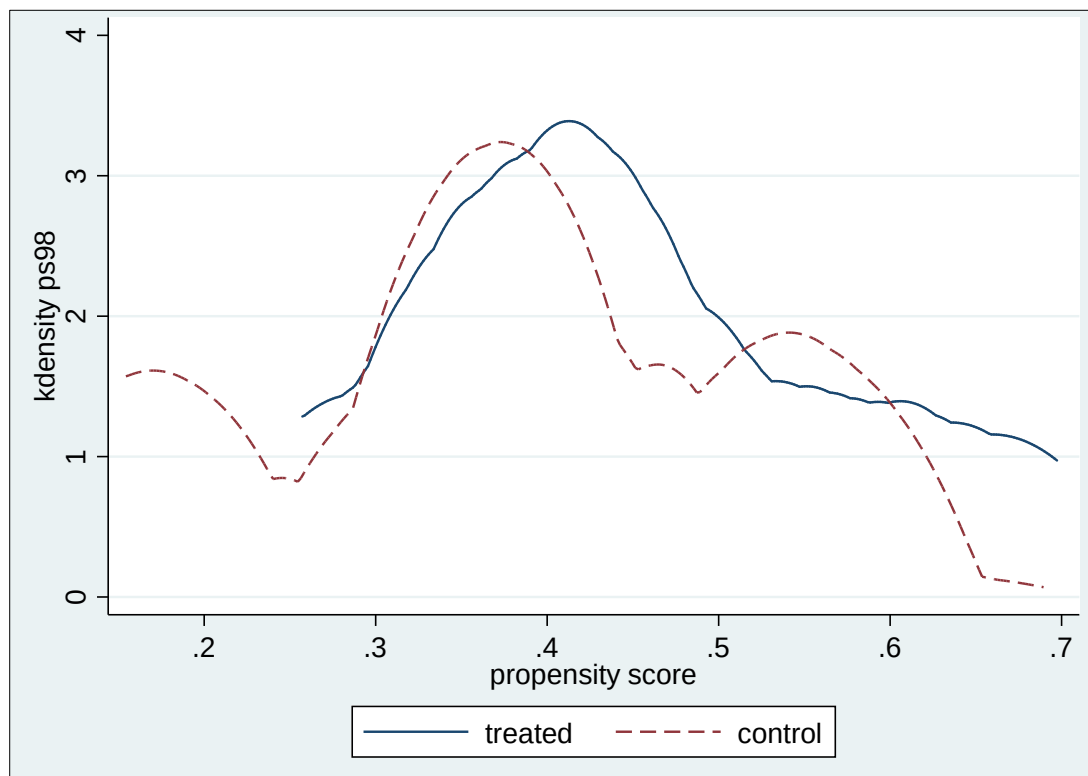


Fig 3.1: Density Distribution of Propensity scores for Users and Non-Users of Climate Services

3.2 Impact of Climate Services on Farm level Operational Decisions

Table 3.3: Impact of Climate Services on Farm level Operational Decisions

Outcome Variables (Operational Decisions)	Matching Algorithm	Treated	Control	ATT (Impact)	Standard error	T-stat
Land preparation	Unmatched	0.7987	0.5221	0.2766***	0.0633	4.37
	Kernel-based Matching (KBM)	0.8028	0.4091	0.3937***	0.1184	3.33
	Nearest neighbour Matching (NNM)	0.7987	0.4177	0.3810**	0.1797	2.12
	Radius Matching (RM)	0.8028	0.4583	0.3444**	0.1591	2.17
Sowing time	Unmatched	0.8987	0.6991	0.1996***	0.0592	3.37
	Kernel-based Matching (KBM)	0.9028	0.7765	0.1263***	0.0400	3.16
	Nearest neighbour Matching (NNM)	0.8987	0.6709	0.2278**	0.0891	2.56
	Radius Matching (RM)	0.9028	0.6389	0.2639***	0.0866	3.05
Irrigation scheduling	Unmatched	0.5887	0.1150	0.4737***	0.0460	10.30
	Kernel-based Matching (KBM)	0.5989	0.2367	0.3622***	0.0880	4.12
	Nearest neighbour Matching (NNM)	0.5887	0.2267	0.3620***	0.0966	3.75
	Radius Matching (RM)	0.5900	0.2243	0.3657***	0.0919	3.98
Fertilizer and pesticide application	Unmatched	0.8587	0.5124	0.3463***	0.0543	6.37
	Kernel-based Matching (KBM)	0.8689	0.4747	0.3942***	0.0985	4.00
	Nearest neighbour Matching (NNM)	0.8587	0.4785	0.3803***	0.1143	3.33
	Radius Matching (RM)	0.8600	0.4675	0.3925***	0.1119	3.51
Harvesting time	Unmatched	0.8387	0.7168	0.1219**	0.0584	2.09
	Kernel-based Matching (KBM)	0.8428	0.6740	0.1688	0.1120	1.51
	Nearest neighbour Matching (NNM)	0.8387	0.5177	0.3210	0.2291	1.40
	Radius Matching (RM)	0.8428	0.5583	0.2844	0.2197	1.29

*** 1% significance level; ** 5% significance level; *10% significance level

The Propensity Scores Matching analysis was employed to estimate the effect of access to climate services on farm level operational decisions by employing three different matching methods. As presented in Table 3.3, the estimated treatment effects were statistically significant for most operational decisions across the matching methods. The robustness of the results was supported by statistically significant t-values and relatively low standard errors. The findings indicated that access to short-term weather forecast information delivered through climate services significantly enhanced farmers' operational decisions across various crop management activities.

For land preparation, the ATT estimates ranged from 34.44 to 39.37 per cent across the matching algorithms, with all estimates being statistically significant. These results suggested that access to climate services enabled farmers to better anticipate favourable weather conditions for land preparation, thereby reducing the risks associated with untimely field operations. Similar findings were reported by Matere *et al.* (2023)^[26], who highlighted the role of short-term weather forecasts in guiding operational decisions and mitigating production risks throughout the cropping season.

The impact of climate services on sowing decisions was positive and statistically significant, with ATT estimates ranging from 12.63 to 26.39 per cent. It could be inferred that access to weather forecast information enabled farmers to make more informed decisions about the identification of suitable sowing dates, thus reducing uncertainty and aligning crop establishment with favourable weather conditions.

It was also found that decision-making related to irrigation scheduling was improved by 36.20 to 36.57 per cent across the three matching algorithms, and the results were highly significant. This implied that access to forecast information enabled farmers to more accurately schedule their irrigation practices, which might have contributed to more efficient water management and reduce exposure to weather-related risks^[27] (Nocezo *et al.*, 2024)

Likewise, decision-making related to fertilizer and pesticide application improved significantly, with ATT estimates ranging from 38.03 to 39.42 per cent. The availability of weather information may have enabled farmers to optimize the timing and application of inputs, thereby improving production efficiency. This finding is consistent with Nepal *et al.* (2024)^[28], who reported that access to weather information supports informed input management decisions, leading to lower production costs and improved farm profitability.

In contrast, the estimated impacts on harvesting decisions ranged from 16.88 to 32.10 per cent but were statistically insignificant across the matching methods. Although climate services appeared to positively influence harvesting decisions, the absence of statistical significance suggested that harvesting operations are determined not only by weather conditions but also by factors such as crop maturity, labour availability, and market considerations.

Overall, the findings indicated that access to climate services, particularly short-term weather forecast information, significantly enhanced farmers' operational decisions related to land preparation, sowing, irrigation scheduling, and input use, whereas its effect on harvesting decisions was limited.

4. Conclusion

This study examined the impact of climate services on farm level operational decisions among groundnut farmers in

Anantapur district using the Propensity Score Matching (PSM) approach. The findings revealed that the utilization of climate services, particularly weather forecasts, had a positive and statistically significant influence on key agricultural decisions, including land preparation, sowing time, irrigation scheduling, and input management practices such as fertilizer and pesticide application. The results were consistent across multiple matching techniques, ensuring the robustness of the estimated impacts.

The study highlighted that access to timely and location-specific climate information could enhance farmers' ability to make informed decisions under conditions of climatic uncertainty. However, the observed variations in impact across different decision domains, particularly in harvesting-related decisions, suggested that the effectiveness of climate services might depend on the nature and timing of information as well as farmers' capacity to interpret and apply it.

It is therefore essential to strengthen efforts to enhance access to climate services among smallholder farmers in regions such as Anantapur district. This could be achieved by promoting the development and dissemination of timely, location-specific, and user-centric climate information, including short-term weather forecasts and seasonal outlooks. In addition, integrating climate services into existing agricultural extension systems and institutional support mechanisms is crucial to improve farmers' awareness, understanding, and effective utilization of such information. Strengthening digital delivery platforms and community based dissemination approaches could further enhance effective outreach and accessibility.

Such interventions have the potential to significantly improve farmers' decision-making capacity under conditions of climatic uncertainty, thereby enhancing agricultural resilience, stabilizing production, and contributing to improved livelihood security among farmers in climate vulnerable regions.

References

1. Nesheim I, Barkved L, Bharti N. What is the role of agro-met information services in farmer decision-making? Uptake and decision-making context among farmers within three case study villages in Maharashtra, India. *Agriculture*. 2017;7(8):70.
2. Hewitt CD, Stone R. Climate services for managing societal risks and opportunities. *Clim Serv*. 2021;23:100240.
3. Tall A, Njinga J. Developing a methodology to evaluate climate services for farmers in Africa and South Asia: workshop report. Copenhagen, Denmark: CGIAR Program on Climate Change, Agriculture and Food Security; 2013.
4. Yegbemey RN, Egah J. Reaching out to smallholder farmers in developing countries with climate services: a literature review of current information delivery channels. *Clim Serv*. 2021;23:100253.
5. Mittal S. Role of mobile phone-enabled climate information services in gender-inclusive agriculture. *Gend Technol Dev*. 2016;20(2):200-217.
6. Mittal S, Hariharan VK. Mobile-based climate services impact on farmers' risk management ability in India. *Clim Risk Manag*. 2018;22:42-51.

7. Hansen JW, Furlow J, Goddard L, Nissan H, Vaughan C, Rose A, *et al.* Scaling climate services to enable effective adaptation action. Rotterdam; Washington (DC): Global Commission on Adaptation; 2019.
8. Rao CA, Raju BMK, Rao AVM, Rao KV, Samuel J, Ramachandran K, *et al.* Assessing vulnerability and adaptation of agriculture to climate change in Andhra Pradesh. *Indian J Agric Econ.* 2017;72(3):375-384.
9. Bohidar S, Senapati AK. Assessing agricultural vulnerability to climate extremes in Rayalaseema and KBKK regions of India: a panel ARDL approach. *Discov Agric.* 2025;3(1):79.
10. K VM, Maiti S, Garai S, Reddy DAK, Sahani S, Panja A, *et al.* Impact of climate services on the operational decision and economic outcome of wheat (*Triticum aestivum*) and rice (*Oryza sativa*) cultivation in Haryana. *Indian J Agric Sci.* 2024;94(3-1):116-123.
11. Anshul A, Mitesh S, Srinivasan G, Buizer J, Finan T, Singh KK, *et al.* Integrating climate information into decision making for building resilience: a case study on farming communities in Bihar, India. *Clim Serv.* 2022;28:100328.
12. Ritu RK, Kaur A. Unveiling Indian farmers' adoption of climate information services for informed decision-making: a path to agricultural resilience. *Clim Dev.* 2025;17(6):557-571.
13. Tall A, Coulibaly JY, Diop M. Do climate services make a difference? A review of evaluation methodologies and practices to assess the value of climate information services for farmers: implications for Africa. *Clim Serv.* 2018;11:1-12.
14. Parapurath F, Veluswamy K. Climatic variability and groundnut crop yield: unveiling the scenario in Anantapur, India. *Int Agric Eng J.* 2025;34(1-4):155-170.
15. Khandker S, Koolwal GB, Samad H. Handbook on impact evaluation. Washington (DC): World Bank; 2009.
16. Rosenbaum PR, Rubin DB. The central role of the propensity score in observational studies for causal effects. *Biometrika.* 1983;70(1):41-55.
17. Sianesi B. An evaluation of the active labour market programmes in Sweden. Working paper. 2001.
18. Khonje M, Mkandawire P, Manda J, Alene AD. Analysis of adoption and impacts of improved cassava varieties in Zambia. In: Proceedings of the 29th Triennial Conference of the International Association of Agricultural Economists; 2015; Milan, Italy.
19. Sharma S. Rural India calling. USID Foundation; 2009.
20. Deressa TT, Hassan RM, Ringler C. Perception of and adaptation to climate change by farmers in the Nile basin of Ethiopia. *J Agric Sci.* 2011;149(1):23-31.
21. Addison M, Bonuedi I, Arhin AA, Wadei B, Owusu-Addo E, Fredua Antoh E, *et al.* Exploring the impact of agricultural digitalization on smallholder farmers' livelihoods in Ghana. *Heliyon.* 2024;10(6):27541.
22. Mwenda E, Muange EN, Ngigi MW, Kosgei A. Impact of ICT-based pest information services on tomato pest management practices in the Central Highlands of Kenya. *Sustain Technol Entrep.* 2023;2(2):100036.
23. Thomas KA, Sanyaolu AS. Utilization of agro-meteorological services among arable crop farmers in Oyo State, Nigeria. *J Agric Ext.* 2017;21(1):47.
24. Tarhule A, Lamb PJ. Climate research and seasonal forecasting for West Africans: perceptions, dissemination, and use? *Bull Am Meteorol Soc.* 2003;84(12):1741-1760.
25. Partey ST, Dakorah AD, Zougmore RB, Ouédraogo M, Nyasimi M, Nikoi GK, *et al.* Gender and climate risk management: evidence of climate information use in Ghana. *Clim Change.* 2020;158(1):61-75.
26. Matere S, Busienei JR, Irungu P, Mbatia OE, Nandokha T, Kweni K. Do farmers use climate information in adaptation decisions? Case of smallholders in semi-arid Kenya. *Inf Dev.* 2024;40(4):602-619.
27. Nocezo YI, Manyike JZ, Zhou L, Ngarava S. The impact of access to climate services on smallholder farmers' cropping decisions and household food security in Elundini municipality, Eastern Cape province. *Front Clim.* 2024;6.
28. Nepal M, Ashfaq M, Sharma BR, Shrestha MS, Khadgi VR, Bruno Soares M. Impact of weather and climate advisories on agricultural outcomes in Pakistan. *Sci Rep.* 2024;14(1):1036.