Africa Development, Volume XLVI, No. 1, 2021, pp. 163-188

(ISSN: 0850 3907)

The Impact of Short Message Services (SMS) Weather Forecasts on Cost, Yield and Income in Maize Production: Evidence from a Pilot Randomised Controlled Trial in Bembèrèkè, North Benin

Rosaine N. Yegbemey*, Aline M. Aloukoutou**
& Ghislain B. D. Aïhounton***

Abstract

In this study we analyse the impact of weather forecasts provided to smallholder maize farmers through mobile phone short message service on self-reported labour costs, crop yield and income. We conducted a pilot field experiment, involving 331 randomly selected eligible farmers in six villages. Randomisation was done at the village level. We used three regression specifications to estimate the impacts: Ordinary Least Squares (OLS), Generalised Estimating Equations (GEE) with a small sample correction and Randomisation Inference (RI). We found that the treatment and control groups were well balanced. Farmers in the treatment group recorded lower labour costs but higher crop yield and income levels. Both the direction and the magnitude of the impact estimates were consistent across the three regression specifications, but significant with the RI model only (for labour costs and yield) or the RI and GEE models (for income). Weather forecasts can have an impact on smallholder farmers' labour, yield and income. These findings are strong evidence of the possibility of using weather-related information and mobile phones to build smallholder farmers' resilience to climate variability. Yet more research is required to build a solid evidence base to inform agricultural policies.

Keywords: Benin, climate services, impact evaluation, maize, randomised controlled trial, smallholder farmers

* Laboratoire d'Analyse et de Recherches sur les Dynamiques Economiques et Sociales (LARDES), Faculté d'Agronomie, Université de Parakou, Bénin.
Email: ynerice@gmail.com; rosaine.yegbemey@fa-up.bj

** Bureau de Recherche et de Développement en Agriculture (Breda-ONG).
Email: alma_aline@yahoo.com

*** Laboratoire d'Analyse et de Recherches sur les Dynamiques Economiques et Sociales (LARDES), Faculté d'Agronomie, Université de Parakou, Bénin. Email: aihountong@gmail.com

Résumé

Le présent article analyse l'impact des informations météorologiques (fournies à travers des SMS sur les téléphones portables) sur les décisions et les performances des producteurs de maïs. Une étude expérimentale pilote était faite impliquant 331 producteurs de maïs éligibles et aléatoirement échantillonnés dans six villages. L'assignation aléatoire a été faite au niveau village. Trois spécifications économétriques ont été utilisées pour mesurer l'impact : les Moindres Carrés Ordinaires (MCO), le modèle d'Equations d'Estimation Généralisé (GEE) avec correction pour échantillon de petite taille et l'Inférence Aléatoire (RI). Les résultats obtenus suggèrent que les groupes traités et contrôle étaient bien équilibrés. Les producteurs du groupe traité ont enregistré des coûts de main-d'œuvre moins élevés, mais des rendements et des revenus plus élevés. Les directions et magnitudes des impacts estimés sont cohérentes pour les trois spécifications et significatives avec le modèle RI uniquement (pour les coûts de main-d'œuvre et le rendement) ou les modèles RI et GEE (pour le revenu). Les informations météorologiques peuvent avoir des impacts sur la main-d'œuvre, le rendement et le revenu des petits producteurs. Ces résultats mettent en évidence la possibilité d'utiliser les informations météorologiques et les téléphones portables pour renforcer la résilience des petits exploitants agricoles face à la variabilité climatique. Cependant, des recherches supplémentaires sont nécessaires pour constituer une base de données probantes permettant d'éclairer les politiques agricoles.

Mots-clés : Bénin, essai contrôlé randomisé, évaluation d'impact, maïs, producteurs agricoles, services climatiques

Introduction

Climate change has been widely considered as the greatest challenge for most sectors in the world especially in developing countries. The effects of climate change will strongly affect African economies due to the fact that agriculture is highly climate-sensitive and there is a limited economic and institutional capacity to cope with and adapt to climate variability and change (Roudier et al. 2011). Evidence on climate change suggests that, by the end of this century, over West Africa there will be further increases in temperature of between 1.1 and 4.8 °C and larger differences in rainfall between wet and dry seasons (IPCC, 2013). As well, Sillmann et al. (2013) reported changes of -5 to -15 per cent in total wet-day precipitation in the region with large uncertainties. Under these predictions, crop yield will significantly decrease implying severe food insecurity problems in the region (Waha et al. 2013; Roudier *et al.* 2011; Schlenker & Lobell 2010; Palazzo et al. 2017). As implications, a review study by Roudier et al.

(2011) revealed a large dispersion of crop yield ranging from 50 to +90 per cent, with a median yield loss of about 11 per cent. By mid-century, the mean estimates of aggregate production change in sub-Saharan Africa for most staple crops, such as maize, sorghum, millet, groundnut and cassava, are predicted to be -22, -17, -17, -18 and -8 per cent, respectively (Schlenker & Lobell 2010). West Africa is projected to experience severe impacts on food production with extreme risks for food security and negative repercussions for human health and employment (Serdeczny et al. 2017; Palazzo et al. 2017).

In Benin, a West African country, evidence shows that rainfall will reduce from 20 to 30 per cent, and yields of maize, cassava, beans, groundnuts, rice, cotton and sorghum will decrease between 3 and 18 per cent by 2025 (MEHU 2011). These projected changes are likely to deepen the already existing, daunting challenges of poverty and food insecurity, as rain-fed agriculture is still a primary source of the economy. Therefore, adapting farming systems to climate change to sustain the livelihoods of rural households has become a major challenge for policymakers and researchers.

Empirical studies have focused on climate change impacts (Challinor et al. 2014; Hathie et al. 2018; Tol 2018; Waha et al. 2017; Wossen et al. 2018), perception (Baudoin et al. 2014; Callo-Concha 2018; Cuni-Sanchez et al. 2019; Debela et al. 2015; Foguesatto et al. 2018; Opiyo et al. 2016) and adaptation (Asrat & Simane 2017; Belay et al. 2017; Callo-Concha 2018; Fadina & Barjolle 2018; Waha et al. 2013; Yegbemey et al. 2014a; Yegbemey et al. 2017) as a way to address climate challenges. In addition, various adaptation strategies, such as the use of improved varieties, chemical fertilisers and pesticides, diversification of income-generating activities, crop diversification and adjustment of cropping practices are documented as imperative (Callo-Concha 2018; Fadina & Barjolle 2018; Wossen et al. 2018; Yegbemey et al. 2014a). However, little is known about the potential of these options to fit with the ongoing and future climate change. As argued by Guan et al. (2017), the optimal prioritisation of adaptation investments requires the assessment of various possible adaptation options and their uncertainties, which are not often the case of current adaptation options.

Some authors showed that farmers are willing to be informed about accurate seasonal climate forecasts (Amegnaglo et al. 2017; Yegbemey et al. 2017) which suggests that the use of climate forecasts is a probable adaptation option. Based on simulation exercises with farmers, Roudier et al. (2014) assessed the role of climate forecasts in smallholder agriculture in two agro-ecological zones of Senegal in West Africa. The findings suggested that the introduction of seasonal and decadal forecasts induced changes in farmers' practices in almost 75 per cent of the cases and led to yield gains in about one-third of the cases, with relatively few losses. However, this study appears subjective as it is purely based on simulation and fails to provide evidence for how these changes affect input allocation and farm performance. This has been also argued by Tall et al. (2018) who highlighted that past studies on climate services were only based on ex-ante evaluation, suggesting the need to move towards experimentally designing climate service programmes that integrate impact pathway on various agricultural outcomes. Whereas ex-ante studies give insights only on possible impacts of climate forecasts for farmers, testing at the farmers' level and assessing the impacts should be a required step to provide sufficient evidence that can inform decision-making.

Against this background, we assess the impact of providing smallholder farmers with weather-related information through mobile phone messages. The central research question is: What is the impact of weather-related information on smallholder farmers' production decisions (i.e. labour allocation) and performance (i.e. yield and income)? The remainder of this article is organised in three main sections. These include a description of the study zone and the methodology, a presentation and discussion of the results and a concluding note summarising the study and its findings.

Since there is a lack of rigorous evidence for the impact of climate services on farmer livelihoods and resilience, our study is a contribution to the literature. Our core research hypothesis suggests that farmers provided with weather-related information will allocate their production resources better and therefore record higher agricultural outputs. The hypothesis testing plan included a field experiment designed as a Clustered Randomised Controlled Trial (CRCT). We analysed the impact of weather-related information (provided to smallholder farmers through mobile phone messages) on the self-reported outcome variables, such as labour allocation, yield and income, and our evidence is that weather-related information can have some positive impact on smallholder farmers' labour, yield and income.

Methodology

This section presents the study area and the empirical strategy we used to test the impact of providing weather-related information on farm performance followed by the sampling design, the description of the data and the limitations of the study.

Study Area

The study was conducted in six villages (Pédarou, Wanradabou/Wanrarou, Beroubouay Est/Ouest, Guessou Sud, Ina and Gessou Nord-Gamia Est) of the municipal area of Bembèrèkè in North Benin. Discussions with key stakeholders in the field allowed us to select villages based on four criteria, including accessibility to the village, the availability of a mobile phone network, a minimum five-kilometre buffer zone between villages and the predominance of maize production. These villages were further assigned treatment or control group status through a public lottery attended by each village representatives.

Bembèrèkè is located between 09°58' and 10°40' N, and 02°04' and 03° E. The area covers about 3,348 square kilometres and contains a population of about 131,255 people (INSAE 2013). About 74.2 per cent of this population live in rural areas and survive largely on agriculture. The production systems are mostly slash-and-burn with the use of rudimentary tools, such as hoes, cutters, etc. The rates of mechanisation, use of improved seed and extension services are still low though there have been some improvements over the past five to ten years. The common crops cultivated include yams, maize, cotton, rice, cassava and sorghum.

The municipal area of Bembèrèkè was primarily selected as it represents one of the major and typical agricultural production areas of Benin. In that respect, Bembèrèkè has the advantage of ensuring a good external validity of the results. Figure 1 presents the map of the study area.

Theoretical framework, study design, sampling and data collection

This study is an impact evaluation that creates a factual (treatment) group and counterfactual (control) group by using an experimental design. The core research hypothesis, that farmers provided with weather-related information will allocate their production resources better and therefore improve agricultural output, suggests that farmers are rational. Consequently, the producer theory was used.

The producer theory is commonly used in microeconomics in general and particularly in agricultural economics. It attempts to explain the principles by which a farmer decides how much of each crop to produce and how much input (e.g. land, labour, capital, fertiliser, etc.) will be needed. This refers to the decision-making process. The theory involves fundamental principles of economics, including the relationship between the quantities and prices of production resources but also between crops and production resources. Typically, farmers tend to maximise their yield (or income) under cost-of-production constraints. Yet, agriculture is also a specific sector where farmers need to factor in several other aspects in their production decisions. Among the most important of these are weather and soil conditions, the social value of the crops, market opportunities, etc.

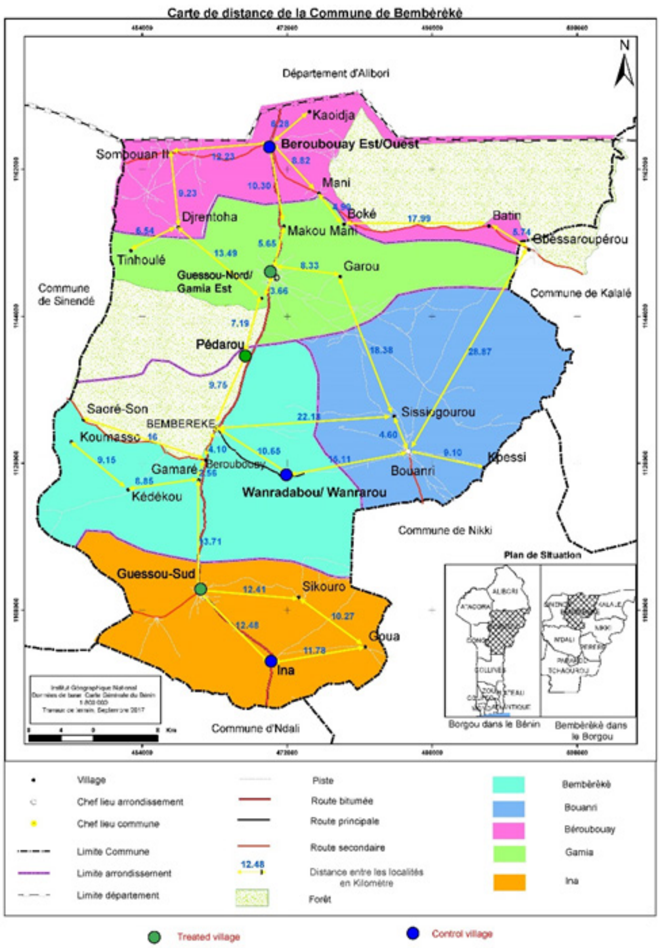

Figure 1: Map of the municipal area of *Bembèrèkè*

Source: Adapted from IGN Benin

With climate change, weather has become a key determinant of yield and thus a major driver of the farmers' production decisions. Unfortunately, in many developing countries like Benin, weather is not under the control of smallholder farmers as their production systems are mostly rain-fed. Unlike other common production resources, such as land or labour, which are quite often limited but known (in terms of quantity and/or price) to farmers, weather is an unknown factor. This is especially true in settings where farmers have no or limited access to weather forecasts. The unknown nature of weather as described here does not undermine the role of local knowledge in helping farmers to anticipate events such as the onset of the rainy season, the possibility of rain, etc. Nevertheless, local or indigenous weather knowledge is not nearly as detailed and precise as weather forecasts are.

Broadly understood as a picture or statement of what the weather is likely to be for the next day or next few days, and usually broadcast on television or radio or printed in a newspaper, a weather forecast is the result of an analysis of the state of the weather in an area with an assessment of likely developments. It can provide very disaggregated and very detailed information, such as the quantity and timing of rainfall, temperature at different time points, wind speed and direction, humidity, etc. The information can be disaggregated to serve different purposes. All this information will likely make weather a 'known' production factor that farmers can, to some extent, integrate in their production decision processes. Based on this extension of production theory, providing smallholder farmers with weather-related information through mobile phone messages is likely to impact positively on production decisions as well as farmers' performance.

Farmers have a number of considerations on which to base their production decisions. These include decisions about methods of producing a desired quantity from a plot of land given its size and available equipment (short-run cost minimisation); the determination of the most profitable quantities of crops to produce on a plot of land (short-run profit maximisation); the determination of the most profitable size of land and equipment to be used (long-run profit maximisation), etc. In this research, we focused on short-run profit maximisation by focusing only on labour allocation, crop yield and income.

The study design involved a Clustered Randomised Controlled Trial (CRCT). The outcome variables were defined as follows:

- Labour allocation: This was measured in XOF (West African CFA franc) through the total labour cost per hectare. It includes household and paid labour involved in the maize production activities, from land preparation to harvest. The value of household labour for the same working time differs between the men, women and children engaged in production process. The following formula was used to calculate the cost of household labour HL):

$$HL = HML + 0.75 \times HWL + 0.5 \times HCL \qquad [1]$$

where HML is the total male labour in the household (in ManDay/ha), HWL is the total female labour in the household (in WomanDay/ha) and HCL is the total child labour in the household (in ChildrenDay/ha), respectively. The total household labour (in ManDay/ha) was then multiplied by the average unit price of labour in the area, which is 1500 XOF/ManDay. Paid labour is typically expressed in XOF/ha and added to the total labour cost of household labour.

- Yield: Quantity of harvest per hectare. This is the total quantity of maize harvested per hectare of cultivated land. To be consistent with the studies by Dillon and Rao (2018) and Kilic et al. (2018) on land size measurement error, we used Global Positioning System (GPS) to track and measure the land size of each respondent. This helped to avoid any misreporting problems that could lead to biased estimates. The crop harvest from an area of 1m^2 has been used to measure maize yield. The total maize yield is then obtained by extrapolating the weight in kilograms obtained from the 1m^2 area to the total area under maize measured with GPS.

- Income: Total net income in XOF. This is obtained by extracting the total production cost from the value of the Gross Product (Income = Gross Product - Total Costs). It is important to note that this is not the farm or household income, as farmers might have other plots of land allocated for crops other than maize. Farmers might also have other income-generating activities that are not accounted for in the outcome variable here.

In this pilot study, the intervention was 'providing weather-related information through mobile phone Short Message Service (SMS)' and the target population was maize farmers. Farmers in the treatment group received a seasonal weather forecast at the beginning of the survey and a daily weather forecast every three days. Farmers in the control group received no information. The study covered the entire agricultural season for 2018 to 2019, starting in April 2018 and ending in December 2018 or January 2019. An agreement was made with the Benin meteorological office to get access to weather forecast information. Village-specific weather information (i.e. rainfall forecasts) from three climate models were averaged and then shared with the treatment group. These models included the European Centre for Medium-Range Weather Forecasts (ECMWF) model (9 km), the Global Forecast System (GFS) model (22 km) and the National Environmental Modelling System (NEMS) model (4 to 12 km). Two field officers from a local NGO, Bureau de Recherche et Développement en Agriculture, were in charge of monitoring the treatment at field level by visiting all the selected producers on a regular basis to ensure that weather information had been received and also to collect farm-level and high-frequency data on production input usage.

The statistical power calculations suggested a minimum sample size of about 300 respondents to be able to detect an effect size as large as a 0.8 standard deviation with 80 per cent of power at a 5 per cent level of significance. In each village, the survey sample consisted of fifty-one to fifty-six eligible maize producers randomly selected after a census survey. Eligibility criteria included: a) farmers should be maize producers; b) farmers should plan to produce maize during the rainy season of 2018/2019; c) farmers should own a mobile phone, including a valid and functional line number; and d) farmers should have the ability to operate (i.e. read SMS on) their mobile phone. Table 1 shows the sample structure.

Table 1: Structure of the sample

Village	**Treatment Status**	**Sample Size at Baseline**	**Sample Size at Endline**
Pédarou	Treated	55	54
Wanradabou/Wanrarou	Control	51	49
Beroubouay Est/Ouest	Control	59	54
Guessou Nord-Gamia Est	Treated	55	54
Ina	Control	55	53
Guessou Sud	Treated	56	49
Total		**331**	**312**

Source: Authors

A number of questionnaire-based surveys were organised by using tablets to collect data on the respondents' socio-economic characteristics as well as production-related inputs and outputs. These surveys included:

- A census survey (in April 2018) to build up the sample framework of eligible smallholder farmers;
- A baseline survey before the onset of the rainy season (in April-May 2018) to capture information on household demographic and socio-economic characteristics, production inputs and outputs prior to the intervention;
- An endline survey (in December 2018) at harvest time to collect data on yield.

In addition to these quantitative surveys, qualitative investigations were conducted at baseline and endline to better understand the situations before and after the intervention.

Data analysis

Following the CRCT design, the data analysis included a number of key steps. These were:

- Balance tests between the control and treatment groups on the outcome variables (i.e. labour, yield, income) as well as key covariates, such as respondents' age, education level, gender, household size, experience in agriculture, farm size, organisation membership, access to credit and contact with extension services. Differences between the treatment and control groups could, with respect to the selected co-variables, have some effects on the outcome variables based on the following assumptions:

  - Age: Age is often linked to greater knowledge (Heubach et al. 2011). Here, it is hypothesised that older farmers could be more knowledgeable and thus allocate their production resources better.
  - Education level: Like age, education is quite often associated with greater knowledge and better skills. Educated farmers could manage their production resources better and record higher yield and income.
  - Gender: In this research, gender was restricted to that of the household head. Many studies in sub-Saharan Africa reported that women have less access to resources (e.g. land, cash and labour), which often undermines their ability to carry out labour-intensive agricultural adjustments or innovations (Groote et al. 1998).
  - Household size: We assumed that larger households have more labour available for performing agricultural activities.
  - Experience in agriculture: Farming experience can potentially increase the probability to take up adaptation options. Additionally, learning from personal experience matters a lot in farmers' decision or behaviour. Learning from experience helps to reduce allocative errors (Huffman 1977). As a result, the more experienced the farmers are, the more likely they are to make rational choices and develop strategies to maximise their profitability.
  - Farm size: A mixed result can be expected betweem farm size and the outcome variables. While larger farms can benefit from economy of scale, small but efficient farms can record higher relative economic performances and larger but less efficient farms can record low relative economic performance.

- Organisation membership: Rural organisations and farmers' organisations in particular are strong social networks for information (Yegbemey et al. 2014b). Organisation membership is thus linked to better access to information.
- Access to credit: Access to credit is a key determinant of farmers' decisions (Shahidur et al. 2004). Access to credit enhances farmers' financial capital, enabling them to take some investment decisions that might be unlikely otherwise.
- Contact with extension services: Farmers who have enjoyed extension advice get more knowledge, skills and practice on improved technologies. They are likely to adopt improved agricultural practices and can adapt to climate change better (Yegbemey et al. 2014b).

• Impact estimate models: Based on the assumption that the control and treatment groups are well balanced, the following regression can be estimated:

$$Y_{ik}=\alpha_k+\beta_k T_{ik}+e_{ik} \qquad [2]$$

where Y_{ik} represents the outcomes of interest, representing labour, yield and income; T is the treatment status of the farmer i; e is the error term and α and β are the coefficients to be estimated. In this regression, β is the impact estimate (i.e. intention to treat - ITT).

This regression will yield biased estimates if the control and treatment groups are not perfectly well balanced. Two other issues arose from the design of the experiment:

- That villages were selected 'manually' and thus it is difficult to argue that they would actually be balanced on both observable and unobservable factors, especially because they are located in different *arrondissements*. Villages (less likely due to the manual matching) and *arrondissements* (more likely) could differ in terms of socio-economic setting (e.g. infrastructure or quality of infrastructure, soil conditions, local labour market, etc.) and this could lead to biased estimates.
- That individual farmers are nested within villages and the randomisation was done at the village level.

To account for these issues, both *arrondissement* fixed effects and cluster-robust error terms were used. *Arrondissement* fixed effects were used to remove unobserved heterogeneity between villages due to the local socio-economic setting at arrondissement level. Cluster-robust standard errors were used to account for the fact that farmers in the same villages might tend to be more alike than observations selected entirely at random. In sum, the first specification regresses the treatment status on the outcome variables while controlling for key covariates and using arrondissement fixed effects as well as cluster-robust standard errors as follows:

$$Y_{ik}=\alpha_k+\beta_k T_{ik}+\Theta_k Z_{ik}+\varphi_k A_{ik}+vce_{ik} \qquad [3]$$

Where Y_{ik} is the k^{th} outcomes of interest of the i^{th} farmer; T is the treatment status of the i^{th} farmer; Z is a matrix of covariates; A represents *arrondissement* fixed effects; e is the error term clustered at village level and α, β, Θ, and φ are coefficients to be estimated.

Equation 3 was estimated by using OLS as the first specification of the study. Nevertheless, such specification in practice can yield unbiased and robust estimates with samples containing large number of clusters. Otherwise, despite the *arrondissement* fixed effects as well as clustered standard errors, the type I error rates are likely to be inflated (p-values would be too small and confidence intervals too narrow) due to the small number of clusters. The number of clusters (six in the current study) was purposively meant to be small due to the pilot nature of the study, which was perceived as a formative evaluation to pre-test an intervention. Yet, the results need to be as robust as possible.

Following Leyrat et al. (2018) mixed-models and generalized estimating equations (GEEs a number of methods can be used to address the problem of small samples in CRCTs with continuous outcomes, though the impact of these methods on power is still unclear. Based on different simulations of the number of clusters, the authors recommend, among other interventions, the use of mixed models with degree-of-freedom corrections, Generalised Estimating Equations (GEEs) with a small-sample correction, and unweighted or variance-weighted cluster-level analysis. To make the best use of the pilot survey, two additional specifications were considered:

- Specification 2: A GEE model with a small-sample correction estimate of Equation 3. Here the correction method used was based on standard errors with bootstrapping, as recommended by Leyrat et al. (2018).
- Specification 3: The Randomisation Inference (RI) method known as a method of calculating regression p-values that take into account any variations in RCT data that arise from randomisation itself. RI as specified for STATA by Hess (2017) was used to estimate Equation 3.

In all the three specifications, β estimates capture the Average Treatment Effect (here an ITT) and echo the causal impact of the intervention. Data analysis was done with STATA 15.1.

Study limitations

We believe that we used the best design (i.e. RCT) to address the (impact) attribution challenge in this impact study. However, despite RCTs being known as the gold standard approach in impact evaluation, they also have limitations that are worth noting. One of the key problems while conducting RCTs is failing to identify a good and valid counterfactual or controlling a number of threats (e.g. spillover, contamination, Hawthorne effects, John Henry effects, courtesy bias, confounding factors risk, inadequate survey instruments, etc.), which can affect the internal validity of the experiment.

In this pilot study conducted in the municipal area of Bembèrèkè, with the main objective to explore the possible impact of weather-related information provided to smallholder farmers through mobile phone messages, on their production decisions and performance, we controlled for the potential threats to internal validity. This was evidenced by the intervention monitoring data and qualitative surveys organised after baseline and harvest. For instance, a CRCT was used and buffer zones of five kilometres were considered between villages involved in the survey, to limit spillover and contamination. Enumerators were well trained on survey techniques to reduce possible Hawthorne effects. A local NGO was used as the implementing agency of the intervention and monthly data collection was routinely conducted simultaneously in the treatment and control groups by the NGO staff to avoid potential John Henry effects.

The potential limitations of the current research are its pilot nature and small sample size. We also did not test alternative options to provide smallholder farmers with weather-related information and compare the impacts. For instance, having several treatment groups can help to compare mediums of communication (e.g. local languages versus French; written SMS versus voice message, etc.). Such an exercise was not possible for this pilot research due to time and resource constraints.

Beyond the technical and common aspects of a good RCT, it is also important to keep in mind a few debates, especially when it comes to the possible policy implications of the current research. RCT has gained a lot of interest among researchers as the preferred approach to measure and showcase rigorous and high-quality evidence of policy-relevant causal effects. As a matter of fact, over the past decades, using RCT has become largely accepted practice in social science in general and particularly in development economics. Nevertheless, RCT does have shortcomings that we think need to be highlighted in the context of this research, which is a pilot study aimed at generating preliminary evidence on what works.

As argued by Deaton and Cartwright (2018), researchers tend to overrate RCTs over other methods of investigation. According to the same authors, randomisation only is not enough to have perfect balance between treatment and control groups, to get perfect estimates of the impact and to know why results happen. These limitations could still be addressed through a sound mixed-methods experiment.

Beyond internal validity, external validity is also an important aspect to consider. The ability to generalise effects estimated from randomised experiments is critical for their relevance to policy (Muller 2015). Following Muller (2015), researchers should do a much more thorough interpretation of the policy relevance of past work, which may not have addressed three important issues: 1) attaining external validity requires ex-ante knowledge of covariates that influence the treatment effect along with empirical information on these variables in the experimental and policy populations; 2) a theoretical replication-based resolution to the external validity problem is unlikely to be successful except for extremely simple causal relations, or in very homogeneous populations, of a kind that appear unlikely in social science; 3) the formal requirements for external validity are conceptually analogous to the assumptions needed for causal identification using observational data.

In the current pilot study, a number of key observable covariates were carefully selected based on the existing literature and researchers' experience. However, we need to be cautious and should not over generalise the results.

Results and Discussion

This section presents the key findings of the study and the subsequent discussion. First, we present some descriptive statistics from the respondents along with the balance tests at baseline. Second, we provide evidence and discuss the findings in terms of impacts on labour, yield and income, respectively.

Descriptive statistics of the respondents and balance tests at baseline

Table 2 presents descriptive statistics for the respondent farmers as well as the balance tests on the outcome variables and a number of key covariates at baseline. We tested balance at both cluster (village) and individual levels and the results are consistent.

Table 2: Descriptive statistics and balance tests at baseline

Variables	Full Sample	Control (C)	Treatment (T)	T-C
Outcome variables				
Labour (XOF/ha)	86165.36 (72255.49)	86142.85 (77292.99)	86187.86 (67090.88)	45.01
Yield (Kg/ha)	2132.39 (1567.98)	2076.20 (1328.328)	2188.58 (1778.2)	172.35
Income (XOF)	1101081.89 (1854657.95)	1055402.02 (2224689.036)	1146761.76 (1395801.80)	91359.73
Covariates				
Age (years)	41.90 (10.29)	42.83 (10.64)	40.98 (9.88)	-1.85
Education (1=Yes/0=No)	0.36 (0.48)	0.34 (0.47)	0.37 (0.48)	0.03
Gender (1=Male/0=Female)	0.95 (0.20)	0.96 (0.19)	0.95 (0.20)	-0.01
Household size (persons)	13.81 (8.89)	14.89 (9.87)	12.74 (7.65)	-2.15**
Experience in agriculture (years)	17.15 (10.35)	18.20 (10.81)	16.10 (9.79)	-2.1
Farm size (ha)	20.39 (22.63)	21.64 (27.37)	19.13 (16.59)	-2.51
Organisation membership (1=Yes/0=No)	0.75 (0.43)	0.78 (0.41)	0.72 (0.44)	-0.06
Access to credit (1=Yes/0=No)	0.52 (0.50)	0.48 (0.50)	0.55 (0.49)	0.07
Contact with extension (1=Yes/0=No)	0.86 (0.34)	0.89 (0.30)	0.82 (0.38)	-0.07

*Significance levels: *10 per cent, **5 per cent, and ***1 per cent.*

Values in brackets are standard deviations.

Most of the respondents were male farmers with lower levels of education. On average, the household head was forty-one years old, with no difference between the treatment and control groups. However, though there was a likelihood of correlation between farming experience and age of household heads, the average farming experience was about thirteen years, with slight significance difference between the treatment and control groups. Households that did not participate in the treatment groups had on average two household members more than participating households. The majority of the respondents belonged to farmers' groups and were also in contact with extension services. About half of the maize producers had access to credit facilities. With regards to the outcomes of interest, there was a good balance between the treatment and control households at baseline.

It is important to note that the intervention monitoring records revealed that about 96 per cent of the smallholder farmers in the treatment villages mentioned that they received the weather-related information on their mobile phone and used this information in their production decision. This suggests a high compliance rate and the impact estimates (the average treatment effect) could be seen not only as an intention to treat (i.e. effect of treatment assignment on outcome, for all farmers assigned to the treatment group either they actually receive the treatment or not) but also as a local average treatment on treated (i.e. effect of treatment on outcome, for farmers who are assigned to the treatment group and actually received the treatment). On the other hand, the attrition rate was about 5.74 per cent (331 respondents at baseline against 312 respondents at endline with a required minimum sample size of 300 respondents).

Impact of weather-related SMS on labour cost

Table 3 shows the impact estimates of the weather-related SMS on labour allocation.

The impact estimates suggest that providing smallholders with weather-related information through mobile phone SMS can help them to reduce the costs of labour. On average, the farmers in the treatment group used slightly less labour than their counterparts in the control group. The impact estimates are consistent across the three regression specifications but significant ($p<.10$) with the RI only. Nevertheless, this result is consistent with the hypothetical expectations with respect to the possible impact of the weather-related information on labour allocation.

Most of the existing studies on the use of SMS in agriculture focus on market information. Through an exploratory literature review on the utility of mobile phone-enabled services for smallholder farmers, Baumüller (2018) reviewed twenty-three publications. Ten reviewed studies were conducted in India and most of them assess the impacts of information on services, including information on prices (nine studies), farming (nine studies) and/or weather (six studies).

Table 3: Impact estimates of weather-related SMS on labour allocation

VARIABLES (Y = LOGLABOUR)	OLS	GEE	RI
Constant	10.704*** (0.336)	10.704*** (0.190)	10.704*** (0.298)
Treatment (1=Treated/0=Control)	**-0.273 (0.301)**	**-0.273 (0.186)**	**-0.273* (0.116)**
Covariates			
Age (years)	0.005 (0.005)	0.005 (0.003)	0.005 (0.006)
Education (1=Yes/0=No)	0.087** (0.041)	0.087*** (0.023)	0.087 (0.044)
Sex (1=Male/0=Female)	0.032 (0.091)	0.032 (0.044)	0.032 (0.092)
Household size (number of persons)	-0.001 (0.002)	-0.0012 (0.001)	-0.0012 (0.002)
Experience in agriculture (years)	-0.007** (0.004)	-0.007*** (0.0028)	-0.007 (0.004)
Maize land size (ha)	-0.014 (.015)	-0.014 (.010)	-0.0012 (0.002)
Organisation membership (1=Yes/0=No)	-0.160*** (0.052)	-0.160*** (0.033)	-0.160** (0.050)
Access to credit (1=Yes/0=No)	0.056 (.058)	0.056 (0.037)	0.056 (0.063)
Contact with extension (1=Yes/0=No)	0.007 (.057)	0.007 (0.025)	0.007 (0.059)
Arrondissement fixed effects			
Beroubouay	0.04 (0.239)	0.040 (0.157)	0.040 (0.094)
Gamia	-0.008 (0.338)	-0.083 (0.165)	-0.083 (0.110)
Ina	0.668*** (0.155)	0.668*** (0.166)	0.668 (0.095)
Summary of the model	R squared = 0.363 F(13,295) =12.96***		R squared = 0.363

*Significance levels: *10 per cent, **5 per cent, and ***1 per cent. Values in brackets are standard errors.*

However, none of these studies assessed the impact of mobile phone-enabled services on labour allocation at the farm-level. ICT programmes could impact under two mechanisms: 1) interventions that can increase farmers' production through use of better farming practices; and 2) interventions that can improve farmers' ability to negotiate better prices for their inputs and outputs (Chiappetta et al. 2015). The results of the present study suggest that, thanks to the weather-related information, farmers in the treatment group were more efficient in allocating labour because they were able to adjust their farming practices to fit the predicted climate. In the past, farmers performed the same production activity several times (e.g. sowing, fertiliser application, etc.) as a result of failures due to climate variability change. As they received accurate weather information, the farmers were empowered to develop more efficient decision-making regarding the allocation of their labour.

Impact of weather-related SMS on maize yield

The results of the impact estimates of the weather-related SMS on maize yield are summarised in Table 4.

The impact estimates suggest that providing smallholders with weather-related information through mobile phone SMS had a positive effect on yield. As in the case of the labour costs, the impact estimates were consistent across the three regression specifications but significant ($p<.05$) with the RI only.

On average, farmers in the treatment group recorded more yield compared with their counterparts in the control group. This result could be explained by the fact that farmers in the treatment groups were able to take more informed agricultural production decisions, such as when to apply fertilisers, etc. The results suggest that providing weather-related information could potentially help farmers improve their productivity. This finding corroborates with Roudier et al. (2014) who suggested through a subjective assessment that weather-related information is associated with changes in farmers' practices and yield gains.

Out of the twenty-three studies reviewed by Baumüller (2018), three looked at the impact of weather information sent by SMS to farmers. This included one study in Colombia which concluded that farmers who received weekly weather information reported 4-7 per cent less weather-related crop losses compared with the farmers in the control group who did not receive this information (Camacho & Conover 2019). Another survey of Indian farmers who were sent regular weather updates showed that most (85 per cent) judged the information as useful. In contrast, Fafchamps and Minten (2012) did not find that service users were able to reduce crop losses after storms compared with control farmers. These results suggest that there is still more conclusive evidence needed on the impacts of weather-related SMS on yield.

Table 4: Impact estimates of weather-related SMS on maize yield

VARIABLES (Y = LOGYIELD)	**OLS**	**GEE**	**RI**
Constant	8.713*** (0.252)	8.713*** (0.102)	8.713*** (0.238)
Treatment (1=Treated/0=Control)	**0.282 (0.180)**	**0.282 (0.183)**	**0.282** (0.107)**
Covariates			
Age (years)	0.004 (0.004)	0.004 (0.002)	0.004 (0.005)
Education (1=Yes/0=No)	0.041 (0.040)	0.041 (0.026)	0.041 (0.041)
Sex (1=Male/0=Female)	0.241 (0.172)	0.241*** (0.082)	0.241 (0.174)
Household size (number of persons)	-0.001(0.003)	-0.001 (0.002)	-0.0014 (0.0038)
Experience in agriculture (years)	-0.0005 (0.001)	-0.0005 (0.0006)	-0.0005 (0.0014)
Maize land size (ha)	-0.0009 (0.014)	-0.0009 (0.0092)	-0.0009 (0.0086)
Organisation membership (1=Yes/0=No)	-0.045 (0.056)	-0.045 (0.032)	-0.045 (0.051)
Access to credit (1=Yes/0=No)	0.035 (0.052)	0.035 (0.024)	0.035 (0.058)
Contact with extension (1=Yes/0=No)	-0.016 (0.045)	-0.016 (0.030)	-0.016 (0.047)
Arrondissement fixed effects			
Beroubouay	0.078 (0.135)	0.078 (0.163)	0.078 (0.110)
Gamia	-0.031 (0.171)	-0.031 (0.156)	-0.031 (0.076)
Ina	-0.267 (0.150)	-0.267 (0.168)	-0.267** (0.093)
Summary of the model	R-squared = 0.16 F(13,295) = 4.58***		R-squared = 0.168

*Significance levels: *10 per cent, **5 per cent, and ***1 per cent.*

Values in brackets are standard errors.

Impact of weather-related SMS on farm income

Table 5 presents the results of the impact estimates of the weather-related SMS on farm income.

Table 5: Impact estimates of weather-related SMS on farm income

VARIABLES (Y = LOGINCOME)	**OLS**	**GEE**	**RI**
Constant	13.556*** (0.447)	13.556*** (0.193)	13.556*** (0.924)
Treatment (1=Treated/0=Control)	**0.286 (0.224)**	**0.286* (0.149)**	**0.286* (0.115)**
Covariates			
Age (years)	0.004 (0.010)	0.004 (0.006)	0.004 (0.011)
Education (1=Yes/0=No)	-0.070 (0.087)	-0.070 (0.063)	-0.070 (0.075)
Sex (1=Male/0=Female)	0.794** (0.322)	0.794*** (0.132)	0.794* (0.370)
Household size (number of persons)	0.004 (0.006)	0.004 (0.003)	0.004 (0.005)
Experience in agriculture (years)	0.002 (0.004)	0.002 (0.002)	0.002 (0.005)
Maize land size (ha)	0.074 (0.068)	0.074 (0.051)	0.074 (0.042)
Organisation member-ship (1=Yes/0=No)	0.085 (0.107)	0.085 (0.077)	0.085 (0.092)
Access to credit (1=Yes/0=No)	0.189** (0.073)	0.189*** (0.041)	0.189* (0.079)
Contact with extension (1=Yes/0=No)	0.151* (0.090)	0.151*** (0.047)	0.151 (0.102)
Arrondissement fixed effects			
Beroubouay	-0.198 (0.251)	-0.198 (0.175)	-0.198 (0.156)
Gamia	-0.283 (0.239)	-0.283** (0.0116)	-0.283*** (0.055)
Ina	-0.670*** (0.119)	-0.670*** (0.120)	-0.670*** (0.070)
Summary of the model	R-squared = 0.169 F(13,295) = 13.87***		R-squared = 0.379

*Significance levels: *10 per cent, **5 per cent, and ***1 per cent. Values in brackets are standard errors.*

The impact estimates suggest that providing smallholder farmers with weather-related information through mobile phone SMS may have a positive effect on farm income. Indeed, the yield gain in the treatment group in this study was not enough to ensure a significant increase in the income. The impact estimates are consistent across the three regression specifications but significant ($p<.10$) with the GEE and RI.

Through a systematic review of the effects of information and communications technology on expanding agricultural markets in developing countries, Chiappetta et al. (2015) reviewed a total of twenty-four studies that examined the impact of ICT on farmers' income. About 75 per cent of these studies (eighteen out of the twenty-four) examined the effects of information provision on prices and found that ICT programs helped to increase income with statistical significance at least at the 10 per cent level.

Conclusion

We investigated the possible impacts of weather-related information provided to smallholder farmers through mobile phone messages on their production decisions (i.e. labour allocation) and performance (i.e. yield and income). The results show that providing weather-related information through mobile phone SMS can help smallholder farmers to reduce their labour costs (by 27 per cent) and improve productivity (by 28 per cent) as well as income (by 29 per cent). Indeed, it was found that farmers in the treatment group recorded lower levels of labour costs but higher levels of yield and income. Furthermore, the directions and magnitudes of the impact estimates are consistent across the three regression specifications but significant with the Randomisation Inference model only (for labour costs and yield), or the Randomisation Inference and Generalised Estimating Equations model with small sample correction (for income). These results imply that in the current settings, of maize production in the study zone, weather-related information through mobile phone SMS had a positive impact on labour, yield and income.

From a behavioural perspective, our findings suggest that smallholder farmers in the study area will use weather-related information to take informed-production decisions. Put another way, thanks to the weather-related information, farmers in the treatment group were able to better organise and plan their farming practices and activities. The positive and significant effect on yield reveals that each farming activity could be planned based on few-day (here, three-day) weather information, which will obviate the need for repetitive sowing, unnecessary weeding or fertiliser application and limit the risk of crop failure. Fertilisers, for instance, need to be applied at the right time. Providing weather-related information allows farmers to anticipate this application by including a known factor in their production decision-making process. The findings are also important from the perspective of food security. Smallholder farmers could use the additional gains in yield to increase food consumption at household level and, where there is a surplus of production, earn additional income from the market.

From a policy perspective, the findings suggest a new potential tool or intervention to support food production and improve food security and income distribution in developing countries like Benin. In that respect, though it remains a pilot experiment, the current study brings fresh evidence to researchers, practitioners and policymakers in their efforts to reduce the food security gap by enhancing overall farm performance, which definitely would contribute to poverty alleviation in times of climate change.

Overall, our study has positive signals for the possibility of using weather-related information and mobile phones as a means to build smallholder farmers' resilience to climate variability. However, given the paucity of evidence on the issue, more evidence would be useful to inform agricultural policies. Even though the rapid spread of mobile phones throughout developing countries, including rural areas, offers a number of opportunities to reach very remote, dispersed and poorly serviced smallholder farmers, researchers could also explore alternative cost-effective ways to provide smallholder farmers with weather-related information at large scale. All this needs additional testing and validation though.

References

Amegnaglo, C.J., Anaman, K.A., Mensah-Bonsu, A., Onumah, E.E. and Amoussouga Gero, F., 2017, 'Contingent valuation study of the benefits of seasonal climate forecasts for maize farmers in the Republic of Benin, West Africa', *Climate Services*, Vol. 6, pp. 1-11. Available online at https://doi.org/10.1016/J.CLISER.2017.06.007.

Asrat, P. and Simane, B., 2017, 'Adaptation benefits of climate-smart agricultural practices in the Blue Nile Basin: Empirical evidence from North-West Ethiopia', in W. Leal Filho, S. Belay, J. Kalangu, W. Menas, P. Munishi and K. Musiyiwa, eds, *Climate change adaptation in Africa. Climate change management*, Amsterdam: Springer. Available online at https://doi.org/10.1007/978-3-319-49520-0_4.

Baudoin, M.-A., Sanchez, A.C. and Fandohan, B., 2014, 'Small scale farmers' vulnerability to climatic changes in southern Benin: the importance of farmers' perceptions of existing institutions', *Mitigation and Adaptation Strategies for Global Change*, Vol. 19, No. 8, pp. 1195-1207. Available online at https://doi.org/10.1007/s11027-013-9468-9.

Baumüller, H., 2018, 'The little we know: An exploratory literature review on the utility of mobile phone-enabled services for smallholder farmers', *Journal of International Development*, Vol. 30, No. 1, pp. 134-154. Available online at https://doi.org/10.1002/jid.3314.

Belay, A., Recha, J.W., Woldeamanuel, T. and Morton, J. F., 2017, 'Smallholder farmers' adaptation to climate change and determinants of their adaptation decisions in the Central Rift Valley of Ethiopia', *Agriculture and Food Security*, Vol. 6, No. 1. Available online at https://doi.org/10.1186/s40066-017-0100-1.

Callo-Concha, D., 2018, 'Farmer perceptions and climate change adaptation in the West Africa Sudan savannah: Reality check in Dassari, Benin, and Dano, Burkina Faso', *Climate*, Vol. 6, No. 2. Available online at https://doi.org/10.3390/cli6020044.

Camacho, A. and Conover, E., 2019, 'The impact of receiving SMS price and weather information on small scale farmers in Colombia', *World Development*, Vol. 123. Available online at https://doi.org/10.1016/j.worlddev.2019.06.020.

Challinor, A.J., Watson, J., Lobell, D.B., Howden, S.M., Smith, D.R. and Chhetri, N., 2014, 'A meta-analysis of crop yield under climate change and adaptation', *Nature Climate Change*, Vol. 4, No. 4, pp. 287-291. Available online at https://doi.org/10.1038/nclimate2153.

Chiappetta, M., Hamza, A., Nagarajan, G. and Zaman, L., 2015, *Systematic review of the effects of information and communications technology on expanding agricultural markets in developing countries*, Arlington, VA: Social Impact, Inc.

Cuni-Sanchez, A., Omeny, P., Pfeifer, M., Olaka, L., Mamo, M.B., Marchant, R. and Burgess, N.D., 2019, 'Climate change and pastoralists: perceptions and adaptation in montane Kenya', *Climate and Development*, Vol. 11, No. 6, pp. 513-524. Available online at https://doi.org/10.1080/17565529.2018.1454880.

Deaton, A. and Cartwright, N., 2018, 'Understanding and misunderstanding randomized controlled trials', *Social Science & Medicine*, Vol. 210, pp. 2-21. Available online at https://doi.org/10.1016/J.SOCSCIMED.2017.12.005.

Debela, N., Mohammed, C., Bridle, K., Corkrey, R. and McNeil, D., 2015, 'Perception of climate change and its impact by smallholders in pastoral/agropastoral systems of Borana, South Ethiopia', *SpringerPlus*, Vol. 4, No. 1, p. 236. Available online at https://doi.org/10.1186/s40064-015-1012-9.

Dillon, A. and Rao, L.N., 2018, 'Land measurement bias: Comparisons from global positioning system, self-reports, and satellite data', *SSRN Electronic Journal*. Available online at https://doi.org/10.2139/ssrn.3188522.

Fadina, A.M.R. and Barjolle, D., 2018, 'Farmers' adaptation strategies to climate change and their implications in the Zou department of South Benin', *Environments*, Vol. 5, No. 1, p. 15. Available online at https://doi.org/10.3390/environments5010015.

Fafchamps, M. and Minten, B., 2012, 'Impact of SMS-based agricultural information on Indian farmers', *World Bank Economic Review*, Vol. 26, No. 3, pp. 383-414. Available online at https://doi.org/10.1093/wber/lhr056.

Foguesatto, C.R., Artuzo, F.D., Talamini, E. and Machado, J.A.D., 2018, 'Understanding the divergences between farmer's perception and meteorological records regarding climate change: a review', *Environment, Development and Sustainability*, Vol. 22, pp. 1-16. Available online at https://doi.org/10.1007/s10668-018-0193-0.

Groote, H. De and Coulibaly, N.,1998, 'Gender and generation: An intra-household analysis on access to resources in southern Mali', *African Crop Science Journal*, Vol. 6, No. 1, pp. 79-95.

Guan, K., Sultan, B., Biasutti, M., Baron, C. and Lobell, D.B., 2017, 'Assessing climate adaptation options and uncertainties for cereal systems in West Africa', *Agricultural and Forest Meteorology*, Vol. 232, pp. 291-305. Available online at https://doi.org/10.1016/J.AGRFORMET.2016.07.021.

Hathie, I., MacCarthy, D.S., Valdivia, R., Antle, J., Adam, M. and Adiku, S.G.K., 2018, 'Climate change impacts on current and future agricultural systems in the semi-arid regions of West Africa' in *Abstracts of the 7th AgMIP Global Workshop*, San José, Costa Rica, 24-26 April 2018.

Hess, S., 2017, 'Randomization inference with stata', *Stata Journal*, Vol. 17, No. 3, pp. 630-651. Available online at https://doi.org/The Stata Journal.

Heubach, K., Wittig, R., Nuppenau, E.-A. and Hahn, K., 2011, 'The economic importance of non-timber forest products (NTFPs) for livelihood maintenance of rural west African communities: A case study from northern Benin', *Ecological Economics*, Vol. 70, No. 11, pp. 1991-2001. Available online at https://doi.org/10.1016/j.ecolecon.2011.05.015.

Huffman, W.E., 1977, 'Allocative efficiency: The role of human capital', *The Quarterly Journal of Economics*, Vol. 91, No. 1, p. 59. Available online at https://doi.org/10.2307/1883138.

Intergovernmental Panel on Climate Change (IPCC), 2013, *Summary for policymakers, Climate Change 2013: The physical science basis,* Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change, Cambridge, UK: Cambridge University Press. Available online at https://doi.org/10.1017/CBO9781107415324.

Kilic, T., Moylan, H., Ilukor, J., Mtengula, C. and Pangapanga-Phiri, I., 2018, *Root for the tubers: Extended-harvest crop production and productivity measurement in surveys*, World Bank Policy Research Working Paper, No. 8618. Available online at https://doi.org/10.1596/1813-9450-8618.

Leyrat, C., Morgan, K.E., Leurent, B. and Kahan, B.C., 2018, 'Cluster randomized trials with a small number of clusters: Which analyses should be used?', *International Journal of Epidemiology*, Vol. 47, No. 1, pp. 321-331. Available online at https://doi.org/10.1093/ije/dyx169.

Ministère de l'Environnment, de l'Habitat et de l'Urbanisme (MEHU), 2011, 'Deuxième communication nationale de la République du Bénin sur les changements climatiques'. Available online at http://www.agrhymet.ne/portailCC/images/pdf/nc2benin.pdf.

Muller, S.M., 2015, 'Causal Interaction and external validity: Obstacles to the policy relevance of randomized evaluations' *The World Bank Economic Review*, Vol. 29 (suppl 1), S217-S225. Available online at https://doi.org/10.1093/wber/lhv027.

Opiyo, F., Wasonga, O.V., Nyangito, M.M., Mureithi, S.M., Obando, J. and Munang, R., 2016, 'Determinants of perceptions of climate change and adaptation among Turkana pastoralists in northwestern Kenya', *Climate and Development*, Vol. 8, No. 2, pp. 179-189. Available online at https://doi.org/10.1080/17565529.2015.1034231.

Palazzo, A., Vervoort, J.M., Mason-D'Croz, D., Rutting, L., Havlík, P., Islam, S., Bayala, J., Valin, H., Kadi, H.A.K., Thornton, P. and Zougmore, R., 2017, 'Linking regional stakeholder scenarios and shared socioeconomic pathways: Quantified West African food and climate futures in a global context', *Global Environmental Change*, Vol. 45, pp. 227-242. Available online at https://doi.org/10.1016/j.gloenvcha.2016.12.002.

Roudier, P., Muller, B., d'Aquino, P., Roncoli, C., Soumaré, M.A., Batté, L. and Sultan, B., 2014, 'The role of climate forecasts in smallholder agriculture: Lessons from participatory research in two communities in Senegal', *Climate Risk Management*, Vol. 2, pp. 42-55. Available online at https://doi.org/10.1016/J.CRM.2014.02.001.

Roudier, P., Sultan, B., Quirion, P. and Berg, A., 2011, 'The impact of future climate change on West African crop yields: What does the recent literature say?', *Global Environmental Change*, Vol. 21, No. 3, pp. 1073-1083. Available online at https://doi.org/10.1016/j.gloenvcha.2011.04.007.

Schlenker, W. and Lobell, D. B., 2010, 'Robust negative impacts of climate change on African agriculture', *Environmental Research Letters*, Vol. 5, No. 1, 014010. Available online at https://doi.org/10.1088/1748-9326/5/1/014010.

Serdeczny, O., Adams, S., Baarsch, F., Coumou, D., Robinson, A., Hare, W., … Reinhardt, J., 2017, 'Climate change impacts in Sub-Saharan Africa: From physical changes to their social repercussions', *Regional Environmental Change*, Vol. 17, No. 6, pp. 1585-1600. https://doi.org/10.1007/s10113-015-0910-2

Shahidur, R., Sharma, M. and Zeller, M., 2004, 'Micro-lending for small farmers in Bangladesh : Does it affect farm households' land allocation decision ?', *The Journal of Developing Areas*, Vol. 37, No. 2, pp. 13-29.

Sillmann, J., Kharin, V.V., Zwiers, F.W., Zhang, X. and Bronaugh, D., 2013, 'Climate extremes indices in the CMIP5 multimodel ensemble: Part 2. Future climate projections', *Journal of Geophysical Research Atmospheres*, Vol. 118, No. 6, pp. 2473-2493. Available online at https://doi.org/10.1002/jgrd.50188.

Tall, A., Coulibaly, J.Y. and Diop, M., 2018, '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', *Climate Services*, Vol. 11, pp. 1-12. Available online at https://doi.org/10.1016/j.cliser.2018.06.001.

Tol, R.S.J., 2018, 'The Economic impacts of climate change', *Review of Environmental Economics and Policy*, Vol. 12, No. 1, pp. 4-25. Available online at https://doi.org/10.1093/reep/rex027.

Waha, K., Krummenauer, L., Adams, S., Aich, V., Baarsch, F., Coumou, D., … Schleussner, C.F., 2017, 'Climate change impacts in the Middle East and Northern Africa (MENA) region and their implications for vulnerable population groups', *Regional Environmental Change*, Vol. 17, No. 6, pp. 1623-1638. Available online at https://doi.org/10.1007/s10113-017-1144-2.

Waha, K., Müller, C., Bondeau, A., Dietrich, J.P., Kurukulasuriya, P., Heinke, J. and Lotze-Campen, H., 2013, 'Adaptation to climate change through the choice of cropping system and sowing date in sub-Saharan Africa', *Global Environmental Change*, Vol. 23, No. 1, pp. 130-143. Available online at https://doi.org/10.1016/j.gloenvcha.2012.11.001.

Wossen, T., Berger, T., Haile, M.G. and Troost, C., 2018, 'Impacts of climate variability and food price volatility on household income and food security of farm households in East and West Africa', *Agricultural Systems*, Vol. 163, pp. 7-15. Available online at https://doi.org/10.1016/j.agsy.2017.02.006.

Yegbemey, R.N., Yabi, J.A., Aïhounton, G.B. and Paraïso, A., 2014a, 'Modélisation simultanée de la perception et de l'adaptation au changement climatique : cas des producteurs de maïs du Nord Bénin (Afrique de l'Ouest)', *Cahiers Agricultures*, Vol. 23, No. 3, pp. 177-187. Available online at https://doi.org/10.1684/agr.2014.0697.

Yegbemey, R.N., Yabi, J.A., Heubach, K., Bauer, S. and Nuppenau, E.-A., 2014b, 'Willingness to be informed and to pay for agricultural extension services in times of climate change: the case of maize farming in northern Benin, West Africa', *Climate and Development*, Vol. 6, No. 2, pp. 132-143. Available online at https://doi.org/10.1080/17565529.2013.867249.

Yegbemey, R.N., Yegbemey, E.O. and Yabi, J.A., 2017, 'Sustainability analysis of observed climate change adaptation strategies in maize farming in Benin, West Africa', *Outlook on Agriculture*, Vol. 46, No. 1, pp. 20-27. Available online at https://doi.org/10.1177/0030727016689638.