Final report RWA-21143 May 2023

Weather and climate information and agricultural productivity in Rwanda

Derek Apell

DIRECTED BY
LSE
UNIVERSITY OF OXFORD
FUNDED BY
UKaid from the British people

Weather and climate information and agricultural productivity in Rwanda

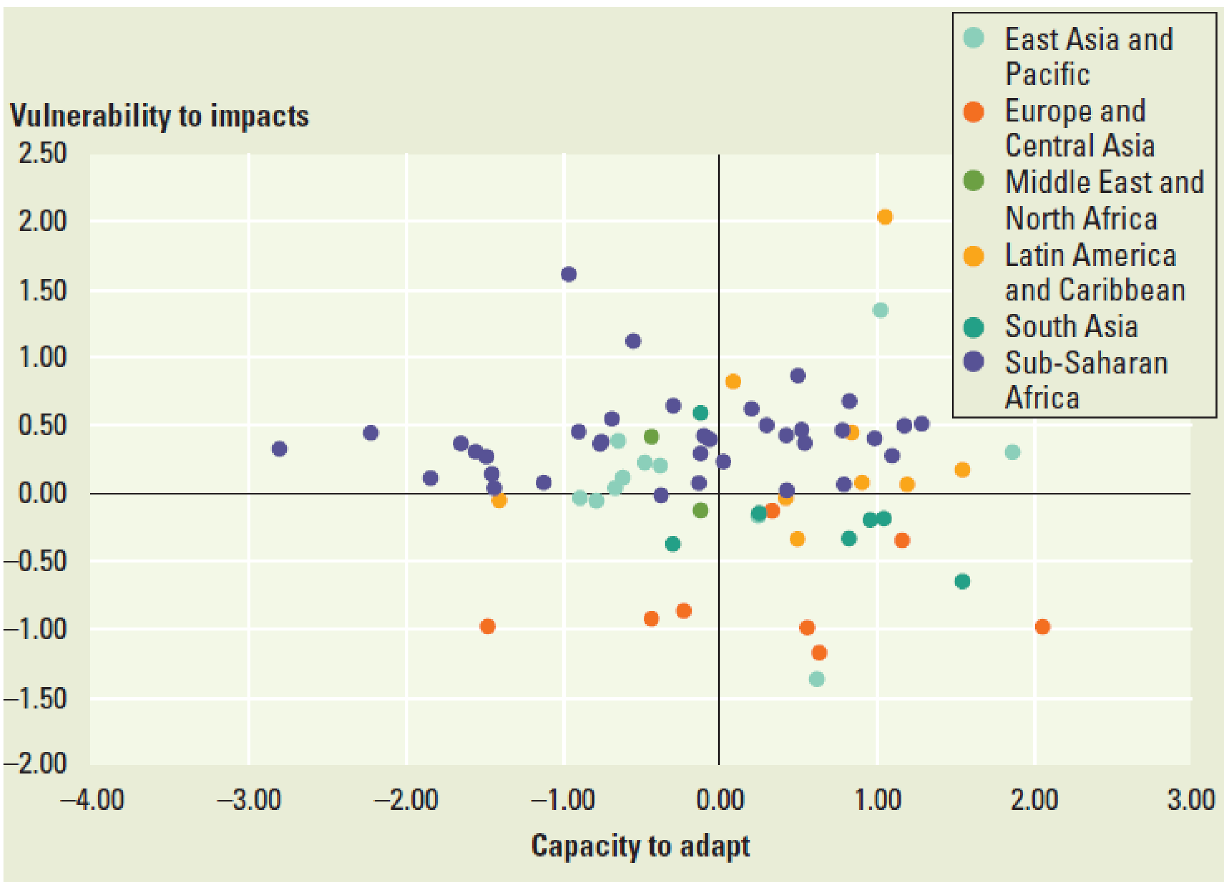
By Derek Apell

Abstract

Climate change poses an immediate and inevitable future challenge for Least Developed Countries whose economies depend on rain-fed agriculture. However, few studies have investigated the role of Weather and Climate Information Systems (WCIS) in boosting resilience to weather shocks. This study evaluates the treatment effect of Rwanda's national WCIS on intensification practices and farm productivity. The study uses cross-sectional data from Rwanda's EICV5 survey and addresses selection bias using Propensity Score Matching. WCIS has a positive and statistically significant treatment effect on adopting intensive practices but no impact on productivity. Further analysis suggests that the role of Rwanda's WCIS in agriculture adaptation to climate change can be enhanced by improving the quality of information disseminated to farmers.

1. Background

Climate change presents a complex challenge for policymakers in the Least Developed Countries (LDCs). The year 2019 was among the three warmest years on record on the African continent (World Meteorological Organization 2022). From the perspective of agricultural producers, long-run rising temperatures are associated with weather shocks—including heat stress, variable rainfall, floods, and droughts. In addition to physical damage to crops and factors of production, weather variability increases risk in both input and output markets, consequently hindering efficient resource allocation. The persistence of weather shocks can perpetuate poverty by preventing the accumulation or depletion of assets needed to escape poverty. (Barrett 2006; Carter and Barrett 2006)



Source: *(World Bank 2010, 280)*

Note: *Capacity to adapt is a composite indicator combining indicators of economic management, structural policies, public sector management, and capacity to absorb finance. Vulnerability is a composite index combining physical impacts and socioeconomic indicators*

Policymakers in the least Developed Countries (LDCs) have deployed ex-ante and ex-post measures in response to the climate challenge. E*x-ante* interventions reduce the adverse effects of adverse weather events, allowing individuals to implement practices and technologies that enhance productivity. *Ex-post* interventions compensate individuals most affected by weather shocks, thus preventing harmful coping mechanisms that could otherwise perpetuate poverty. The most common interventions implemented *ex-post* programs in response to climate shocks as non-contributory social safety nets, including public works and subsidy schemes and transfers.

The most salient *ex-ante* interventions against weather shocks include weather index insurance stress-resistant varieties, extension services, and weather information and climate Information Systems. Weather index insurance compensates policyholders based on a measurable index, such as adverse rainfall, rather than actual losses. Agricultural extension services provide farmers with agronomic techniques to prevent crop failure due to adverse weather. The Climate Services Partnership defines Weather and Climate Information Systems as initiatives that "produce, translate, transfer, and use climate knowledge and information for decision-making and planning." It entails publishing seasonal forecasts from climate models to reduce uncertainty and enable informed farm decision-making (Klopper, Vogel, and Landman 2006). Finally, stress-resistant varieties are genetically bred to withstand adverse conditions.

Concern amongst policymakers and research has fueled a growing literature evaluating the effectiveness of the climate adaptation measures implemented. However, while the empirical evidence on *ex-post* interventions is well established, the empirical evidence on *ex-ante* interventions is growing and subject to debate. According to (Grosh 2008, 335), cash transfers lower administrative costs but are information intensive. She also argues that In-kind transfers help to alleviate hunger, albeit with high administrative costs. General subsidies have low administrative costs but high inclusion errors and impose a high fiscal burden. Public works programs are socially beneficial but administratively demanding.

To date, limited research has been done on the efficacy of *ex-ante* climate adaptation measures at scale. For example, weather insurance is observed to be moderately effective in field trials, but selection bias renders it commercially unviable at scale (Rosenzweig and Mobarak 2013; Mobarak and Rosenzweig 2014). Agriculture extension services effectively promote profit-enhancing technologies but suffer from low coverage rates in several LDCs (Beaman et al. 2014; BenYishay and Mobarak 2014). Stress-resistant varieties are observed to reduce yield variability and production risk in multiple contexts (Bairagi et al. 2021; Dar et al. 2013) but require substantial investment to customize biophysical attributes to each context (Lemoine 2018). (Yegbemey, Bensch, and Vance 2023) find significantly higher labor productivity from farmers accessing weather forecasts; however, the yield effects vary by crop.

Compared with other *ex-ante* measures, Weather and Climate Information Systems (WCIS) have higher coverage rates on the African continent but are the least studied. In East Africa, for example, studies in Kenya, Ethiopia, Tanzania, and Uganda estimate coverage rates to range between 15–82% (Vaughan et al. 2019, 6). Vaughan further argues that despite the high coverage, empirical research on the impact of WCIS is limited. He argues that this stems from the public goods nature of WCIS and the complex diffusion of information through information networks imposing difficulty on rigorous evaluation. To date, only (Yegbemey, Bensch, and Vance 2023) have conducted a field experiment on the impact of WCIS. Crucially, no study to date has evaluated the efficacy of WCIS at scale. Evidence on the effectiveness of WCIS would facilitate an evidence-based cost-benefit analysis with other *ex-ante* climate adaptation measures. Addressing this knowledge gap is essential due to the increased sensitivity of agriculture to extreme weather conditions in the LDCs where WCIS is as important input as seed, fertilizer, or equipment (World Meteorological Organization 2020)

To bridge the evidence gap, we evaluate the impact of accessing weather and climate information on agricultural productivity in Rwanda. The Rwandan Climate and Weather Information System is among the most advanced in Africa and, thus, an ideal case study. The Rwandan Meteorological Agency publishes a sophisticated suite of information tools and products for Agriculture. In 2017, the agency was the first on the continent to adhere to the World Meteorological Organization standards on weather forecast quality (Hansen et al. 2021, 8). In addition, Rwanda has one of the highest coverage rates, with roughly 80% of the population accessing WCIS.

We estimate the impact of accessing WCIS on agriculture intensification and productivity by analyzing household data from the EICV survey using Propensity Score Matching (PSM). The EICV survey only observes individuals after they have received WCIS; thus, a simple OLS regression would estimate a biased treatment effect. Therefore, PSM is used to construct a comparable group of individuals that are similar in all relevant pre-treatment characteristics from a sample of the untreated group. This technique is made possible by the comprehensive set of variables relating to agriculture, access to WCIS, and household characteristics captured in the EICV survey.

2. Data and Empirical Strategy

2.1. Data

The data analyzed in this study are drawn from the Rwanda Fifth Integrated Household Living Conditions Measurement Survey (EICV-5). The survey was conducted between September 2016 and August 2017 by the National Institute of Statistics of Rwanda and was designed to be nationally representative geographically and thematically. The EICV survey sampling methodology followed a two-stage strategy. In the first stage, 1,260 nationally representative primary sampling units (PSU) were drawn from the census sampling frame by Probability Proportional to Size method (PPS) (NISR 2019, 6). In the second stage, ten households were drawn from each selected rural and twelve from each selected urban PSU, generating a sample size of 14,580. The representative sampling approach allows for reliable inference of sample estimates to the population. The EICV-5 survey also covers a comprehensive set of variables allowing us to generate significant explanatory power of the outcome variable, agricultural incomes while accounting for the different sources of observable heterogeneity.

2.2. Empirical strategy

This study employed descriptive and inferential statistics and a reduced-form econometric model to analyze the data. Descriptive statistics such as mean and standard deviation were used to present summary statistics of variables concerning sample households' demographic and socioeconomic characteristics. Inferential statistics, such as the T-test and Chi-square test, were used to test the statistical significance across a range of relevant characteristics between households that received WCIS and those that did not. The T-test was also used to evaluate the statistical significance of differences between the two outcome variables—intensification and productivity—between households that received WCIS and those that did not. Agricultural incomes are calculated as the aggregate crop and livestock production value subtracted from factor and input costs.

Our guiding theoretical framework is drawn from the Koundouri—Vangelis—Tzouvelekas Theory of Production Under Uncertainty. This framework suits our objective because it analyzes the link between production risks —like weather variability—and farmers' decisions to adopt agriculture innovations (Koundouri, Nauges, and Tzouvelekas 2006, 7–

10). The theory provides the testable hypothesis that in regions where production is sensitive to exogenous climatic conditions, risk-averse farmers adopt mitigation instruments to reduce the variability of their expected production. The explanatory power of this framework has been rigorously tested across a range of technologies, including insurance ((Falco et al. 2014)), Irrigation (Koundouri, Nauges, and Tzouvelekas 2006), and grain storage bags (Omotilewa, Gilbert, and Ainembabazi 2019).

Building on the Koundouri—Vangelis—Tzouvelekas, the current study tests the hypothesis that enhancing certainty of production risk through access to Weather and Climate Information encourages farmers to adopt intensive practices. When rigorously testing this hypothesis, we were confronted with the problem of designing a counterfactual as the only available data for this research did not observe individuals before reviving WCIS. This means that individual observable characteristics (e.g., wealth, education, gender, age, risk tolerance) and unobservable characteristics (e.g., risk appetite) can lead to systematic differences between adopter and non-adopter populations that can influence measured impacts and hence bias estimated impacts of these decisions.

The "gold standard" for addressing the problem of counterfactuals when evaluating development interventions is to employ Randomized Control Trials (RCTs) (World Bank). However, RCTs were not viable in the current study due to the non-random allocation of farm households into receivers (treated group) and non-receivers (control groups). The alternative to the experimental approach is to use quasi-experimental approaches, which seek to create, using empirical methods, a comparable control group that can serve as a reasonable counterfactual (World Bank 2009, 53). In the current study, among the available non-experimental approaches, we implement the Propensity Score Matching technique due to the nature of data available for analysis.

2.3. Propensity Score Matching for evaluating program treatment effects.

The basic idea behind Propensity Score Matching is to construct a comparable group of individuals that are similar in all relevant pre-treatment characteristics from a sample of the untreated group. The first step in implementing PSM involves estimating a statistical model (Probit or Logit) in which the probability of being assigned to treatment or the *propensity score* is explained by several characteristics X. The propensity score ranges from 0 to 1 and can be expressed as a non-linear combination of the pre-treatment characteristics X.

$$P(T_i = 1 \mid X_i) = \Phi\,(X'_i\,\delta)$$

The PSM estimator's key to consistently estimating the Average Causal Effect (ACE) is the Conditional Independence Assumption (CIA). The Conditional Independence Assumption holds that the potential values of outcome variables (Y_{oi}, Y_{1i}) are conditionally independent when conditional on the list of important covariates X. Whereas fulfilling the CIA can be subject to the high dimensionality of the characteristics X, the PSM theorem provides for conditional independence of the outcome variables to the treatment conditional on the Propensity score (PX_i).

Once the Scores are estimated, the next step is to match individuals with similar score levels. The two approaches for matching propensity scores generally fall into Greedy and Optimal Matching. In the present study, we use a One-to-One matching algorithm, ensuring that treated and non-treated individuals have equal propensity scores. If the Conditional Independence Assumption (CIA) is satisfied, the PSM estimator of the Average Treatment Effect can be expressed as:

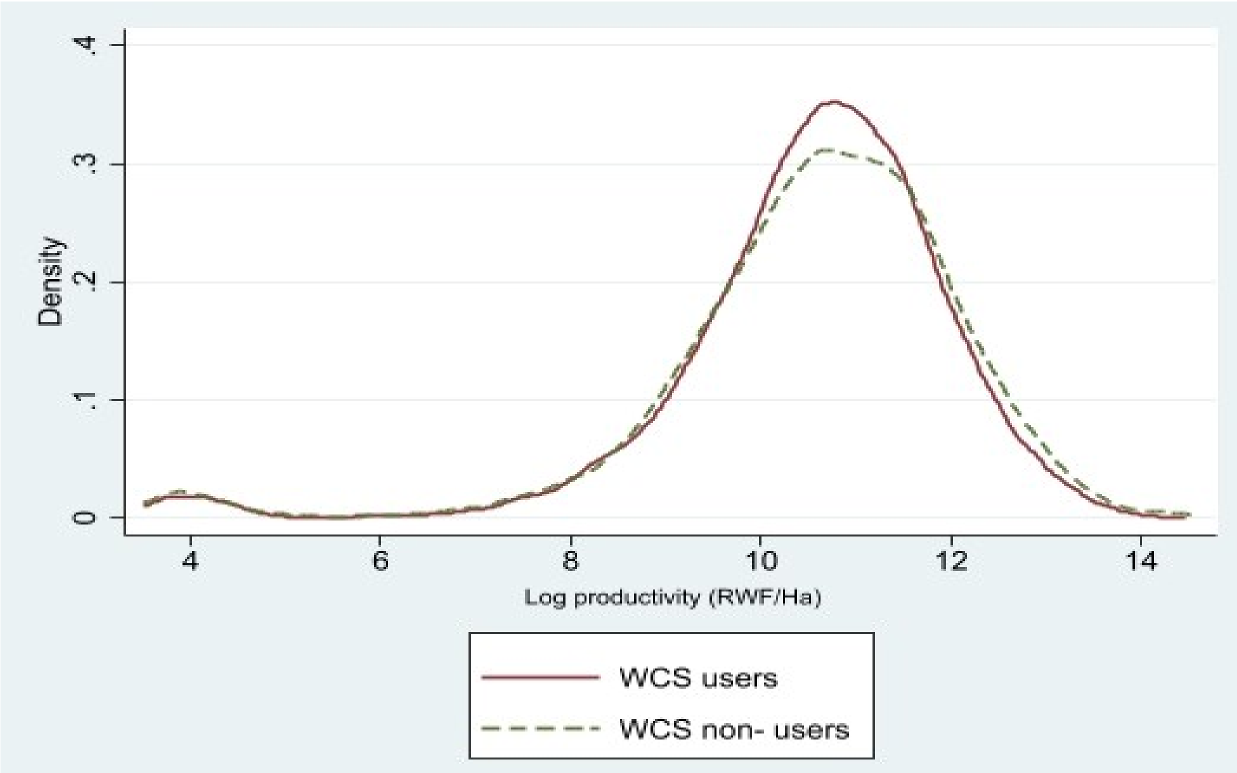
$$\widehat{ACE} \approx \sum_{S} \overline{(\overline{Y}_{1s}} - \bar{Y}_{0s})$$

The above equation means that the PSM estimator is the mean difference in outcomes between the treated and untreated groups (World Bank 2009, 57).

Several techniques are available to check covariate balancing during the matching process. One approach is by observation, where the distribution of propensity scores is plotted conditional on belonging to treatment and control samples. The distribution of propensity scores for the two samples must be similar to satisfy the balance condition.

The second approach is by statistically comparing the means of covariates across the treatment and control samples. A two-sample t-test (before and after Matching) can test for statistical differences in covariate means between the treated and untreated groups or balance between the group (). Satisfying treatment and control group balance ensures that pre-treatment covariate variables do not drive observed differences in outcomes.

Figure 2: Kernel density plot of agricultural productivity (RWF/Ha)



Descriptive statistics for the covariate household characteristics are presented in Table 1. From the results, we note that the use of WCIS is associated with a higher likelihood of use of fertilizer with a statistically significant difference at the 5% significance level. In contrast, differences use of Irrigation and improved seeds between WCIS users and non-users are not statistically distinguishable at the 5% level. Consequently, the productivity distribution by WCIS use shown in Figure 2 overlap in the two samples suggesting no statical difference. The differences in means of explanatory variables between WCIS users and non-users is not statistically significant at the 5% level.

Among the seven socioeconomic variables considered for the study, only average land size was found to be statistically higher at the 10% level for WCIS users than non-users. These observations suggest that WCIS users, although similar across various characteristics, are more likely to practice agricultural intensification. These results are consistent with other studies that observe a higher technology adoption rate resulting from WCIS adoption, such as (Djido et al. 2021) in Ghana and (Ouedraogo et al. 2015) in Burkina Faso.

Table 1. Descriptive results. Mean values with standard deviations in parentheses.

	WCIS Users (n=7301)		WCIS non-users (n=5273)		t-test /χ^2 – test (P-value)	
Outcome variables						
Modern seed (1=Yes)	33.7	(0.060)	27.7	(0.064)	1.95	(0.051)
Fertilizer (1=Yes)	51.9	(0.077)	43.7	(0.083)	2.47	(0.014) **
Irrigated (1=Yes)	15.1	(0.046)	12.4	(0.047)	1.16	(0.246)
Productivity (Rwf/Ha)	8098.8	(1,659.95)	6393.4	(1129.71)	1.71	(0.088)
Market access variables						
Market proximity (Km)	7.6	(0.09)	7.3	(0.153)	0.92	(0.355)
Information						
Radio (1=Yes)	43.5	(0.060)	42.8	(0.070)	0.2	(0.84)
Mobile (1=Yes)	65.4	(0.060)	63.0	(0.074)	0.76	(0.445)
TV (1=Yes)	1.1	(0.027)	0.9	(0.071)	0.33	(0.738)
Membership to associations						
Cooperative (1=Yes)	4.0	(0.025)	3.8	(0.033)	0.17	(0.863)
Consolidated land (1=Yes)	34.4	(0.074)	31.5	(0.074)	0.92	(0.358)
Agricultural credit (1=Yes)	19.1	(0.043)	18.0	(0.036)	0.43	(0.669)
Socio-economic variables						
Improved wall (1=Yes)	77.4	(0.071)	80.7	(0.108)	-1.23	(0.22)
Improved floor (1=Yes)	87.4	(0.059)	88.5	(0.108)	-0.51	(0.61)
Safe water (1=Yes)	49.0	(0.240)	49.4	(0.245)	-0.13	(0.894)
Electricity (1=Yes)	9.1	(0.062)	10.2	(0.107)	-0.56	(0.573)
Female head (1=Yes)	24.4	(0.054)	20.8	(0.060)	1.27	(0.203)
HoH Age (Yrs)	47.2	(0.204)	46.3	(0.271)	0.87	(0.384)
HoH finished primary (1=Yes)	25.1	(0.060)	25.7	(0.078)	-0.23	(0.819)
Household size	5.0	(0.025)	4.9	(0.030)	0.89	(0.373)
Farm size (Ha)	53.7	(2.728)	46.8	(5.367)	1.97	(0.049) *
Province						
Southern	23.7	(0.050)	27.7	(0.059)	-1.37	(0.171)
Western	20.2	(0.050)	14.9	(0.060)	2.11	(0.036) *
Northern	17.5	(0.042)	19.7	(0.050)	-0.85	(0.393)
Eastern	38.6	(0.060)	37.7	(0.062)	0.27	(0.784)

*,**,*** indicate statistical significance at 10%, 5%, 1% levels respectively

2.4. Econometric model estimation results

The causal effect of WCIS use on agricultural productivity and intensification is estimated using Propensity Score Matching. Our analysis employed a One-to-One matching algorithm. In the following paragraphs, we present the estimates of propensity scores and the Average Treatment Effect (ATT), and the post-matching quality assessment.

Estimation of propensity scores

The conditional probability of household use of WCIS is estimated using a Logistic Regression model for a binary outcome variable. The model considered all observable covariates that determine WCIS use and agricultural productivity based on (Bryan et al. 2013) 's determinants of climate adaptation strategies in Kenya. The results are given in Table 2. Overall, covariate variables have statistically significant explanatory power of WCIS use as evidenced by the Likelihood ratio exceeding the critical value for n=12,544.

When comparing the distributions of covariates treated (n=7301) and control (n=5243) samples, we observed statistically significant differences at the 5% level for 9 of the 10 covariates. Amongst the statistically significant variables, only land consolidation and household size are positively associated with agricultural productivity, while ownership of radio, tv, improved water, and farm size are negatively associated. While initially paradoxical, this observation is likely to be explained by the fact that all wealth variables are positively associated, and the negative relationship between agricultural productivity and farm size is well-established in the empirical literature (Gollin, 2019)

Estimation of the average treatment effect on the treated (ATT)

The average Treatment Effect on the Treated (ATT) is estimated using a One-to-One Matching algorithm. The matching process uses 12,574 of the 14,580 households with matched pairs of equal propensities. The results are presented in Table 3. In addition to the mean values of the outcome variables in columns 1 and 2, Table 3 contains mean differences between treatment and control (3), bootstrapped standard errors (4), and t-statistics (5). The Student T-Statistic tests the hypothesis developed in the previous section that WCIS use results in higher adoption of intensification practices and, consequently, higher agricultural productivity.

The results show a statistically significant increase in improved seed and fertilizer use but no evidence of a treatment effect on agricultural productivity. This is a somewhat surprising result, firstly because whilst it is partially consistent with the theoretic predictions, the results differ from previous research that found gains to agricultural productivity from WCIS, including in other contexts such as (Anuga et al. 2019) in Ghana (Lo and Dieng 2015) in Senegal and (Phillips et al. 2002) in Zimbabwe.

Table 2: Propensity score estimation

	Coeff	Std. Err	Z
Distance to market (Km)	0.005	0.003	1.38
Radio (1=Yes)	-0.352	0.025	-13.83***
Mobile phone (1=Yes)	-0.025	0.027	-0.90
TV (1=Yes)	-0.353	0.060	-5.87***
Agriculture cooperative (1=Yes)	-0.169	0.056	-3.01***
Consolidated land (1=Yes)	0.058	0.027	2.15**
Agricultural credit (1=Yes)	0.168	0.035	4.82
Improved wall materials (1=Yes)	0.020	0.032	0.61
Improved floor materials (1=Yes)	0.134	0.038	3.53
Improved water source (1=Yes)	-0.053	0.027	-1.99**
Electricity (1=Yes)	-0.235	0.038	-6.13***
Female head (1=Yes)	0.027	0.031	0.87
Household head age	0.000	0.001	-0.03
Household head finished primary (1=Yes)	-0.012	0.027	-0.44
Household size	0.042	0.006	6.76***
Farm size (Hectares)	0.000	0.000	-2.04
Kigali	-0.438	0.070	-6.25***
Southern Province	-0.147	0.033	-4.46***
Western Province	-0.305	0.034	-8.93***
Northern Province	-0.257	0.036	-7.07***
Constant	0.272	0.069	1.46
Log Likelihood	773.53		
Number of observations	12,544		
Likelihood Ratio (LR) $\chi2$ (19)	43.81		
Prob > $\chi2$	0.00		
Pseudo R2	0.04		

***,**,* indicate statistical significance at 10%, 5%, 1% levels respectively

Matching quality analysis

We evaluated the quality of the One-to-One match first graphically in Figures 3 Figure 3. Graphically we observe significant overlap in propensity scores between individuals in the treatment and control groups. However, while they are illustrative, graphical evaluation may be imprecise, therefore we evaluated the match quality using statistical tests.

Looking at the t-test results after matching in the first column of Table 5, we observe that the statically significant difference between treated and control groups that was observed for the radio variable is now insignificant, and the pre-match statistically insignificant variables remain likewise. This shows that the matching process effectively balanced the distributions of the covariates in the matched sample. Likewise, the Standardized Percentage bias for most variables (Column 2, Table 3) appears to be less that than 0.25 as recommended by the (Ho et al. 2007) criterion.

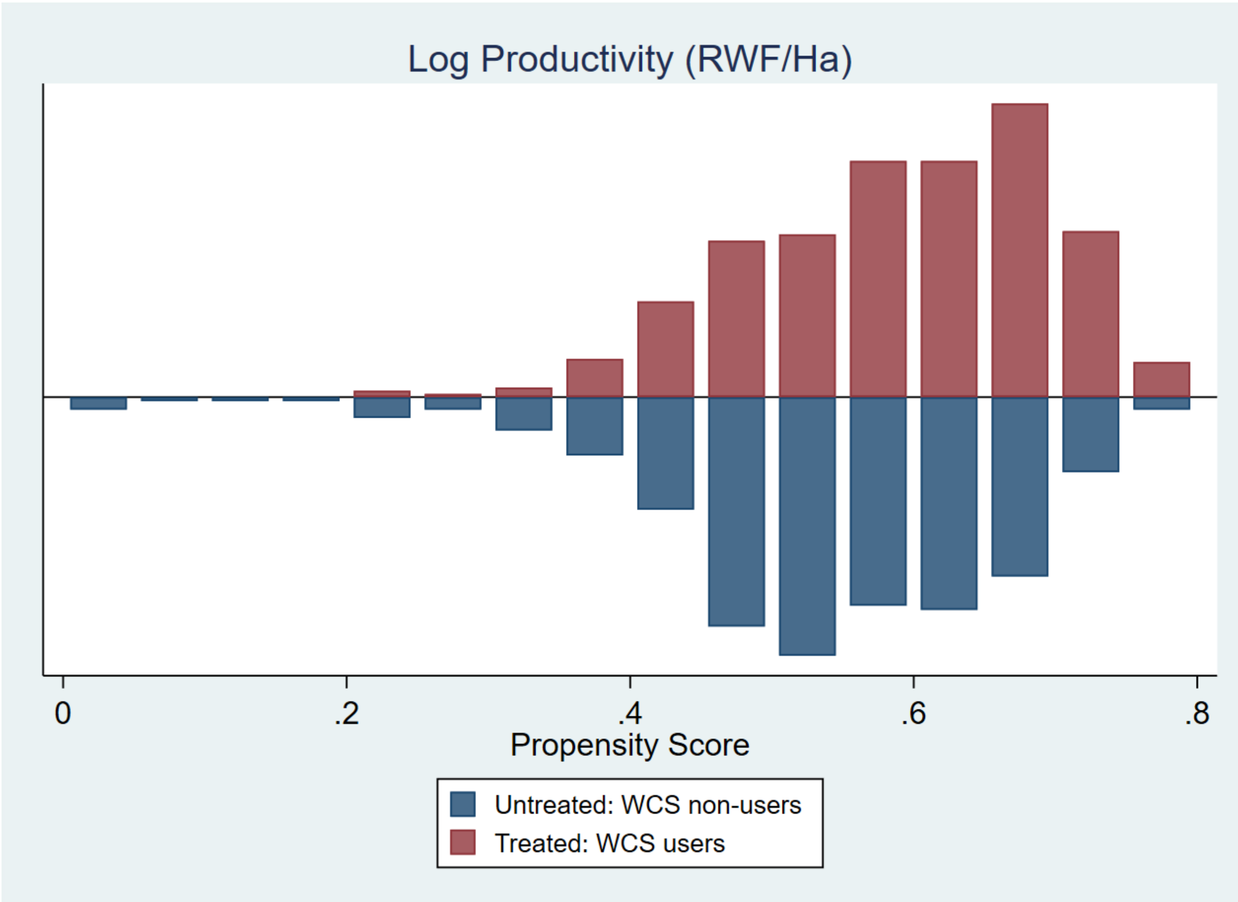
In addition to the post-estimation t-test and standardized percentage bias statistics, other measures of covariate imbalance presented in Table 4 also indicate that the One-to-One match effectively balances the pre-treatment characteristics.

Table 3: One-to-One Matching Results of Average Treatment Effect on the Treated (ATT)

Outcome variable	Sample	1.Treated	2.Control	3.Difference	4.Std. Err	5.T-Stat
Log productivity	Unmatched	1.40	1.33	0.07	0.19	0.35
	ATT	1.40	1.36	0.04	0.22	0.17
Improved seed use	Unmatched	0.33	0.31	0.02	0.03	0.68
	ATT	0.33	0.26	0.08	0.04	1.81**
Fertilizer use	Unmatched	0.52	0.49	0.03	0.04	0.76
	ATT	0.52	0.42	0.09	0.05	1.92**
Irrigation Use	Unmatched	0.15	0.16	-0.01	0.03	-0.38
	ATT	0.15	0.14	0.02	0.04	0.43

*,**,*** indicate statistical significance at 10%, 5%, 1% levels respectively

Figure 3: Propensity scores for 7301 treated and 5273 untreated with Log Productivity (RWF/Ha) as the outcome variable



Discussion and Policy Implications

Our key finding from this research is that the treatment effect of accessing WCIS is a higher adoption of intensification practices. However, treated households do not experience productivity gains resulting from WCIS.

These findings are partially consistent with the Koundouri—Vangelis—Tzouvelekas theory of technology adoption under uncertainty. On the one hand, we find that risk-averse farmers adopt risky technologies certainty of future conditions is reduced. On the other hand, WCIS users do not reap adequate returns from adoption. We propose two complementary hypotheses for the weak link between WCIS and productivity. The first is the quality of the WCIS received in its efficacy and usability. Whereas our dataset does not provide information on the quality of the WCIS, the statistically significant but small magnitude ATT in Table 3 on seed use (0.08) and fertilizer (0.08) seems to support this hypothesis.

How do these results compare with previous research on ex-ante evaluations? Similar to Rwanda's WCIS, crop insurance to farmers is observed to shift farm practices towards risker higher return activities in South West China (Cai et al. 2009) and India (Cole et al. 2013; Cole, Giné, and Vickery 2017). However contrary to the findings in to the current study resistant varieties in India are observed to generate productivity gains up to 45% (Dar et al. 2013). One limitation of this analysis is that using cross-sectional data from 2016/17 means that the results are generalizable to periods of comparable biophysical conditions.

Table 3: One to one Matching quality analysis: t-test and standardized percentage bias

	T-Test (P-value)	Standardized percentage bias
Distance to market (Km)	0.971 (-0.04)	-0.2
Radio (1=Yes)	0.638 (0.47)	3.1
Mobile phone (1=Yes)	0.214 (1.24)	8.4
TV (1=Yes)	0.255 (1.14)	4.3
Agriculture cooperative (1=Yes)	0.472 (0.72)	4.2
Consolidated land (1=Yes)	0.944 (0.07)	0.5
Agricultural credit (1=Yes)	0.798 (0.26)	1.7
Improved wall materials (1=Yes)	0.29 (-1.06)	-6.7
Improved floor materials (1=Yes)	0.351 (-0.93)	-5.6
Improved water source (1=Yes)	0.161 (1.4)	9.3
Electricity (1=Yes)	0.501 (-0.67)	-4.2
Female head (1=Yes)	0.199 (-1.29)	-8.9
Household head age	0.944 (-0.07)	-0.5
Household head finished primary (1=Yes)	0.819 (-0.23)	-1.5
Household size	0.146 (1.46)	9.7
Farm size (Hectares)	0.336 (0.96)	1.9
Southern Province	1	0
Western Province	0.805 (-0.25)	-1.7
Northern Province	0.348 (-0.94)	-6.5

The second hypothesis relates to the adequacy of intensification practices in driving farm productivity in the Rwandan context. To test this hypothesis, we re-analyze the model in Table 1 and include the intensification outcome variables as explanatory variables of farm productivity in Table 4. The table shows that seed fertilizers are positively and statistically associated with farm productivity, providing evidence against the second hypothesis. In sum, the evidence presented in this study supports the conclusion that the quality of the WCIS drives the observed weak link between WCIS and farm productivity.

Table 4: Rwanda Farm productivity determinants

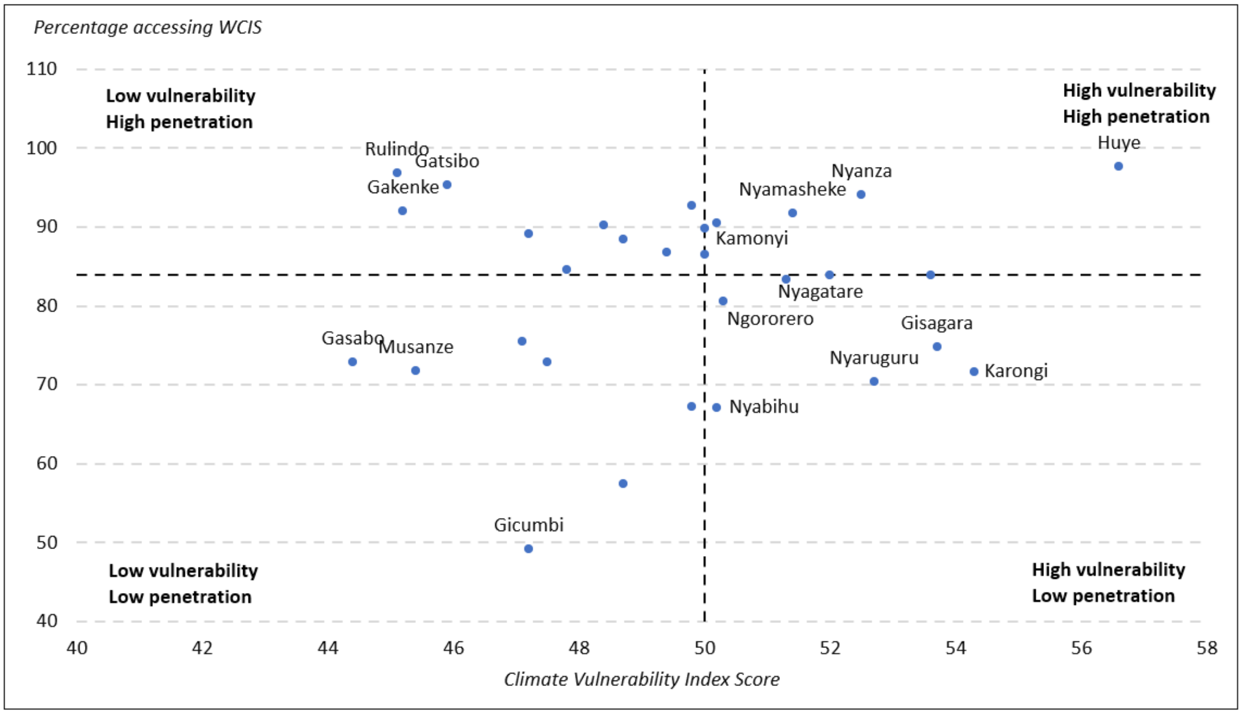
	Coeff	Std. Err	Z
Use improved seed (1=Yes)	0.165	0.038	4.33***
Use fertilier (1=Yes)	0.702	0.036	19.48***
Use Irrigation (1=Yes)	0.101	0.047	2.17**
Distance to market (Km)	0.020	0.005	4.28***
Radio (1=Yes)	0.408	0.035	11.71***
Mobile phone (1=Yes)	0.357	0.037	9.58***
TV (1=Yes)	-0.326	0.081	-4.03***
Agriculture cooperative (1=Yes)	0.007	0.077	0.1
Consolidated land (1=Yes)	0.345	0.038	9.04***
Agricultural credit (1=Yes)	0.444	0.047	9.35***
Improved wall materials (1=Yes)	-0.122	0.044	-2.79***
Improved floor materials (1=Yes)	-0.028	0.052	-0.54
Improved water source (1=Yes)	0.080	0.036	2.21**
Electricity (1=YesO	-0.121	0.053	-2.29**
Female head (1=Yes)	0.003	0.042	0.07
Household head age	0.018	0.001	16.34***
Household head finished primary (1=Yes)	0.117	0.037	3.16***
Household size	0.086	0.009	10.13***
Land size (Hectares)	0.000	0.000	5.93***
Southern Province	0.549	0.095	5.8***
Western Province	-0.038	0.096	-0.4
Northern Province	0.722	0.097	7.47***
Eastern Province	0.965	0.094	10.29***
Constant	0.272	0.069	1.46
Log Likelihood	117.63		
Number of observations	12,359		
R-Squared	0.1799		
Adjusted R-Squared	0.1784		

*,**,*** indicate statistical significance at 10%, 5%, 1% levels respectively

Conclusion and recommendations

Whereas this study contradicts previous research that found positive effects of WCIS on agricultural productivity, it differs fundamentally from previous studies. Most previous research evaluated pilot WCIS programs that do not predict performance at scale. Indeed (List 2022)argues that implementation challenges controlled for in a pilot phase come to the fore, resulting in different outcomes at scale. Therefore, in the context of increasing resilience to inevitable climate impacts, a priority for future research is developing a rigorous understanding of how the suitability of WCIS can be improved in different contexts.

Figure 4: Classification of districts by climate vulnerability and penetration of Weather and Climate Information Services (WCIS)



Source: Author calculations based on EICV Data and REMA(2019)

Note: The four quadrants are deliniated by the median score of vulnerability and penetration rates indices across districts in 2018

Similarly, Rwandan policymakers should prioritize existing WCIS resources where there are most needed. We propose prioritizing resources according to current WCIS penetration rates and assessing climate vulnerability. In regions the most vulnerable to climate change, such as the five districts in the lower right quadrant of Figure 4, authorities should prioritize investment in WCIS infrastructure. In regions with high vulnerability and WCIS penetration, such as the four districts in the top right quadrant, authorities could prioritize customizing WCIS to local contexts by increasing the role of data users in generating WCIS information. Regions on the left half of Figure 4 that are less vulnerable to climate change's effects may face weak incentives to adopt WCIS; thus, awareness campaigns are most appropriate in these contexts.

References

Anuga, Samuel Weniga, Chris Gordon, Emmanuel Boon, and Justice Musah-Issah Surugu. 2019. "Determinants of Climate Smart Agriculture (CSA) Adoption among Smallholder Food Crop Farmers in the Techiman Municipality, Ghana." *Ghana Journal of Geography* 11 (1): 124–39. https://doi.org/10.4314/gjg.v11i1.

Bairagi, Subir, Humnath Bhandari, Subrata Kumar Das, and Samarendu Mohanty. 2021. "Flood-Tolerant Rice Improves Climate Resilience, Profitability, and Household Consumption in Bangladesh." *Food Policy* 105 (December): 102183. https://doi.org/10.1016/j.foodpol.2021.102183.

Barrett, Christopher B. 2006. "Rural Poverty Dynamics: Development Policy Implications - Barrett - 2005 - Agricultural Economics - Wiley Online Library" 32 (S1): 45–60. https://doi.org/10.1111/j.0169-5150.2004.00013.x.

Beaman, Lori, Dean Karlan, Bram Thuysbaert, and Christopher Udry. 2014. "Selection into Credit Markets: Evidence from Agriculture in Mali." Working Paper. Working Paper Series. National Bureau of Economic Research. https://doi.org/10.3386/w20387.

BenYishay, Ariel, and A. Mushfiq Mobarak. 2014. "Social Learning and Communication." Working Paper. Working Paper Series. National Bureau of Economic Research. https://doi.org/10.3386/w20139.

Bryan, Elizabeth, Claudia Ringler, Barrack Okoba, Carla Roncoli, Silvia Silvestri, and Mario Herrero. 2013. "Adapting Agriculture to Climate Change in Kenya: Household Strategies and Determinants." *Journal of Environmental Management* 114 (January): 26–35. https://doi.org/10.1016/j.jenvman.2012.10.036.

Cai, Hongbin, Yuyu Chen, Hanming Fang, and Li-An Zhou. 2009. "Microinsurance, Trust and Economic Development: Evidence from a Randomized Natural Field Experiment." Working Paper. Working Paper Series. National Bureau of Economic Research. https://doi.org/10.3386/w15396.

Carter, Michael R., and Christopher B. Barrett. 2006. "The Economics of Poverty Traps and Persistent Poverty: An Asset-Based Approach." *The Journal of Development Studies* 42 (2): 178–99. https://doi.org/10.1080/00220380500405261.

Cole, Shawn, Xavier Giné, Jeremy Tobacman, Petia Topalova, Robert Townsend, and James Vickery. 2013. "Barriers to Household Risk Management: Evidence from India." *American Economic Journal: Applied Economics* 5 (1): 104–35. https://doi.org/10.1257/app.5.1.104.

Cole, Shawn, Xavier Giné, and James Vickery. 2017. "How Does Risk Management Influence Production Decisions? Evidence from a Field Experiment." *The Review of Financial Studies* 30 (6): 1935–70. https://doi.org/10.1093/rfs/hhw080.

Dar, Manzoor H., Alain de Janvry, Kyle Emerick, David Raitzer, and Elisabeth Sadoulet. 2013. "Flood-Tolerant Rice Reduces Yield Variability and Raises Expected Yield,

Differentially Benefitting Socially Disadvantaged Groups." *Scientific Reports* 3 (November): 3315. https://doi.org/10.1038/srep03315.
Djido, Abdoulaye, Robert B. Zougmoré, Prosper Houessionon, Mathieu Ouédraogo, Issa Ouédraogo, and Ndeye Seynabou Diouf. 2021. "To What Extent Do Weather and Climate Information Services Drive the Adoption of Climate-Smart Agriculture Practices in Ghana?" *Climate Risk Management* 32 (January): 100309. https://doi.org/10.1016/j.crm.2021.100309.
Falco, Salvatore Di, Felice Adinolfi, Martina Bozzola, and Fabian Capitanio. 2014. "Crop Insurance as a Strategy for Adapting to Climate Change." *Journal of Agricultural Economics* 65 (2): 485–504. https://doi.org/10.1111/1477-9552.12053.
Grosh, Margaret E., ed. 2008. *For Protection and Promotion: The Design and Implementation of Effective Safety Nets*. Washington, D.C: World Bank.
Hansen, James, D Kagabo, G Clarkson, J Furlow, and F Fondela. 2021. "Climate Services for Agriculture: Empowering Farmers to Manage Risk and Adapt to a Changing Climate in Rwanda | CIAT." https://ciat.cgiar.org/ciat-projects/climate-services-for-agriculture-empowering-farmers-to-manage-risk-and-adapt-to-a-changing-climate-in-rwanda/.
Klopper, E., C.H Vogel, and W.A Landman. 2006. "Seasonal Climate Forecasts – Potential Agricultural-Risk Management Tools? | SpringerLink" 76: 73–90.
Koundouri, Phoebe, Céline Nauges, and Vangelis Tzouvelekas. 2006. "Technology Adoption under Production Uncertainty: Theory and Application to Irrigation Technology." *American Journal of Agricultural Economics* 88 (3): 657–70. https://doi.org/10.1111/j.1467-8276.2006.00886.x.
Lemoine, Derek. 2018. "Estimating the Consequences of Climate Change from Variation in Weather," Working Paper Series, , September. https://doi.org/10.3386/w25008.
List, John. 2022. *The Voltage Effect: John A. List*. https://www.thevoltageeffect.com/.
Lo, Hm, and M. Dieng. 2015. "Impact Assessment of Communicating Seasonal Climate Forecasts in Kaffrine, Diourbel, Louga, Thies and Fatick (Niakhar) Regions in Senegal: Final Report for CCAFS West Africa Regional Program." In . https://www.semanticscholar.org/paper/Impact-assessment-of-communicating-seasonal-climate-Lo-Dieng/3e3fac4b5afc73c6eef65a7dbf399785d148aacf.
Mobarak, Ahmed Mushfiq, and Mark Rosenzweig. 2014. "Risk, Insurance and Wages in General Equilibrium." Working Paper. Working Paper Series. National Bureau of Economic Research. https://doi.org/10.3386/w19811.
NISR. 2019. "EICV 5 - Main Indicators Report 2016/17 | National Institute of Statistics Rwanda." https://www.statistics.gov.rw/publication/eicv-5-main-indicators-report-201617.
Omotilewa, O, J.R Gilbert, and J.H Ainembabazi. 2019. "Subsidies for Agricultural Technology Adoption: Evidence from a Randomized Experiment with Improved Grain Storage Bags in Uganda - Omotilewa - 2019 - American Journal of

Agricultural Economics - Wiley Online Library" 101 (3): 732–72. https://doi.org/10.1093/ajae/aay108.

Ouedraogo, Mathieu, Robert Zougmore, Silamana Barry, Some Leopold, and Baki Grégoire. 2015. *The Value and Benefits of Using Seasonal Climate Forecasts in Agriculture: Evidence from Cowpea and Sesame Sectors in Climate-Smart Villages of Burkina Faso*. https://doi.org/10.13140/RG.2.1.4958.5682.

Phillips, Jennifer, D Deane, Leonard Unganai, and A Chimeli. 2002. "Implications of Farm-Level Response to Seasonal Climate Forecasts for Aggregate Grain Production in Zimbabwe." *Agricultural Systems* 74 (February): 351–69. https://doi.org/10.1016/S0308-521X(02)00045-8.

Rosenzweig, Mark, and A.M Mobarak. 2013. "Informal Risk Sharing, Index Insurance, and Risk Taking in Developing Countries - American Economic Association." https://doi.org/DOI: 10.1257/aer.103.3.375.

Vaughan, Catherine, James Hansen, Philippe Roudier, Paul Watkiss, and Edward Carr. 2019. "Evaluating Agricultural Weather and Climate Services in Africa: Evidence, Methods, and a Learning Agenda." *WIREs Climate Change* 10 (4): e586. https://doi.org/10.1002/wcc.586.

World Bank. 2009. "Handbook on Impact Evaluation : Quantitative Methods and Practices." https://documents.worldbank.org/en/publication/documents-reports/documentdetail/650951468335456749/handbook-on-impact-evaluation-quantitative-methods-and-practices.

———. 2010. "World Development Report 2010 : Development and Climate Change." https://documents.worldbank.org/en/publication/documents-reports/documentdetail/201001468159913657/world-development-report-2010-development-and-climate-change.

World Meterological Organization. 2020. "SOFF: Establishing the Systematic Observations Financing Facility | World Meteorological Organization." https://public.wmo.int/en/resources/library/soff-establishing-systematic-observations-financing-facility.

———. 2022. "Provisional State of the Global Climate 2022." https://storymaps.arcgis.com/stories/5417cd9148c248c0985a5b6d028b0277.

Yegbemey, Rosaine N., Gunther Bensch, and Colin Vance. 2023. "Weather Information and Agricultural Outcomes: Evidence from a Pilot Field Experiment in Benin." *World Development* 167 (July): 106178. https://doi.org/10.1016/j.worlddev.2022.106178.