Impact of the Seasonal Climate Forecasts on Farm Household Income in Rural Senegal

Thierno Malick Diallo*
Department of Economics, University of Gaston Berger, Saint-Louis, Senegal.
E-mail: malikidiallo@gmail.com

Malick Ndiaye
Department of Economics, University of Gaston Berger, Saint-Louis, Senegal.
E-mail: elmalickoul@gmail.com

*Corresponding author

Abstract

The seasonal climate forecasts are often regarded as a key strategic tool in terms of reducing the negative impact of climate variability and shocks on crop yields. Nevertheless, there is little empirical evidence on the impact of climate forecasts on farmers' livelihoods. In this article, we use the propensity score matching method to estimate the impact of climate services on farm household income in rural Senegal. Findings indicate that using climate services results in an average gain of farm income, ranging from 988 to 1221 euros per household. However, the results are not significant. This suggests that seasonal forecasts are not, in their current form, an effective instrument for improving the farm households' living conditions.

Keywords: Seasonal climatic forecasts; Propensity score matching; Senegal.

Résumé

Les prévisions climatiques saisonnières sont souvent considérées comme un outil stratégique clé pour réduire l'impact négatif de la variabilité climatique et des chocs sur les rendements des agricoles. Cependant, les évidences empiriques concernant l'impact des prévisions climatiques sur les moyens de subsistance des producteurs sont rares. Dans cet article, nous utilisons la méthode d'appariement du score de propension pour évaluer l'impact de l'utilisation de l'information climatique sur le revenu des ménages agricoles en milieu rural sénégalais. Les résultats indiquent que la hausse du revenu des ménages agricoles consécutive à la prise en compte des prévisions climatiques dans l'appareil de production varie entre 988 euros et 1221 euros. Cependant, cet impact ne s'avère pas significatif. Ceci suggère que les prévisions saisonnières ne constituent pas, sous leur forme actuelle, un instrument efficace pour améliorer les conditions de vie des ménages agricoles.

Mots-clés : prévisions climatiques saisonnières ; score de propension ; revenu ; Sénégal.

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Introduction

Despite their historical adaptation to weather fluctuations, farmers have been increasingly faced the problem of climate change over the past two decades (Morton, 2007; Senaratne & Scarborough, 2011). The lenght the of rainy season varies as well as the number of rainy days (Sultan & Janicot, 2003; Traore, et al., 2013).

Farmers in sub-Saharan Africa and South Asia are particularly affected by the climate change, because these regions already have high temperatures and low adaptive capacity (Schmidhuber & Tubiello, 2007). Like other Sahelian countries, Senegal has experienced seventeen times of drought over a period of 30 years, and the rainfall has declined by 30-40% over the last three decades (Seck et al. 2005). According to Funk et al. (2012), the temperatures have increased by 9°C (degrees Celsius) since 1975 across the country. This climatic variability is likely to lead to an irreversible desertification process resulting in lower crop yields. The seasonal climatic forecasts are a key strategic tool for farmers to reduce the negative impact of climate variability on crop production (Roncoli, 2006; Nyong, et al., 2007), as they include the expected starting and ending dates of the rainy season, the duration of the season and that of dry spells (Klemma & McPhersona, 2016; Traore et al., 2014). In addition, the seasonal climatic forecasts help farmers to foster better decisions about their crop diversification strategies (Crane, et al. 2010). Besides, these forecasts can be an endogenous system of climatic information which enables farmers to choose plots of land to be cultivated, types of crop varieties and planting date (Zongo, et al., 2016). Hence, an effective climatic forecast reduces uncertainty. It does so first by reducing the spread of possible outcomes for the upcoming season relative to the climatological distribution, and then by conveying shifts in the central tendency of climatic outcomes (Meza, et al., 2008).Moreover, farmers having access to weather information tend more to make change regarding their farming practices (Wood, et al., 2014), as seasonal forecasts have considerable potential for improving livelihoods in areas with high interannual variability of precipitation (Roncoli, 2006; Ash, et al ., 2007; Hansen, et al ., 2011).

In Senegal, it is estimated that a 50% drop in precipitation and a 5 °C rise in temperatures could decrease crop yields by 86% compared to current yields, which would negatively affect the farm income (UNDP, 2009). Under these circumstances, we believe that seasonal climate forecasts can have positive impact on farmer’s income, and, hence, rigorous impact evaluation analyses are critical to fully harness the potential benefits associated with such forecasts and to understand the limits of their application. Our article focuses on this perspective. It aims at evaluating the impact of seasonal climate forecasts on farm household income of agricultural households in rural Senegal. We find that seasonal climate forecasts positively influence farm income. However, the results are not significant.

The rest of the article is organized as follows. A review of the literature is presented in the second section. The third section describes the empirical framework. The fourth section presents the data and the descriptive statistics. The fifth section reports the econometric results while the sixth section concludes.

1. Review of the literature

Understanding how climate variability influences agricultural decision-making provides a basis for predicting the mechanisms by which advanced climate information in the form of seasonal forecasts can benefit agriculture. In recent decades, climatologists have improved their ability to predict seasonal climate (Palmer & Anderson 1994, Martin et al., 2000, Murphy et al., 2001). These seasonal climate forecasts are based on the ocean-atmosphere interaction, so that the temperatures of surface of the sea determine the future states of atmospheric disturbance (Washington & Downing, 1999).

Seasonal forecasting methods can provide information beyond the seasonal average conditions over large areas (Gong, et al., 2003, Moron, et al., 2006). The total precipitation for a season are the result of the frequency of precipitation and average intensity (Klemma & McPhersona, 2016). At the local level, the predictability of total seasonal precipitation is determined by the predictability of precipitation frequency (Morton 2007, Mishra et al.2008).
In Senegal, from July to September, Moron, et al., (2006) find that i) the seasonal frequency and the seasonal quantity of rains are predictable from SST; (ii) the daily average intensity of the precipitation is spatially inconsistent and largely unpredictable on a regional scale; (iii) point estimates of the predictability and proficiency of seasonal precipitation are subject to high sampling variability.
A number of seasonal forecasting systems have been developed recently. Most of these systems use the phenomenon El Niño Oscillation southern (ENSO) in association with other climate indicators such as cloud cover, water vapor and agronomic data (Hammer & Holzworth, 1996; Meinke & Hammer, 1997; Podbury, et al., 1998; Orlove, and al., 2000).
There is an interesting literature explaining the economic impact of the seasonal forecasts on the agricultural systems: (Byerlee & Anderson, 1982; Fox, et al., 1999; Mjelde & Dixon, 1993; Hammer & Holzworth, 1996; Roudier, 2012; Sultan, et al., 2013). These authors have shown that farmers who use seasonal forecasting are not only less vulnerable to agricultural risks but also earn higher incomes. However, an experience in southwestern Burkina Faso suggests relatively limited economic gains for farmers (Dabiré, et al., 2011).
Yet, the importance of seasonal forecasts in agricultural activities is sometimes difficult to assess because their impact depends on many factors, including farmers' risk attitudes, insurance, the political environment and the scale of adoption (Meza, et al., 2008).
Research suggests that African farmers are particularly interested in the seasonal forecast. However, the communication systems responsible for dissemination are poorly developed (Archer, 2003; Eakin, 2000; Kirshen & Flitcroft, 2000; Vogel, 2000; Phillips, et al., 2001; Ziervogel, 2004; Ingram, et al., 2002). As forecasts are not widely used, it is difficult to assess their impact on agriculture (Ziervogel and Calder, 2003).

2. Empirical framework

Following Rosembaum & Rubin (1983), we use the propensity score technique to evaluate the impact of the seasonal climate forecasts on farmers' incomes. This method relies on matching individuals based on the propensity score.

The score, denoted $P(X) = \Pr(T = 1|X)$, refers to the probability of receiving the treatment as a function of observable characteristics X.

We have two groups: the treated, i.e. farm households that incorporate information from seasonal forecasts into their farming activities, and the untreated or comparison group, i.e. farm households that do not use information from seasonal forecasts.

Let T be a binary variable equal to 1 if the farmer integrates information about seasonal climate forecasts and 0 if not, and Y the outcome variable which is the annual income of the farmer. Y_0 is the income of the untreated farmer and Y_1 captures that of the treated. The effect of the treatment on the treated farmers is:

$$\Delta\overline{Y} = E[Y_1|T=1, P(X)] - E[Y_0|T=1, P(X)]$$

$\Delta\overline{Y}$ cannot be estimated a priori because the component $E[Y_0|T=1, P(X)]$ is unobserved. However, the propensity score method is based on the conditional independence assumption that the farmer's income is independent of the treatment, which is conditional on the propensity score. Formally, the assumption can be written as follows:

$$(Y_0, Y_1) \perp T|P(X)$$

From this assumption, we deduce: $E[Y_0|T=1, P(X)] = E[Y_0|T=0, P(X)]$

Thus, the impact of the treatment on the treated farmers becomes:

$$\Delta\overline{Y} = E[Y_1|T=1, P(X)] - E[Y_0|T=0, P(X)]$$

First, we estimate the propensity score by a logit model. Given the binary nature of the treatment variable, the score can be estimated either by a probit or a logit model. The choice of variables for estimating the propensity score is also an important step. In accordance with the conditional independence assumption, we only include variables which are supposed to have a significant influence on both the probability of receiving treatment and the outcome variable (Caliendo & Kopeinig, 2008; Smith & Todd, 2005). More specifically, we select variables that can explain both farmers' incomes and their propensity to integrate seasonal forecasts information into the farming activities. These variables include household characteristics (age of the household head, the gender of household head, the household size, the number female and male farmers within the household) and shocks affecting the household (Out-of-season rains, poor rains, pests invasion, increase in price of inputs) and geographical variables (i.e. the regions).

Second, we evaluate the quality of the propensity score based on both determining the balancing property[1] and the common support area[2].

Third, we finally perform the matching using several methods to ensure the robustness of the results. More specifically, we use the nearest neighbor method, the kernel matching method as well as the radius matching method. The purpose here is to artificially construct a counterfactual (i.e., a control group) comparable to the treated group so as to have an unbiased estimate of the effect of the treatment on the treated.

3. Data and Descriptive Statistics

The data used in this study come from the "*Enquête Rurale sur l'Agriculture, la Sécurité alimentaire et la Nutrition*" (ERASAN) conducted in 2014 by three state structures with the support from the World Food Program. The main objective of ERASAN was to evaluate the 2014/2015 the crop season, but also to understand the prevalence of food insecurity and malnutrition among rural children aged 6 to 59 months.

The survey includes a household questionnaire with nine sections. However, considering the orientation of our study which is to determine the impact of the seasonal forecast on farmers' income, only six sections are used. These are: Identification, Composition and Agricultural

[1] If the propensity score is properly estimated, there should no longer be significant differences between the treated group and the control group after matching.

[2] The existence of a common support area implies that for any set of independent variables (X), there must be a treatment and control in order to ensure the validity of the matching process (Rosenbaum and Rubin, 1983).

Activities of the Household, Agricultural Equipment and Processing of Agricultural Products, Income and Household Spending and Meteorology.

The ERASAN sampling frame consists of a stratified sample of 5989 farm households residing in rural areas. The two-stage sampling has been used in the survey. A total of 861 Enumeration Areas (EA) were drawn in the first degree in the 42 rural departments of the country. In the second degree, it was drawn by simple random sampling about 7 households in each EA.

Finally, our sample consists of 1056 farm households divided into two groups, depending on whether or not farmers integrate seasonal climate forecasts in their farming activities. We have 430 farm households in the first group (the treated group) and 626 in the second group (the control group).

Table 1 below presents descriptive statistics on all the variables used in this study. Results are presented for all farm households in the sample and separately for treated and untreated the farm households. We find that households in the treatment group have a higher annual income than those in the control group. Thus, taking climate information into account seems to have a positive impact on farmers' income. Most farm households are managed by men, with 96.5% in the treated group and 96.9% in the control group. The average age of the household head is about 52 years in the first group and 51 years in the second group. These two groups are almost identical in size. However, treated households have almost female farmers and more male farmers than untreated households.

Besides, treated households suffer more from shocks such as the increase in price of inputs and out-of-season rains. On the other hand, untreated households are more exposed to the pests invasion and poor rains. The geographical distribution also reveals that treated households are more concentrated in Louga (23.7%), Ziguinchor (19.5%), Kaffrine (18.1%) and Diourbel (12.7%). Thus, seasonal climate forecasts are more frequently used in these regions.

Table 1 : Descriptive statistics

Variables	Total		Treated households		Untreated households	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Outcome variable						
Annual inccome (in euros)	1922	432.6	2318	993.21	1650	259.82
Independent variables						
Characteristics of the household						
Male-headed household	.967	.005	.965	.008	.969	.006
Age of head	51.375	.443	51.818	.664	51.072	.592
Household size	15.151	.293	15.388	.497	14.988	.357
Number of female farmers	3.461	.086	3.197	.120	3.642	.119
Number of male farmers	4.303	.097	4.318	.160	4.292	.123
Shocks affecting the household						
Increase in price of inputs	.731	.013	.741	.021	.723	.017
Pests invasion	.456	.015	.455	.024	.456	.019
Poor rains	.833	.011	.820	.018	.841	.014
Out-Of-season rains	.129	.010	.202	.019	.079	.010
Regions						
Dakar (b)	.005	.002	.009	.004	.003	.002
Diourbel (b)	.169	.011	.127	.016	.198	.015
Fatick (b)	.043	.006	.009	.004	.067	.0100
Kaffrine (b)	.260	.013	.181	.018	.314	.018
Kaolack (b)	.092	.008	.104	.014	.084	.011

Source: Authors' calculations based on the survey data

Table 1 : Descriptive statistics (continued)

Variables	Total		Households treated		Households untreated	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Reegion						
Kédougou (b)	.006	.002	-	-	.011	.004
Kolda (b)	.004	.002	-	-	.007	.003
Louga (b)	.165	.011	.237	.020	.116	.012
Matam (b)	.027	.005	.020	.006	.031	.007
Saint-Louis (b)	.021	.004	.006	.004	.031	.007
Sédhiou (b)	.035	.005	.055	.011	.020	.005
Tambacounda (b)	.041	.006	.009	.004	.063	.009
Thiès (b)	.032	.005	.041	.009	.025	.006
Ziguinchor (b)	.092	.008	.195	.019	.022	.005

Source: Authors' calculations based on the survey data.

4. Econometric results

4.1. Propensity score estimation

As mentioned, we estimated the propensity score using the logit model. However, it is important, before presenting the econometric results, to ensure the quality of the estimated propensity score. We evaluate this based on the balancing test and the common support area.

Table 2 in appendix gives the results of the balancing test materialized by comparison tests of average or percentage depending on the quantitative or qualitative nature of the variables. Propensity score matching is of good quality if there are no significant differences in mean or percentage between the two household groups. In many cases, the comparison of pre- and post-matching results reveals that the initial differences between the treated and control households significantly decreased after matching. These results show that the matching procedure is correct in that it balances the characteristics of the two groups of farmer.

The graph 1 in appendix shows also a good overlap in the distribution of the propensity scores of farmers in the treated and control groups. This indicates the existence of a fairly large common support area, which reveals that the two groups are quite comparable. Besides, Graph 2 in appendix shows a clear difference in the distribution of propensity scores before matching. On the other hand, we note that these overlap after the matching procedure, which means that matching has made the two farmers groups comparable.

Based on the results in Table 2 and graphs 1 and 2, we can use the propensity score estimates to assess the impact of seasonal forecasts on farm income. It is worth mentioning that farm households not included in the common support area are excluded from the rest of the study. Of the 1056 farm households in our initial sample, 613 households in the control group and 429 in the treated group are in the common support area, leading to a final sample of 1042 farm households.

The results of the logit model determining the probability of a rural farm household to integrate seasonal climate forecasts into its farming activities are reported in Table 3 below. We find that the size of the farm household, the number of female famers within the household, the increase in price of inputs, the out-of-season rains are the main factors that influence farmers' propensity to take into account the climate information.

Table 3: Estimation of the propensity score: logit model

Variables	Coef.	St. Err.	P-value
Characteristics of the household			
Male-headed household	-.507	.331	0.125
Age of head	.0021	.005	0.683
Household size	.019	.009	0.030**
Number of female farmers	-.111	.033	0.001***
Number of male farmers	.003	.027	0.909
Shocks affecting the household			
Increase in price of inputs	.694	.221	0.002***
Pests invasion	-.108	.158	0.494
Poor rains	-.044	.217	0.839
Out-of-season rains	.845	.220	0.000***
Region[a]	*Yes*	*Yes*	*Yes*
Number of observations	1042		
Pseudo R2	0.1768		
LR chi2 (20)	171.17		

Source: Authors' calculations based on the survey data.

Notes: * significant at 10%; ** significant at 5%, *** significant at 1%. Standard Errors are robust to heteroscedasticity. [a] A series of binary variables capturing the regions is also included to take into account the geographical heterogeneity.

More specifically, it appears that larger households are more likely to use climate information for their agricultural activities. However, farmers 'propensity to take into account seasonal climate forecasts decreases with the number of female farmers within the household. Households facing shocks such as increase in price of inputs and out-of-season rains are more likely to use seasonal climate forecasts in their farming activities, perhaps to better cope with these types of shocks.

4.2. Estimating the average treatment effect on the treated

In this section, we estimate the average treatment effect on the treated. More precisely, we aim at assessing the impact of the use of seasonal climate forecasts on farm income. Table 4 below presents the results on the basis of three different estimation methods. The standard errors are obtained by the bootstrap method with 100 replications.

The results indicate that taking climate information into account has a positive effect on farmers' income, regardless of the method used. The increase in farmers' income incorporating climate forecasts varies between 988 euros and 1221 euros depending on the method used to perform the matching. However, this positive impact is not statistically significant if one refers to the confidence intervals.

Thus, there are no income differences between farmers integrating climate information in their farming activities and those who did not. This result is contrary to those of Byerlee & Anderson (1982), Fox et al. (1999), Roudier (2012) and Sultan et al. (2013) indicating that the use of seasonal climate forecasts improves farmers' income.

That being said, the result does not prove surprising to some extent. Indeed, among farmers who integrate climate information into their farming activities, only 39% of them consider it to be generally satisfactory.

Table 4 : Impact of climate forecasts on farmers' incomes

	Nearest neighbor	Kernel matching	Radius matching
Annuel income[a]	1108 euros	988 euros	1221 euros
Confidence interval	[-561398.9; 2035950]	[-641259.8 ; 1955465]	[-712012.2; 2336687]
Number of observations	1,042	1,042	1,042
Number of replications	100	100	100

[a] The annual income is expressed in CFA in the database, but we converted it to euros at the rate of 665.3.
Source: Authors' calculations from the survey data.

Conclusion

In this study, we evaluated the impact of the seasonal climate forecasts on farmers' incomes,
using a sample of 1042 farm households in rural Senegal.

Based on a logit model, we found that the propensity of farmers to take seasonal climate forecasts into account decreases with the number of female farmers within the household but increase with the household size. The propensity to use climate information is also higher among households facing shocks such as increase in price of inputs and Out-of-season rains.

Furthermore, while the descriptive statistics indicate that farm households incorporating climate information into their farming activities have higher annual incomes than those that do not integrate this information, we found from different matching methods that the differences in income between the two groups are not statistically significant. However, the result is not surprising to some extent as among farmers who integrate climate information into their farming activities, less than half (39%) rate it as satisfactory on the whole. This suggests that the seasonal climate forecasts do not, in their current form, improve farmers' living conditions.

In this context, policy makers should help farmers to better use climate data for agricultural business planning and water resource optimization. Using such data in real-time would enable better decision-making in crop management and boost agricultural productivity for rural households. That said, the fostering of climate forecasting services cannot be dissociated from other climate-smart tools, such as crop insurance. Their combination is critical to keep farmers resilient while allowing them to increase their productivity.

References

Archer, E. (2003). Identifying underserved end-user groups in the provision of climate information. *Bulletin of the American Meteorological Society*, 84(11), p. 1525–1532.

Ash, A. et al. (2007). Constraints and opportunities in applying seasonal climate forecasts in agriculture. *Australian Journal of Agricultural Research*, Volume 58, p. 952–965.

Banque Mondiale (2014). Situation Economique et Sociale du Sénégal: Apprendre du passé pour un avenir meilleur.

Banque Mondiale (2014). Agriculture, valeur ajoutée (% du PIB). Retrieved from http://donnees.banquemondiale.org.

Byerlee, D. & Anderson, J. R. (1982). Risk, utility and the value of information in farmer decision making. Review of Marketing and Agricultural Economics, 50(3), pp. 231-246.

Caliendo, M., & Kopeinig, S. (2008). Some practical guidance for the implementation of propensity score matching. *Journal of Economic Surveys* 22: 31–72.

Crane, T. A. et al. (2010). Forecast skill and farmers' skills: seasonal climate forecasts and agricultural risk management in the Southeastern United States. *Weather, Climate, and Society*, Volume 2, p. 44–59.

Dabiré, W., Barbier, B. & Andrieu, N. (2011). Evaluation ex-ante de la prévision saisonnière climatique en petit paysannat burkinabé. *Revue d'élevage et de médecine vétérinaire des pays tropicaux*, 64(1-4), pp. 43-50.

Direction de la prévision et des études économiques (DPEE). (2013). Politique Agricole, Productivité et Croissance à Long Terme au Sénégal, Document d'Etude.

Eakin, H. (2000). Smallholder maize production and climatic risk: a case study from Mexico. *Climatic Change*, Volume 45, p. 19–35.

Fox, G., Turnera, J. & Gillespie, T. (1999). The value of precipitation forecast information in winter wheat production. *Agricultural and Forest Meteorology*, 95(2), pp. 99-111.

Funk, C. C. & Brown, M. E. (2009). Declining global per capita agricultural production and warming oceans threaten food security. *Food Security*, Volume 1, p. 271–289.

Gong, X. F., Barnston, A. G. & Ward, M. N. (2003). The effect of spatial aggregation on the skill of seasonal precipitation forecasts. *Journal of Climate*, Volume 16, p. 3059–3071.

Gourdji, S. M. et al. (2013). An assessment of wheat yield sensitivity and breeding gains in hot environments. *Proc. R. Soc. Lond. B*, Volume 280, pp. 2012-2190.

Hammer, G. L. & Holzworth, D. (1996). The value of skill in seasonal climate forecasting to wheat crop management in a region with high climatic variability. *Australian Journal of Agricultural Research*, 47(5), pp. 717-737.

Hansen, J. W., Mason, S. J., Sun, L. & Tall, A. (2011). Review of Seasonal Climate Forecasting for Agriculture in Sub-Saharan Africa. *Experimental Agriculture*, 47(2), pp. 205-240.

Hathie, I., Amikuzuno, J., MaCarthy, D. S. & Diancoumba, M. (2013). Economic Impacts of Climate change on farmers in Nioro du Rip, Senegal: *An integrated assessment.* AgMIP, UKaid.

Ingram, K. T., Roncoli, M. & Kirshen, P. (2002). Opportunities and constraints for farmers of West Africa to use seasonal precipitation forecasts with Burkina Faso as a case study. *Agricultural Systems*, 74(3), p. 331–349.

Kirshen, P. & Flitcroft, I. (2000). Use of seasonal precipitation forecasting to improve agricultural production in the Sudano-Sahel: an institutional analysis of Burkina Faso. *Natural Resources Forum*, Volume 24, p. 185–195.

Klemma, T. & McPhersona, R. A. (2016). The development of seasonal climate forecasting for agricultural producers. *Agricultural and Forest Meteorology*, 232(2017), p. 384–399.

Marteau, R. et al. (2011). The onset of the rainy season and farmers' sowing strategy for pearl millet cultivation in Southwest Niger. *Agricultural and Forest Meteorology*, 151(10), pp. 1356-1369.

Martin, R. V., Washington, R. & Downing, T. E. (2000). Seasonal maize forecasting fo Zimbabwe derived from an agro climatological model. *Journal of Applied Meteorology*, Volume 39, pp. 1473-1479.

Meinke, H. & Hammer, G. L. (1997). Forecasting regional crop production using SOI phases: an example for the Australian peanut industry. *Australian Journal of Agricultural Research*, Volume 48, pp. 789-793.

Meza, F. J., Hansen, J. W. & Osgood, D. (2008). Economic Value of Seasonal Climate Forecasts for Agriculture: Review of Ex-Ante Assessments and Recommendations for Future Research. *Journal of applied meteorology and climatology*, Volume 47, pp. 1269-1286.

Mishra, A. et al. (2008). Sorghum yield prediction from seasonal rainfall forecasts in Burkina Faso. *Agric. Forest Meteorol*, Volume 148, p. 1798–1814.

Mjelde, J. W. & Dixon, B. L. (1993). Valuing the lead time of periodic forecasts in dynamic production systems. *Agricultural Systems*, Volume 42, pp. 41-55.

Moron, V., Robertson, A. W. & Ward, M. N. (2006). Seasonal predictability and spatial coherence of rainfall characteristics in the tropical setting of Senegal. *Monthly Weather Review*, Volume 134, p. 3248–3262.

Morton, J. F. (2007). The impact of climate change on smallholder and subsistence agriculture. *Proc. Natl Acad. Sci*, 104(50), p. 19680–19685.

Murphy, S. et al. (2001). Seasonal forecasting for climate hazards: prospects and responses. *Natural Hazards*, Volume 23, p. 171–196.

Nicholls, N. (1999). Cognitive illusions, heuristics, and climate prediction. *Bulletin of the American Meteorological Society*, Volume 80, p. 1385–1397.

Nyong, A., Adesina, F. & Osman, E. B. (2007). The value of indigenous knowledge in climate change mitigation and adaptation strategies in the African Sahel. *Mitigation and Adaptation Strategies for Global Change*, 12(5), pp. 787-797.

O'Brien, K., Sygna, L., Naess, L., Kingamkono, R., & Hochobeb, B. (2000). Is information enough? User responses to seasonal climate forecasts in Southern Africa. CICERO.

Orlove, B. S., Chiang, J. C. H. & Cane, M. A. (2000). Forecasting Andean rainfall and crop yield from the influence of El Nino on Pleiades visibility. *Nature*, Volume 402, pp. 68-71.

Palmer, T. & Anderson, D. (1994). The prospects for seasonal forecasting – a review paper. *Quarterly Journal of the Meteorological Society*, Volume 120, p. 755–793.

PAM (2010). Analyse Globale de la Vulnérabilité, de la Sécurité Alimentaire et de la Nutrition (AGVSAN) au Sénégal

Phillips, J. G., Makaudze, E. & Unganai, L. (2001. Current and potential use of climate forecasts for resource-poor farmers in Zimbabwe. In: Impacts of El Nino and Climate Variability on Agriculture, *American Society of Agronomy Special Publication Series,* Volume 63, p. 87–100.

Podbury, T., Sheale, T. C., Hussain, I. & Fisher, B. S. (1998). Use of El Nino climate forecasts in Australia. *American Journal of Agricultural Economics*, 80(5), pp. 1096-1101.

Quiggin, J., Adamson, D., Chambers, S. & Schrobback, P. (2010). Climate change, uncertainty, and adaptation: the case of irrigated agriculture in the Murray-Darling basin in *Australia. Can. J. Agr. Econ.*, Volume 58, p. 531–554.

Roncoli, C. (2006). Ethnographic and participatory approaches to research on farmers' responses to climate predictions. *Climate Reshearch*, 33(1), pp. 81-99.

Rosenbaum, P., & Rubin, D. (1983). The central role of the propensity score in observational studies for causal effects. *Biometrika*, 70(1), 41–55.

Roudier, P. (2012). Climat et agriculture en Afrique de l'Ouest : Quantification de l'impact du changement climatique sur les rendements et évaluation de l'utilité des prévisions saisonnières, Paris: Ecole des Hautes Etudes en Sciences Sociales (EHESS).

Schmidhuber, J. & Tubiello, F. N. (2007). Global food security under climate change. *Proc. Natl Acad. Sci.*, 104(50), p. 19703–19708.

Senaratne, A. & Scarborough, H. (2011). Coping with climatic variability by rain-fed farmers in dry zone, Sri Lanka: towards Understanding adaptation to climate change. Paper presented at the 55th annual national conf. for *Australian Agricultural and Resource Economics* Society (AARES), 8–11 February, p. 23.

Smith J., & Todd P. (2005), "Does Matching Overcome LaLonde's Critique of Non experimental Estimators?", *Journal of Econometrics*, 125(1-2),305-353.

Sovacool , B. K. (2011). Hard and soft paths for climate change adaptation. *Climate Policy*, 11(4), p. 1177–1183.

Sultan, B. & Janicot, S. (2003). The West African Monsoon Dynamics. Part II: The preonset and onset of the summer monsoon. *American Meteorological Society*, Volume 16, pp. 3407-3427.

Sultan, B., Roudier, P. & Quirion, P. (2013). Les bénéfices de la prévision saisonnière dans l'agriculture en Afrique de l'Ouest. *Sécheresse*, 24(4), pp. 304-313.

Traore, B. et al. (2013). Effects of climate variability and climate change on crop production in southern Mali. *European Journal of Agronomy*, Volume 49, pp. 115-125.

USAID (2009). Projet Croissance Economique. La chaine de valeur mil&sorgho: Options stratégiques de développement au Sénégal. International Resources Group (IRG).

Vogel, C. (2000). Usable science: an assessment of long-term seasonal forecasts among farmers in rural areas of South Africa. *South African Geographical Journal*, Volume 82, p. 107–116.

Washington, R. & Downing, T. E. (1999). Seasonal forecasting of African rainfall: prediction, responses and household food security. *The Geographical Journal*, Volume 165, p. 255–274.

Wood, S. A. et al. (2014). Smallholder farmer cropping decisions related to climate variability across multiple regions. *Global Environmental Change*, Volume 25, p. 163–172.

Ziervogel, G. (2004). Targeting seasonal climate forecasts for integration into household level decisions: the case of smallholder farmers in Lesotho. *The Geographical Journal*, 170(1), p. 6 –21.

Ziervogel, G. & Calder, R. (2003). Climate variability and rural livelihoods: assessing the impact of seasonal climate forecasts. *Area*, 35(4), p. 403–417.

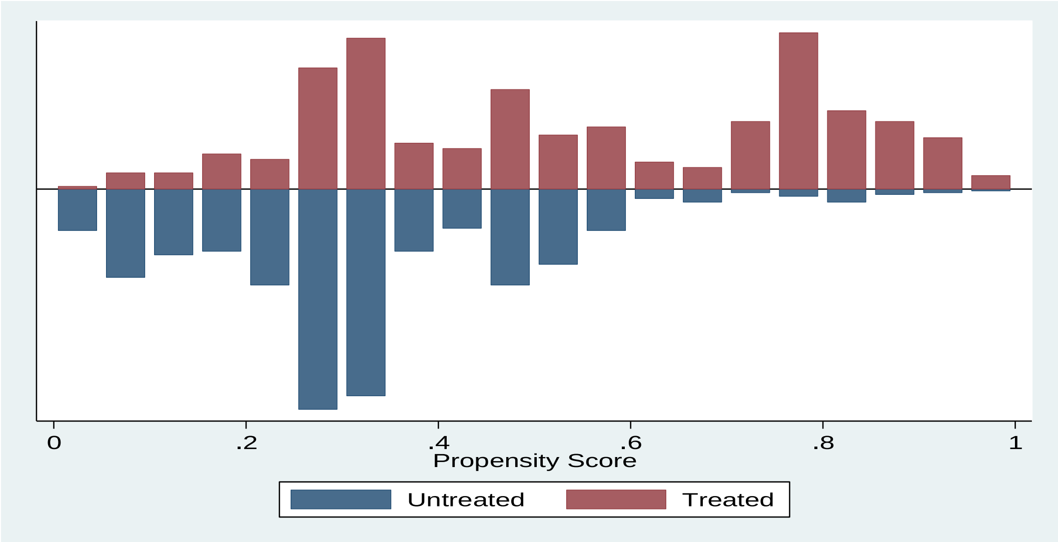
Zongo, B. et al. (2016). Farmers' Perception and Willingness to Pay for Climate Information in Burkina Faso. *Journal of Agricultural Science*, 8(1), pp. 175-187.

Table 2 : *Balancing test*

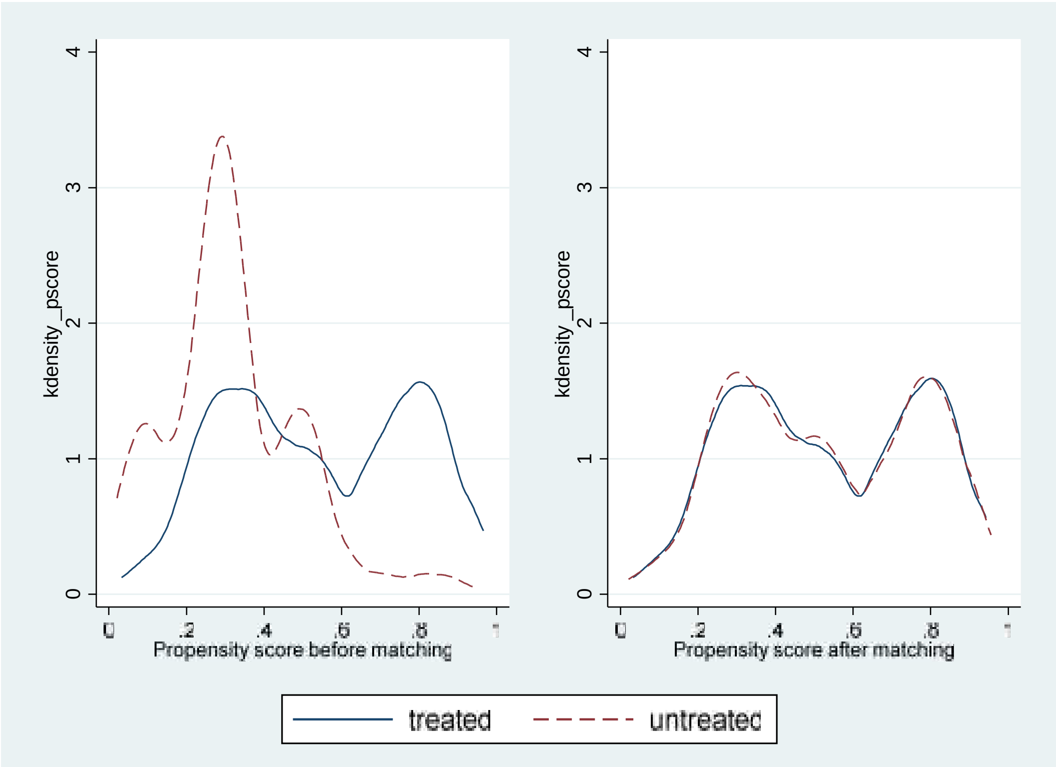
Variables	Sample	Mean		%bias	%reduct	t-test	
		Treated	Control		|bias|	t	P>|t|
Male headed household	Before matching	.96503	.969	-2.2		-0.35	0.723
	After matching	.96462	.95729	4.1	-84.8	0.55	0.582
Age of the head of household	Before matching	51.818	51.132	4.8		0.77	0.444
	After matching	51.587	52.016	-3.0	37.5	-0.46	0.644
Household size	Before matching	15.343	14.992	3.7		0.59	0.556
	After matching	15.394	14.902	5.1	-40.3	0.76	0.449
Number of active women in the household	Before matching	3.2051	3.6166	-15.3		-2.41	0.016
	After matching	3.2193	3.1744	1.7	89.1	0.26	0.794
Number of active men in the household	Before matching	4.289	4.2936	-0.1		-0.02	0.981
	After matching	4.2972	4.7486	-14.3	-9728.3	-1.87	0.062
Increase in prices of inputs	Before matching	.74359	.72757	3.6		0.58	0.565
	After matching	.74057	.69161	11.1	-205.6	1.58	0.114
Invasion of insects or birds	Before matching	.45455	.46003	-1.1		-0.17	0.861
	After matching	.45047	.48055	-6.0	-448.1	-0.88	0.381
Poor rains	Before matching	.82051	.8385	-4.8		-0.76	0.446
	After matching	.82311	.71442	28.9	-504.3	3.78	0.000
Off-season rains	Before matching	.2028	.07993	35.8		5.88	0.000
	After matching	.1934	.14991	12.7	64.6	1.68	0.093
Region	Before matching	7.69	5.5759	54.7		8.84	0.000
	After matching	7.6156	7.9116	-7.7	86.0	-1.01	0.313

Source: Authors' calculations from the survey data

Appendix B



<u>Graph 1</u> : Common support area
Source: illustration of the authors from the survey data



<u>Graph 2 </u>: Distribution of propensity scores before and after matching
Source: illustration of the authors from the survey data