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Transforming climate science into usable services: The effectiveness of co-production in promoting uptake of climate information by smallholder farmers in Senegal

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ABSTRACT

Does the provision of weather and climate information services (WCIS) enhance farmer's use of forecasts in informing farm decisions? This paper assesses the effectiveness of the Multi-disciplinary Working Group (MWG) – a WCIS co-production initiative in Senegal in influencing farmers uptake of weather and climate information (WCI). WCIS are increasingly gaining importance and widely touted as critical in helping farmers adapt to climate variability. While there have been various WCIS initiatives producing and translating climate data into tailored information and knowledge in different parts of the world, there is hardly any rigorous evidence assessing their effectiveness in improving uptake. In this assessment, we use innovative survey methods and apply rigorous analytical approaches that control for self-selection bias to establish causal linkages between the MWG and use of WCIS. Our findings indicate that MWGs are positively associated with farmers' awareness, access and uptake of WCI resulting in farm management responses depending on the type of information used. The presence of MWGs generally increases farmer's awareness of WCI by 18%, access by 12% and uptake by 10%. Furthermore, use of seasonal forecasts is generally associated with a higher proportion of farmers using improved seed, fertilizers and manure, but negatively with crop diversification within MWG locations. This suggests that participatory approaches in the provision of tailored climate information and advisory services can lead to higher uptake and use among farmers in informing farm management responses for better adaptation to climate change. We highlight lessons for improved evaluations of WCIS in future.

Practical implications

In recent years, much attention has been paid to improving the provision of weather and climate information services (WCIS) i.e. the packaging and dissemination of down-scaled and actionable weather and climate information (WCI) that meets the needs of end users[1]. Robust weather and climate information can be vital in helping users mitigate, adapt and build resilience to climate variability and change. As a consequence, there have been increasing implementation of various structured participatory models in producing WCI in sub-Saharan Africa (SSA). However,

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[1] Consistent with Hansen et al. (2019), we distinguish between weather and climate in that weather is the fluctuating state of the atmosphere around us, characterized by temperature, wind, precipitation, clouds and other elements. It is a simple concept that people experience and try to understand and factor into decision-making on a daily basis. Therefore, in this study, examples of weather information are forecasts with shorter lead times e.g., 10 day, 3-4 days and daily forecasts. Climate, on the other hand, is much more complex concept referring to the average weather and its variability over a certain time span. Climate is therefore inherently probabilistic. Examples of climate information includes seasonal forecast on onset and cessation of rainfall.

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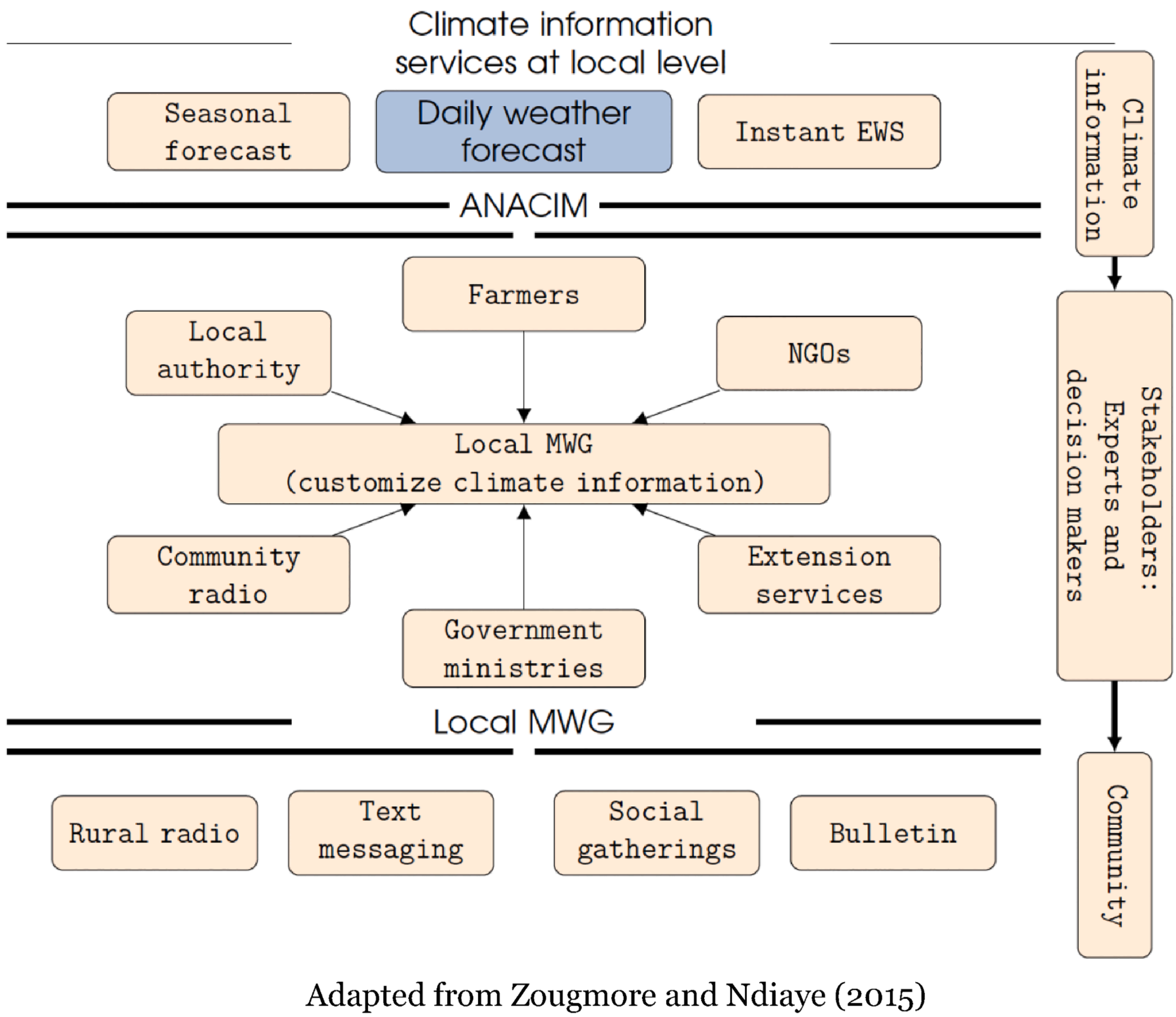


Fig. 1. Conceptual schematization of the MWG co-production model.

there is still a lack of rigorous evidence that show the causal effects of such models in improving the usability of climate information services. A well-designed evaluation study should be able to not only measure the changes in impact indicators between the group that benefit but also determine the extent to which those changes can be directly attributed to the intervention or program being evaluated.

There are two broad factors that make impact evaluation of WCIS particularly challenging relative to other agricultural interventions. First, climate information epitomizes two inherent characteristics of a global public good, that of being non-rivalrous, and non-excludable in consumption (Gunasekera, 2010; Tesfaye et al., 2018; Vaughan et al., 2019). The non-rivalrous nature of WCI means that once generated, the marginal or additional cost of replicating and supplying the same information to other users is very low and uptake by one user does not infringe or diminish use by others. The non-excludable nature of WCI emanates from the fact that once generated, it is practically impossible and potentially expensive to prevent anyone from benefiting from the service (Gunasekera, 2010). This makes it difficult to distinguish between those who benefit from the intervention and those who do not, complicating efforts to identify a control sample that does not have access to the information (Tall et al., 2018; Vaughan et al., 2019). In impact evaluation literature, this is referred to as contamination or spill-over effect of the treatment. Second, the link between WCI uptake and livelihood impacts is not a direct one. As Hansen (2005) argues, WCI has no intrinsic value on its own, but rather the value is derived from improved farm decisions made based on the information received resulting in positive livelihood outcomes.

While there is an emerging body of empirical studies that assess the benefits of different WCIS programs (e.g., Clarkson et al., 2019; Dayamba et al., 2018; Stats4SD, 2017; West et al., 2018), most of them identify and measure impact through general associations between uptake of WCI and changes in various behaviours and outcomes. There is still a gap in evidence for evaluations that use more rigorous methods for establishing and validating the causal links between uptake of WCI and changes in behaviour and welfare of users. More specifically, there is a lack of evidence that (i) compare treatment and control groups as most resort to assessing and drawing conclusions based only on participants or beneficiaries of the program precluding the counterfactual case: what would have happened had the beneficiaries not received the treatment?; (ii) use more rigorous analysis that control for self-selection bias from observed and unobserved factors and; (iii) go beyond focussing on farmers' perceived changes and consider plot level farm management responses on input use and crop outputs.

This study assesses the effectiveness of the Multi-disciplinary Working Group (MWG) — a structured WCIS in Kaffrine Senegal — that co-produces actionable weather and climate information to respond to the needs of farmers in informing their decision. The MWG is centred around continuous and sustained interactions across multiple actors in ensuring that WCI is appropriately tailored to make it more usable for farmers. More specifically, the study looks at the impact of the MWG on farmers' awareness, access and uptake of WCI. The study addresses some of the challenges in impact evaluation of WCIS in three ways. First, we use an innovative survey design approach that enables us to have two sub-sample of farmers, one that is exposed to the MWG (treatment) and another without exposure (counterfactual). This ability to have a counterfactual enables us to consider the case: what would have happened in the absence of the intervention? The study was conducted in two districts; i) Kaffrine where MWGs had been established and operational since 2015 constituting the treatment group and ii) Kaolack region where there was no functional MWG and hence the control group. This means within each of these groups, we are able to further categorize sampled farmers into users and non-users of WCI, which are: seasonal forecasts on the amount of rainfall, onset and cessation; weather forecasts for 10-days, 2–3 days; and instant forecasts for extreme events. Second, we use rigorous econometric approaches (the Local Average treatment effect (LATE) model) to minimize the bias in estimation caused by unobserved factors due to self-selection of participants or program design. Third, this study goes beyond eliciting farmers' perceptions of how they used climate information to inform farm decisions by considering plot level crop production data. Empirical evidence in assessing WCIS using rigorous impact evaluation techniques, as we do in this study, is hardly available.

The CGIAR Research Program on Climate Change, Agriculture and Food Security (CCAFS) has worked closely with Senegal's National Meteorological Agency (ANACIM) since 2011 to develop locally relevant climate information services and enhance the capacity of partners to communicate this information to end users. The national MWG is composed mainly of the Department of Agriculture (DA), the Institute of Agricultural Research of Senegal (ISRA), the Ecological Monitoring Center (CSE), the National Agricultural and Rural Council Agency (ANCAR), the National Agricultural Insurance Company of Senegal (CNAAS), and ANACIM (Ndiaye et al., 2013). The aim was; 1) developing WCIS that are tailored to the needs of the users; 2) enhancing the capacity of partners who were tasked to communicate climate information to farmers; and 3) enhancing the transmission of WCI and agricultural advisories for farmers (see Fig. 1).

We find that the presence of an MWG has a positive and significant effect on farmers' awareness, access, and uptake of seasonal forecasts, daily weather forecast, and instant forecasts. In addition, exposure to the MWG also positively influences the behaviour changes made by farmers that use WCI.

1. Introduction

Weather and Climate Information Services (WCIS) refer to the transformation of climate and weather related data into tailored information and knowledge that help users make informed decisions across different sectors. It involves the sustained engagement of diverse actors in the production, translation and transfer of Weather and Climate Information (WCI) products such as forecasts, projections, and agricultural advisories that are responsive to the needs of users (Hansen et al., 2019; Tall et al., 2018). Provision of tailored WCIS is widely regarded as a potential strategy that can help smallholder farmers in SSA in managing the risks associated with climate variability and change through informed farming decisions (Hansen et al., 2011; Roncoli et al., 2009; Roudier et al., 2014; Vaughan and Dessai, 2014)[2]. Yet, in reality, despite continuous advances in climate modelling and prediction and improvements in seasonal lead time, Africa's capacity for climate observation is insufficient and marked with a decline in the quantity and quality of weather stations (Dinku et al., 2016). Further compounding this problem, particularly in SSA, is a general lack of awareness, understanding, access and capacity in using this unfamiliar information, reluctance to integrate climate information into decision making, and poor understanding of scientific uncertainties (Dinku et al., 2014; Hansen et al., 2011).

The field of WCIS is emerging, and in recent years, a lot of attention has been paid to improving the quality of weather and climate information by ensuring that it is tailored to meet the needs of end users. Considerable amount of climate change research has been conducted and decision-makers at the local and resource management level are actively seeking to increase their climate information uptake. However, there is a persistent gap between climate knowledge production and its subsequent use (Lemos et al., 2012). This gap may largely be due to a disconnect between the needs of users and the information produced by scientists. Scientists may assume that the knowledge they are producing is useful when they engage in research, but without a complete understanding or appreciation of what users need, this knowledge may not be actionable to decision makers. Users in turn, may not know or may have unrealistic expectations of how knowledge fits their decision-making and may choose to ignore the information, despite its usefulness (Lemos et al., 2012; Porter and Dessai, 2017). It has thus become increasingly important for climate scientists and purveyors of climate information to deliberately co-develop climate knowledge with users to improve practical use and hence its uptake (Briley et al., 2015; Meadow et al., 2015). Such efforts aim to narrow down the climate information usability gap; that is, if users of climate information can explain more clearly what makes it usable, then scientists can deliver exactly what is needed (Lemos et al., 2012; Porter and Dessai, 2017; Prokopy et al., 2017). Mauser et al., 2013 suggested a framework of interdisciplinary and transdisciplinary co-creation of knowledge in which diverse actors (producers, purveyors and end-users) are involved in the co-design, co-production and co-dissemination of climate knowledge and information products. The co-design phase often starts with the development of a shared framing of the problem, which places scientific knowledge within the social, cultural, and political contexts. The co-production phase involves conducting integrated research that taps into the diverse expertise of all actors involved. The last phase involves co-dissemination of the knowledge to all intended beneficiaries. This iterative approach involves bottom-up and inclusive interaction of diverse actors that hold different knowledge, experience and expertise along the climate information value chain. It helps in bridging the communication and knowledge gap and builds stronger relationships based on trust and respect across the different actors. One of the criticisms of why traditional models of knowledge production often fail is because they tend to be very 'top down' and linear in nature (Cash et al., 2003). Structured participatory communication processes help in creating a conducive environment for co-learning among farmers, researchers and climate information providers resulting in better understanding and more willingness by end users to use of climate information in informing decisions (Carter et al., 2019; Vaughan and Dessai, 2014).

According to Cash et al. (2003), climate information is likely to be effective in influencing decision making if it is perceived by stakeholders to be credible, salient and legitimate. A commonly cited approach to ensure that climate information services meet this criteria and hence useful to decision-makers is through co-production, an integrated and iterative approaches that leverages on the expertise of different actors to ensure that climate science is appropriately tailored into services that meet the needs of end-users (Bremer et al., 2019; Dilling and Lemos, 2011; Lemos and Morehouse, 2005; Vedeld et al., 2019). Examples of participatory WCIS that enable end-users, like farmers, to integrate climate information into their decision making within SSA include; the Enhancing National Climate Services initiative (ENACTS) implemented

[2] Throughout the paper, we refer to WCIS and weather and climate services interchangeably

in countries like Ethiopia, Tanzania and Mali (Dinku et al., 2016), the Participatory Integrated Climate Services for Agriculture (PICSA) (Dorward et al., 2015) implemented in countries such as Zimbabwe, Malawi, Rwanda, Tanzania, Mali and Senegal (Dayamba et al., 2018) as well other efforts under the Global Framework for Climate Services Adaptation Program in Africa (GFCS-APA) in various parts of Africa (Pathak and Lúcio, 2018). While the theoretical underpinnings of participatory approaches are well understood, there is still a lack of rigorous evaluations assessing their effectiveness in enhancing users' uptake (Vincent et al., 2018).

This study makes two contributions to the existing evidence base on use of WCI. First, a methodological one in that we use an innovative survey design approach in combination with rigorous econometric methods that minimize self-selection bias, a ubiquitous problem in expost evaluation. Empirical evidence in assessing the benefits of WCIS using rigorous impact evaluation techniques, as we do in this study, is hardly available. Second, an empirical one in that our study is framed to rigorously evaluate the effectiveness of a large-scale, nationwide WCIS co-production model in the diffusion of WCI, something that is also very rare in existing literature. To the best of our knowledge, there is no peer-reviewed study that has carried out a rigorous quantitative assessment of a WCIS program while controlling for self-selection bias between the beneficiaries and non-beneficiaries of the program.

We assess the effectiveness of the Multi-disciplinary Working Group (MWG)— a participatory co-production model that fosters interactions between different actors that produce, translate, transfer, and use WCI, ensuring that they are appropriately tailored to meet the needs of end-users. Two broad types of weather and climate information are produced and transmitted through the MWGs; i.e. seasonal information (forecasts on total rainfall amount, its onset and date of cessation) and weather information (10-day forecasts, 2–3 days forecasts and instant forecasts for extreme events) as well as other complementary information such as agricultural advisories. Specifically, we analyse the effect of the MWGs in improving farmers' awareness, access and uptake of weather and climate information, as well as how this information is used to improve decision-making by the farmers. We use primary data collected in Senegal and apply instrumental variable approach to account for selection bias[3]. Given data limitations, we do not claim to provide unassailable evidence based on this one case study, but offer preliminary insights on rigorous evaluation of WCIS from a demand side or user perspective which is a vital component in the general discourse on assessing the costs and benefits of WCIS to society.

2. Review of empirical studies on the development of WCIS

Several studies have documented the processes, barriers and successes of uptake of climate information for decision making and these have mainly focused in Europe and the USA (e.g., Dilling and Lemos, 2011; Kirchhoff et al., 2015; McNie, 2007; Meadow et al., 2015; Prokopy et al., 2017). Most of these studies find that WCIS proved to be efficient in educating potential users about the strengths and limitations of climate science and improving the production, dissemination, and use of climate information. Despite the outlined benefits, there is not much empirical evidence showing the benefits of WCIS programs. However, over the last 5 years a number of WCIS models have been designed and implemented in several countries in Africa and the progress documented (e.g., Clarkson et al., 2019; Dayamba et al., 2018; Dinku et al., 2017; Dorward et al., 2015; Pathak and Lúcio, 2018; West et al., 2018). Evidence from these studies, has mostly been through qualitative means limited to subjective opinions of beneficiaries on the benefits of WCIS without counterfactual evidence from non-beneficiaries.

For instance, a qualitative study by Clarkson et al. (2019) showed that PICSA has been successful in influencing farmers' behaviour in Ghana. However, quantitative evidence of the effect of these co-production models in SSA is still missing. Use of weather and climate information services, specifically seasonal forecasts, has been shown to affect farmers' practices and behaviors (Hassan and Nhemachena, 2008; Ingram et al., 2002). Behavior changes among farmers include; planting early maturing and drought tolerant crops or varieties, crop diversification, varying the planting and harvesting dates, diversifying to non-farm activities, uptake of soil and water conversation techniques and use of irrigation (Hassan and Nhemachena, 2008; Ingram et al., 2002). Other farm management responses that were observed across different countries in SSA in response to information on seasonal forecasts include; adjusting the use of fertilizers, increasing post-harvest storage, intercropping, changing or mixing crop types, adjusting crop densities, reducing herd sizes, changing planting time and sometimes relocating to other places (Ziervogel et al., 2005; Luseno et al., 2003; O'Brien et al., 2000). In addition, Roudier et al. (2012) notes that benefits from seasonal forecasts mostly depends on the type of season, whether it is good or bad.

There have been a few quantitative studies on the effect of WCIS in SSA. For example, Maggio et al. (2019) use longitudinal data and propensity score matching to compare farmers use of seasonal forecasts in informing on farm management responses, before and after the El-Niño Southern Oscillation among farmers in Zambia. Lo and Dieng (2015) assessed the impact of seasonal climate forecasts on yields in Senegal using test plots. In this case, various WCI were used to adjust management decisions regarding a specific treatment plot throughout the season, after which yields from the test plot would then be compared to those of control plots where more traditional practices were employed. If well designed, test plots have the advantages of providing a counterfactual, capturing decision-making and potentially overcoming challenges of farmer recall and the elicitation of sensitive economic information (Vaughan et al., 2019). A major challenge with using test plots is that real life management decisions that small-scale farmers make may not compare with decisions that agronomists make in the test plots, where conditions can be controlled. Patt et al. (2005) used a two-year dataset and a control group to estimate the impact of farmer participation in participatory climate information workshop on yields in Zimbabwe. The methodology was based on a multivariate regression analysis that controls for use of forecast and locations. Although the study found that farmers who participated in the workshops had significantly more yields, no strong connection could be made between management responses to the forecast and increased in yields.

Roncoli et al. (2002) used a combination of household surveys and focus group discussions on farmers' decisions and local knowledge on a sample of 23 farmers in Burkina Faso and found that capacity to respond adequately to climate forecasts was hindered by their poor access to necessary inputs and by risk aversion. Other studies that estimated the benefits of using WCI based on household surveys include; Ouedraogo et al. (2018) who assessed the effects of using seasonal climate forecasts on yields in Burkina Faso; Rao et al. (2015) who assessed the effect of climate communication strategies on farmers yields in Kenya; Anuga and Gordon (2016) who estimated the effects of use climate information on yields in Ghana; Stats4SD (2017) who estimated the impact of use of WCI in Malawi and Tanzania. Most of these studies have shown positive effects of using WCI on different livelihood outcomes. However, these studies do not control for self-selection bias between groups that are exposed to WCIS and those not exposed. Additionally, these studies assume a direct link between use of WCI and livelihood outcomes, yet infact, uptake of WCI influences livelihood outcomes through other pathways such as the adoption of certain seed varieties or different farm management responses. Climate information has no intrinsic value, but rather the value comes from improved farm decisions made based on the

[3] The rest of the paper is as follows; section 2 presents a brief review of co-production of climate information and the effect of WCIS on farmers' behaviour. Section 3 presents the methodology section; Section 4 presents the results and discussion while section 5 concludes the paper with some policy recommendations and areas of further research.

Fig. 2. A focus group discussion on use of weather and climate information among women in Kaffrine, Senegal.

information received resulting in positive livelihood outcomes (Hansen, 2005). A few studies have highlighted some of the empirical and practical challenges when evaluating causal impacts of access and use of WCI on farmers' livelihoods (see Chiputwa et al., 2019; Tall et al., 2018; Vaughan et al., 2019).

3. Methods

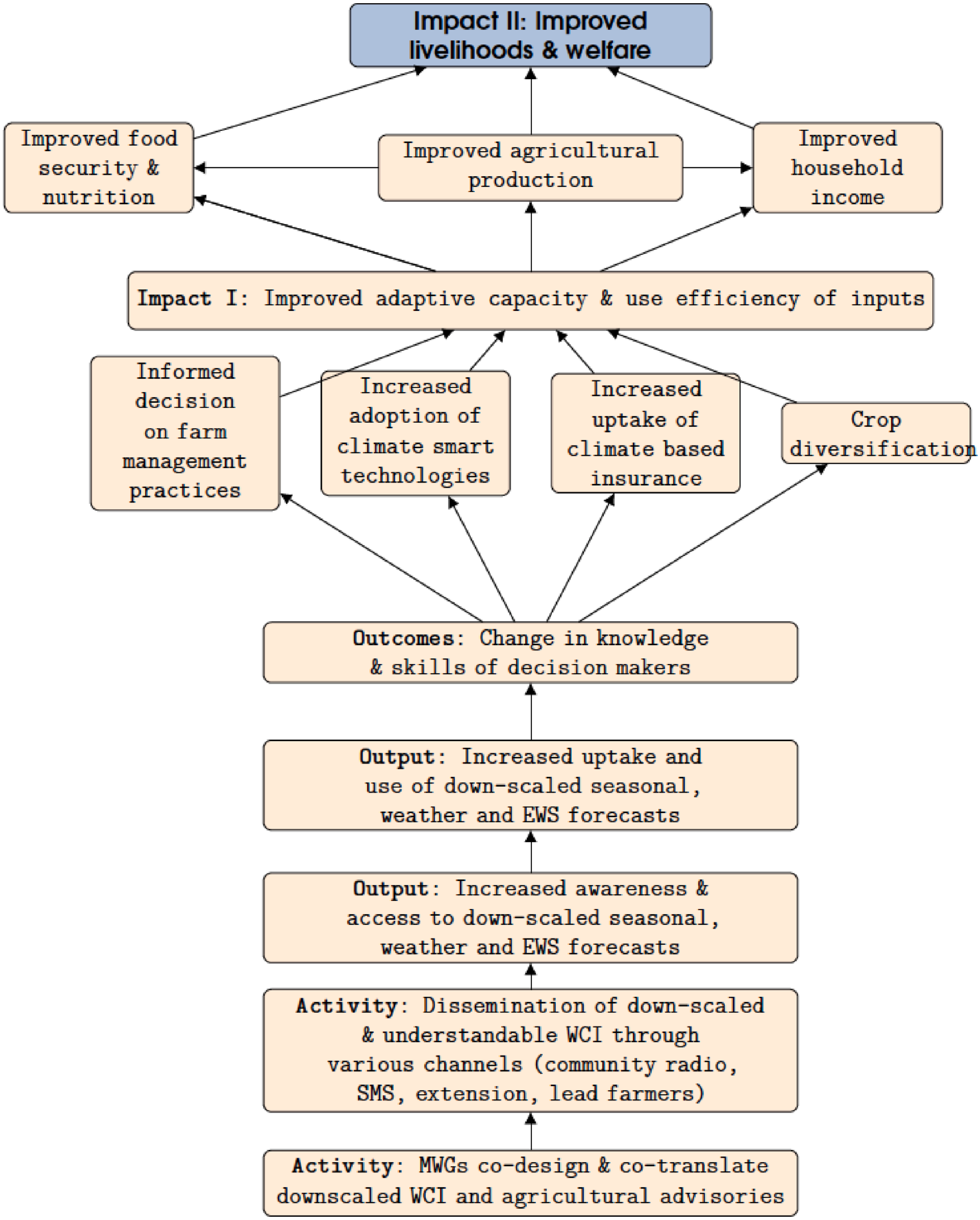
3.1. The MWG co-production model and its hypothesized impact pathways on farmers in Senegal

The MWGs were first initiated by the AGRHYMET Regional Centre as a response mechanism to a devastating drought in the early 1980s among Permanent Interstate Committee for Drought Control in the Sahel (CILSS) countries in West African Sahel. The MWGs were a platform for engagement where meteorologists and stakeholders from different sectors such as agriculture and water would collaborate and develop early warning information (Hansen et al., 2019). The MWGs being assessed in this study were first piloted in 2011 in Kaffrine district with partnership from CCAFS, ANACIM and were piloted with the collaboration of As shown in Fig. 1, the MWGs in Senegal operate at both the national and local levels. They constitute a decisive and inclusive body that translates weather and climate information into downscaled and actionable information for farmers. Local MWGs which consist of farmers, climatologists, agricultural scientists, extension and technical service agents, local farmers' organizations, media, NGOs, women-based organizations and other relevant local entities within the districts, are set up to closely monitor climatic events and phenomena, and translate climate forecasts into timely advisory services that help guide farmers into making informed decisions (Ouedraogo et al. 2018)[4]. Seasonal forecasts are updated between June and August of each year and translated into agricultural advice by the multidisciplinary working group (MWG). Once produced, information is disseminated directly through short message services (SMS) to a number of farmers within ANACIM's SMS database, the MWGs, community radios, the Rural Department for Development Services (SDDR), and local administrative authorities (CCAFS, 2015). In the department of Kaffrine, the MWG includes representatives of the de- centralized administrative services (Ministry of Agriculture, Livestock, Environment, etc.), NGOs and Union des Radios Associatives et Communautaires du Senegal (URAC). This group meets every 10-days and discusses how climate information related to agronomic advice can be translated into actionable information for farmers. The outcomes of these discussions are delivered to *relais* farmers through radio, cell phone calls, SMS or word of mouth. *Relais* farmers are progressive farmers, or leaders of farmers' organizations, or farmers with strong influential power (for example religious leaders, community leaders) who are in charge of delivering the information to other farmers. They are selected by the district SDDR to convey climate information in their villages but not all villages have a *relais* farmer. *Relais* farmers share the information with fellow farmers through SMS, phone calls and by word of mouth. Farmers also receive the CIS directly by listening to the community radios or from the SDDR agent. Local MWGs also manage an early warning system (EWS) based on climate information received from ANACIM. They meet every 10 days and produce a report with agricultural advice that is shared with policymakers and farmers through a special program broadcast on community radios. The interactive radio programming allows listeners to share feedback, including additional information, views and requests for clarification. Fig. 2 shows focus group discussion with women on the use of weather and climate forecasts in one of the MWG communes in Kaffrine being facilitated by local extension agent.

Fig. 3 conceptualizes the hypothesized impact pathways through which uptake of CIS under the MWG model in Senegal occurs[5]. We start by distinguishing and highlighting the linkages between activities of the MWGs, the outputs generated, the outcomes which result from use of outputs and the resulting impacts on the the livelihoods and welfare of

[4] For a more in-depth discussion on how the MWGs in Senegal operate and are set up (see CCAFS, 2015; Ndiaye et al., 2013; Ouedraogo et al., 2018).

[5] This is a simplified version of the impact pathways based on key informant interviews and focus group discussions.



Source: Adapted from Chiputwa et al., 2019.

Fig. 3. Hypothesized impact pathways of weather and climate information under the MWG model in Senegal.

farmers. As highlighted in Fig. 1, the MWGs are participatory and iterative models consisting of multiple actors that co-produce downscaled WCI on seasonal forecasts (total amount of rain, onset and cessation) and weather forecasts 2–3 days, 10 days, and instant EWS. For example, seasonal forecast is translated (from its scientific form) and communicated to farmers with an indication of its probability, in easily understandable language, giving farmers the capacity to make informed farm management responses (Ndiaye et al., 2013). The different forecasts and agricultural advisories are then disseminated to end-users through various channels that include community radio, SMS, extension and lead farmers. Based on the bottom-up approach and inclusiveness of the MWG approach, the assumption is that downscaled WCI

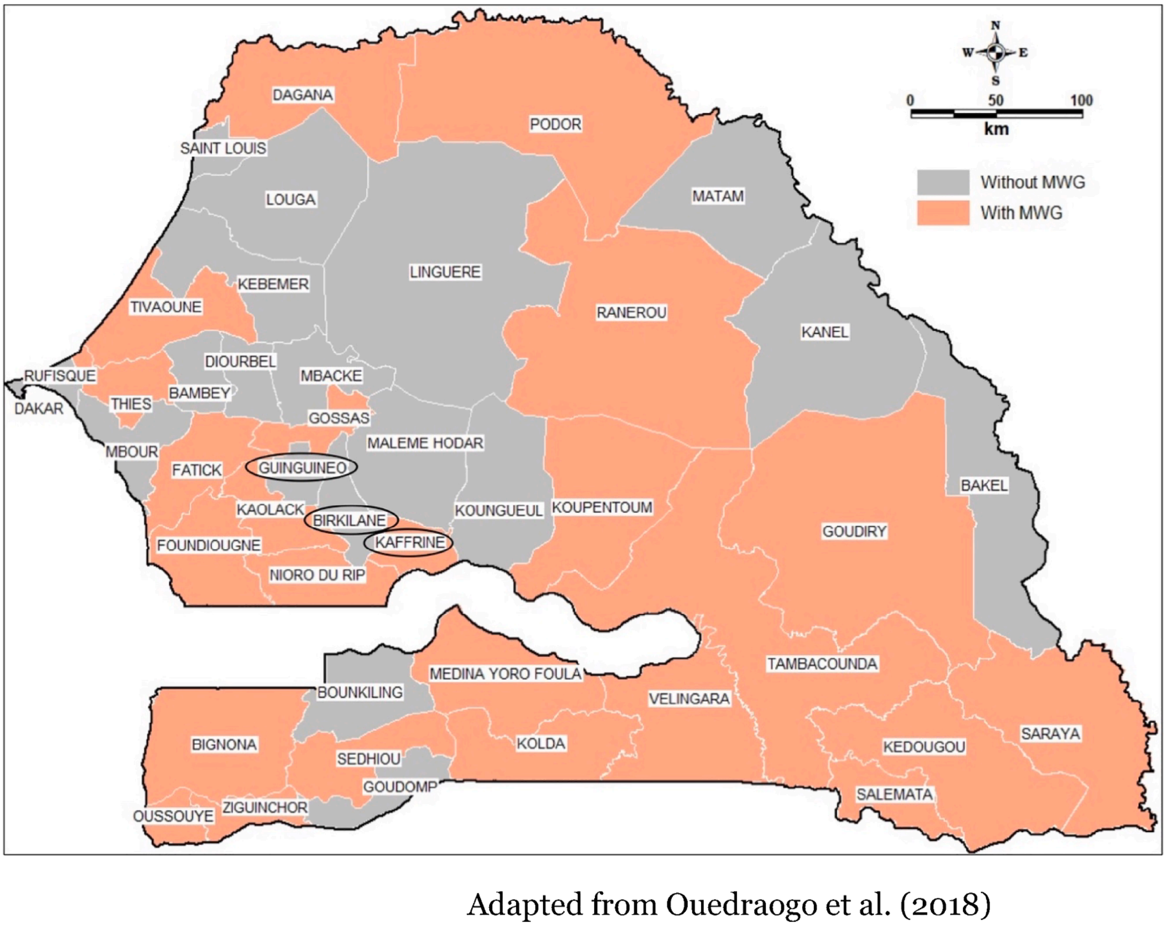


Fig. 4. Map of Senegal showing the sampled districts (circled) and presence of functional MWGs.

disseminated are credible, salient and legitimate which drives increased interests of end users like farmers. This results in greater awareness of and access to WCI which is instrumental in increasing their uptake and use in informing farm decisions, which we refer to as direct outputs of the project[6]. The uptake of WCI and advisory services by farmers changes their knowledge and skills and leads to behaviour changes in farming management decisions. These behaviour changes enable households to buffer their agricultural production and other livelihood activities against climate risks and are referred to as outcomes. Some of these include adjustment in the timing of farm decisions, inputs used, livelihood diversification, uptake of climate index-based insurance and adoption of climate-smart technologies. These outcomes may contribute to a reduction in crop failure and livestock losses, as well as reduction in farm income fluctuations which in turn translate into short-term impacts e.g., improved agricultural productivity and improved incomes. Finally, these short-term impacts result in longer term impacts, such as improved livelihood resilience and reduced poverty levels.

3.2. Survey data

We used primary data collected from the sampled sites in Senegal through individual household surveys using structured questionnaires. The questionnaire was first set up in English and French; and then translated and administered by carefully trained enumerators using the local language, *Wolof*. The questionnaire captured various indicators that included household information (e.g., demographics, education, asset ownership, income generating activities); farm characteristics and agricultural production (e.g., plot characteristics, crop and livestock data, crop varieties grown); other off-farm crop production livelihood strategies[7]. In addition, the questionnaire also collected detailed information on household's awareness of, access to and use of weather and climate services such as seasonal forecasts on rainfall onset and cessation and short-term weather services such as weekly and daily forecasts. All questions on uptake of WCI and the farm management responses informed at plot level were in reference to the agricultural season for 2016, which was just prior to the household survey. We use the Margalef index as a proxy for crop diversification. It measures the species richness of crop diversity by simply counting the number of different crop species in a given area. It is defined as the number of species S recorded, corrected for the total number of individual N summed over species (Magurran, 2004; 1988). In this study, we define S as the number of crops grown in the season prior to the household survey and N as the total hectares of crops grown in that season. Empirical studies that have used this index include (Di Falco and Chavas, 2009). The sampling strategy was built on a stratified random sampling design. First, we purposively selected districts that met the following two criteria, i) having access to a functional MWG that had been established and operational since 2011 as well as receiving tailored WCI and agricultural

[6] Effective uptake and use of climate services is also influenced by other factors such as socio-economic status, assets, and institutional support such as access to credit, seeds and fertilizer.

[7] The questionnaire was very broad and here we only highlight some sections that are relevant to this paper.

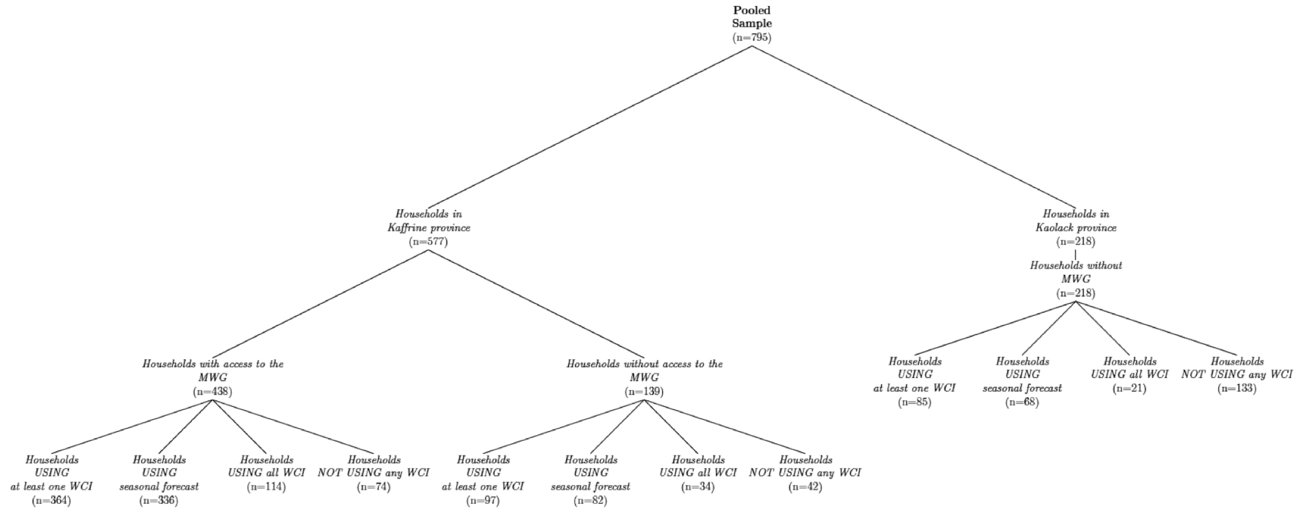


Fig. 5. Composition of sampled households by MWG and use of WCI.

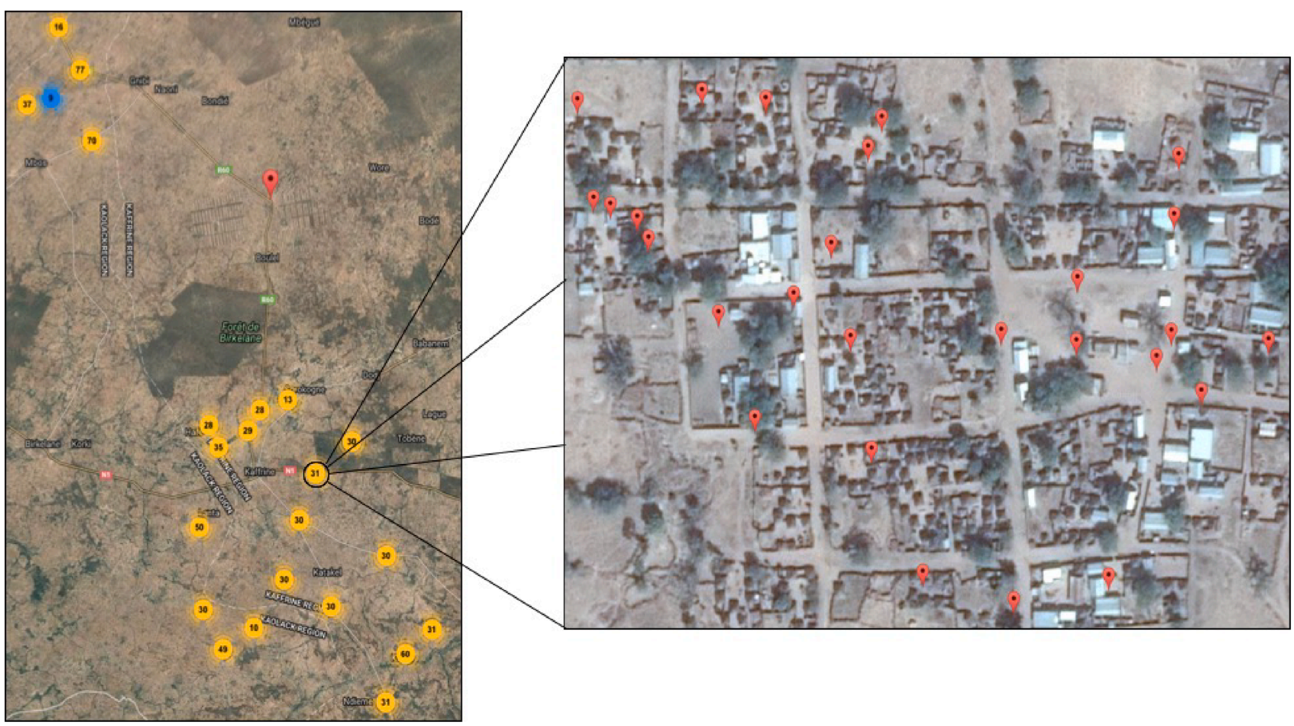


Fig. 6. Map showing the distribution of sampled households in a specific cluster location within Kaffrine district.

advisories from a local radio station, and ii) having no exposure to an MWG but having access to WCI through e.g., local radio stations[8]. Fig. 4 spatially maps the occurrence of functional MWGs by district in Senegal. Within Kaffrine region, we purposively selected two districts i.e. Kaffrine (with access to MWG) and Birkilane (with no access to MWG). Within Kaffrine district, the rural communes of Kahi, Kathiote and Mbignick were selected on the basis that they had been more exposed to WCIS compared to the other communes. Within each of these communes, two to four villages were randomly selected, and 30 farmers randomly selected from a list of households provided by the village head. The district of Guinguineo in Kaolack region was selected as an additional control group as having no access to a functional MWG but receiving WCIS from a local radio station. In Guinguineo district, eight villages were randomly selected from Panal Wolof commune, followed by a random selection of 30 households per village. The Kaffrine and Kaolack regions both lie in livelihood zone SN 10: Rainfed Groundnuts and Cereals, as classified by the Famine Early Warning System Network (FEWS-NET) based on households having similar livelihood patterns and access to markets (http://fews.net/livelihoods). The survey targeted heads or the second most important decision maker in each household. In the end, a total of 795 households were selected and interviewed during the survey; 577 households in Kaffrine region and 218 households in Kaolack region. The reason for over-sampling Kaffrine region

[8] This sampling criteria was informed by spatial mapping of functional MWGs as outlined in Ouedraogo et al. 2018 based on their performance. Fig. 4 in Ouedraogo et al. (2018), shows that the MWGs in the Kaffrine district (our treatment group) had held on average up to 6 meetings in 2017 alone, while the control group region Birkilane and Guinguineo did not have any functional MWGs.

was because it consisted of two sub-groups of farmers (i) those with access to the local MWGs that are functional and hold regular meetings based on the characterization in Ouedraogo et al. (2018)[9]. As shown in Fig. 5, a total of 438 farmers in Kaffrine districts had access to MWGs while the remaining 139 in Birkilane did not have access as shown in the sample composition. Fig. 6 shows the distribution and geo-referenced locations of some of the sampled households in one of the clusters within Kaffrine district.

3.3. Modelling the adoption decision and empirical estimation using the counterfactual ATE framework

In general, adoption of a technology is normally defined as a binary or dichotomous choice, taking the value of one for adopters and zero for non-adopters. This can be further extended, depending on the type of technology being considered, to include the extent or intensity of adoption. In this study, we consider the impact of uptake and use of different weather and climate information. More specifically, we consider the impact of using six types of weather and climate information products i.e. total amount of rainfall for the season; onset of rains; cessation of rains, daily weather forecasts (2–3 days and 10 days); and instant forecasts of extreme events. First, an individual can only access or receive a particular weather and climate information if they are already aware of it. A household is considered to be aware of an innovation when their information level on the technology exceeds a minimum threshold (Adegbola and Gardebroek, 2007). Therefore, awareness of and having the ability to receive or access a particular WCI are necessary but not sufficient conditions that the individual will be able to use this information to influence their farming decisions. Second, an individual can only uptake and use weather and climate information for decision making if they are simultaneously aware and have the means to access or receive the information. Hence, we combine uptake and use as one decision, which is defined as a binary variable and for each individual and takes the value of 1 for a household that uses a particular forecast to inform their farm management responses, and 0 if they do not. This implies that for each household, we are able to observe whether they used any one or a combination of the six weather and climate information products. A household is classified as a WCI user if in the 2016 agricultural season, used at least one of the six types of WCI to adjust their on-farm decisions. Non-users, on the contrary, are households that used neither of the six WCI to inform their farming decisions.

In addition to these six individual WCI use decisions, we also consider an integrated binary measure, which takes the value one, if the household uses at least one of the six WCI, and 0 if not. The farm management responses informed by use of WCI depend on the type and timescale of the information provided. For example, while seasonal forecasts provide a general overview of the season, they can not elaborate on day-to-day weather fluctuation. It is important that the uptake decision is conditional on (i) the household being aware of at least one type of weather or climate information, its attributes and the potential net benefits (utility); and (ii) the household having the means to receive this information. Awareness is expressed as a dummy variable for each WCI and takes a value of 1 if the household is knowledgeable of a particular weather and climate service and 0 if otherwise. Access is measured as a binary variable that takes the value of 1 for each weather and climate service that the household is able to receive from one or more sources like radio, extension workers, or from fellow farmers, and 0 if otherwise. The use decision is a function of the expected benefits from the uptake of WCI, which depends on the attributes of the WCI in question such as source and accuracy, as well as other socioeconomic factors (e.g., age and education level of farmer, farm size) and institutional factors (e.g., access to extension, inputs and outputs markets).

The impact of a given WCI is difficult to assess because information alone has no intrinsic value. The value is only realized when this information is translated into farming decisions that result in positive benefits or utility for the user. We model a household's decision to uptake and use a WCI product based on a random utility framework on household decision-making under imperfect information.. Under this framework, we assume that a household makes the choice to use a particular WCI based on the maximization of an underlying utility function, U , which is determined by a set of farm and household variables, X and can be represented in the form:

$$\mathrm{MAX}U = f(X) \tag{1}$$

We assume that household i will use one or a combination of WCI types j, where $j(j = 1,\ldots 6)$, if the utility U_{ij} derived is greater than the utility U_{im} of not using WCI. Since the utilities cannot be observed, they can be expressed as a function of observable elements and can be represented by latent variable model as:

$$I^{*} = U_{ij} > U_{im} \ \forall m \neq j \tag{2}$$

If a linear relationship is assumed, I^{*} can be written as:

$$I_{ij} = \beta_j X_i + u_{ij} \tag{3}$$

where I_{ij} the indirect utility level associated with the jth WCI and determined by a broad set of observed household and farm characteristics, and institutional factors X_i, as well as unobserved factors affecting the uptake decision contained in u_{ij}.

To estimate the causal effects of a the MWG program, we follow the theoretical framework of the Average Treatment Effect (ATE), also known as the potential-outcomes model (Rubin, 1974)[10]. The ATE framework is based on the idea that every subject has different potential outcomes depending on the group they are assigned. In this case, the potential outcomes of a household that use WCI will be different from those of a household that does not use WCI. Under the potential-outcomes framework, we estimate the average treatment effect (ATE), the average treatment effect on the treated (ATT), the average treatment effect on the untreated (ATU) by comparing the expected values of the outcomes of users and non-users in actual and counterfactual scenarios, hence the importance of having treatment and control groups in the survey design. This allows measuring the change in the outcome that is attributable to the MWG. However, it is not possible to simultaneously observe the with and without treatment scenarios since the same individual or household cannot be in the two states at the same time. While it is not possible to estimate the difference in observed outcomes for the same individual at a given point in time, an average difference can be calculated for different households in these two scenarios.

To illustrate this mathematically, for a population of N households a farmer i has two hypothetical potential outcomes: I_{ij}^{o} is the observed outcome variable if they use one or a combination of j WCI, and I_{ij}^{1} is the observed outcome variable if they do not use WCI. The *ATE* can be non-parametrically identified from the joint distribution of I, X conditional on MWG exposure ($w = 1$) and can be represented as:

$$E(I|X, w = 1) = f(X\beta), \tag{4}$$

where f is a known function of the vector of covariates determining WCI uptake, X, and β are the unknown parameter vectors that can be estimated by maximum likelihood estimation (MLE) procedures using

[9] Kaffrine department has one of the 21 MWGs that were most operational and held at least six regular meetings.

[10] Outcomes under Rubin's potential-outcomes framework refers to the condition or circumstance of a subject with and without treatment. This should not be confused with outcomes in the MWG impact pathways as presented in Fig. 3, which refer to behavioral changes resulting from uptake of WCI.

observations I and X from the exposed sub-sample with I as the dependent variable. With the estimated parameters β, the predicted values are computed for all observations in the sample, including the sub-sample of the non-exposed. The average of these predicted values, $f(X\widehat{\beta})$, for values $i = 1, 2, \cdots, n$, to compute *ATE* for the pooled sample, *ATT* for the exposed sub-sample and *ATU* for the non-exposed sub-samples. These can be presented as:

(i) the *ATT* which measures the change in the probability to adopt WCI for those who had access to MWG;

$$\widehat{ATT} = \frac{1}{N_w}\sum wf(X\widehat{\beta}) \tag{5}$$

(ii) the *ATU* which measures the potential impact on farmers in the control group that were not exposed to the MWG if in fact they are exposed to the MWG;

$$\widehat{ATU} = \frac{1}{N - N_w}\sum(w-1)f(X\widehat{\beta}) \tag{6}$$

(iii) is the weighted average of *ATT* and *ATU* and measures the impact of being exposed to the MWGs on the entire population of users and non-users of WCI.

$$\widehat{ATE} = \frac{1}{N}\sum f(X\widehat{\beta}) \tag{7}$$

To analyze the impact of the MWG on use and uptake of WCI as well the resulting impact on farmers' behavioral changes, we use the instrumental variable approach based on the local average treatment estimator (LATE) (Angrist and Imbens, 1995). As already highlighted, not all individuals that were aware or had access to a particular WCI would actually translating into farm management responses. In such a case, it is reasonable to measure the impact of MWG only in the group of compliers. Following Abadie (2003), we estimate the treatment effect only in the sub-group of compliers using the local average treatment effect "LATE". Our estimation method is as follows:

$$\widehat{LATE} = \frac{1}{\widehat{P}(w=1)}\sum_{i=1}^{n_1}\widehat{k}_i \cdot h(I_i, X, \widehat{\theta})|w = 1, \tag{8}$$

with$\widehat{k}_i$, the complier weight, h, the Local Average Response Function (LARF) and $\widehat{\theta}$, a vector of parameters to be estimated. $w = 1$ is the treatment indicator in the sub-group of farmers exposed to access or awareness and X is a vector of control variables consisting of farmer characteristics (e.g., age, education and sex of household head); farm factors (e.g., farm size, altitude, location dummies, access to MWG) and institutional factors (e.g., distance to markets, access to extension). We first estimated the probability of adoption in the sub-group of farmers with exposure to access or knowledge $\widehat{P}(w = 1)$ as well as the complier weight,$\widehat{k}_i$. In a second stage, compute $\widehat{LATE}$ by simply applying above-mentioned formula. Since we use a two-stage procedure with some parameters in the second stage estimated in the first stage, we adopt a bootstrap procedure to consistently estimate the $\widehat{LATE}$'s standard errors. Both the *ATE* and the *LATE* are typically estimated using a two-stage least squares regression approach. The first-stage involves a probit specification that includes all observable factors that affect uptake of WCI.

4. Descriptive statistics

4.1. Differences in WCI use and farm management responses disaggregated by MWG and province

Table 1 presents differences in awareness, access and use of WCI as well as farm management responses between farmers with access to MWGs versus those without access. Farmers with access to MWGs were more aware, had better access and used a significantly higher number of WCI in making farming decisions than those in without MWGs. Similarly, farmers that had access to MWGs had implemented significantly more farm management responses. Use of improved seeds and chemical fertilizers was also significantly higher among farmers with access to MWGs. However, the use of manure was more common among farmers without access to the MWGs. We use the Margalef index as a proxy for crop diversity and find that farmers that had access to the MWGs were less likely to diversify crops compared to those without MWGs.

Table 1
Differences in awareness, access and use of WCI and behaviour changes among sampled farmers disaggregated by their exposure to the MWG.

	Without MWG		With MWG	
	Mean	Std. dev	Mean	Std. dev
Awareness, access and use of WCI				
Number of WCI known	4.45	1.74	4.93***	1.35
Number of WCI accessed	4.11	1.80	4.53**	1.54
Number of WCI used	3.60	1.88	4.18***	1.65
Number of behaviour changes made	4.74	4.25	8.46***	4.95
Behaviour changes made				
Number of crops grown in 2016	3.22	1.47	3.33	1.29
Use of improved seed (dummy)	0.25	0.43	0.33	0.47
Use of manure (dummy)	0.52	0.50	0.36***	0.48
Use of chemical fertilizers (dummy)	0.34	0.48	0.72	0.45
Crop diversification[a]	2.18	0.42	2.06***	0.34
Observations	357		438	

Notes: Std. dev: Standard deviation; *, **, *** denotes significance level at 10%, 5% & 1%, respectively.
[a] Measured as the Margalef Index.

Table 2 presents the mean differences between WCI users and non-users disaggregated by region. . Generally, users in the two regions were more aware and had better access to different WCI than non-users. This could have been due to lack of knowledge on the value and net benefits derived from using WCI. In addition, WCI users in both regions were more likely to apply chemical fertilizers and use improved seeds compared to non-users. The relative proportions are however higher in Kaffrine region (with access to MWGs) compared to Kaolack region (with no access to MWGs). Similarly, comparing the two regions, farmers in Kaffrine who used WCI implemented significantly more farm management responses compared to WCI users in Kaolack, which can be attributed to the presence of MWGs.

Fig. 7 shows the link bewteen behavioral changes made at the farm level for the 2016 agricultural season among sampled farmers and the number of WCIS products used. The results point to a positive correlation between the number of WCI products used and behavioral changes made , but more interestingly that the intensity is highest among farmers with access to MWGs. For illustration purposes, the same figure illustrates that a farmer using two different WCI forecasts will on average implement; (i) four behaviour changes if they are in Kaffrine and have access to the MWGs; (ii) three behaviour changes if they are in Kaffrine and do not have access to the MWGs; and (iii) one behaviour change if they are in Kaolack and have no access to the MWG.

The descriptive statistics in this sub-section show that exposed to MWGs tend to be more aware, have better access, use more WCI products and implement more behaviour changes than their non-exposed counterparts. However, there may be systematic differences (in e.g., resource endowment and risk preferences) that exist between WCI users and non-users, consequently making these correlations non-causal. In order to properly analyse the link between WCI use, the presence of an MWG and implications on behaviour changes, we have used the treatment effects model that accounts for the observed and unobserved differences among sampled farmers in the next section.

Table 2
Differences in awareness, access and use of WCI and behaviour changes among sampled farmers disaggregated by district.

	Kaffrine (n = 577)				Kaolack (n = 218)			
	Non-users (n = 116)		Users (n = 461)		Non-users (n = 133)		Users (n = 85)	
	Mean	Std. dev	Mean	Std. dev	Mean	Std. dev	Mean	Std. dev
WCIS awareness and use								
Number of WCI known	3.87	1.71	4.93***	1.35	3.23	2.05	4.45***	1.74
Number of WCI accessed	3.40	1.58	4.53***	1.54	2.57	1.79	4.11***	1.80
Number of WCI used	0.00	0.00	4.18***	1.65	0.00	0.00	3.60***	1.88
Number of behaviour changes	0.00	0.00	8.46***	4.95	0.00	0.00	4.74***	4.25
Farm management responses								
Number of crops grown in 2016	3.20	1.80	3.33	1.29	3.70	1.52	3.22*	1.47
Use of improved seed (dummy)	0.19	0.39	0.33**	0.47	0.09	0.29	0.25**	0.43
Use of manure (dummy)	0.31	0.47	0.36	0.48	0.32	0.47	0.52**	0.50
Use of chemical fertilizers (dummy)	0.57	0.50	0.72**	0.45	0.25	0.44	0.34	0.48
Crop diversification[a]	2.03	0.30	2.06	0.34	2.31	0.41	2.18*	0.42
Institutional factors								
Access to extension (dummy)	0.16	0.37	0.33***	0.47	0.07	0.26	0.15	0.36
Exposure to MWG	0.66	0.48	0.79**	0.41	0.00	0.00	0.00	0.00

Notes: Std. dev: Standard deviation; *, **, *** denotes significance level at 10%, 5% & 1%, respectively.
[a] Measured as the Margalef Index.

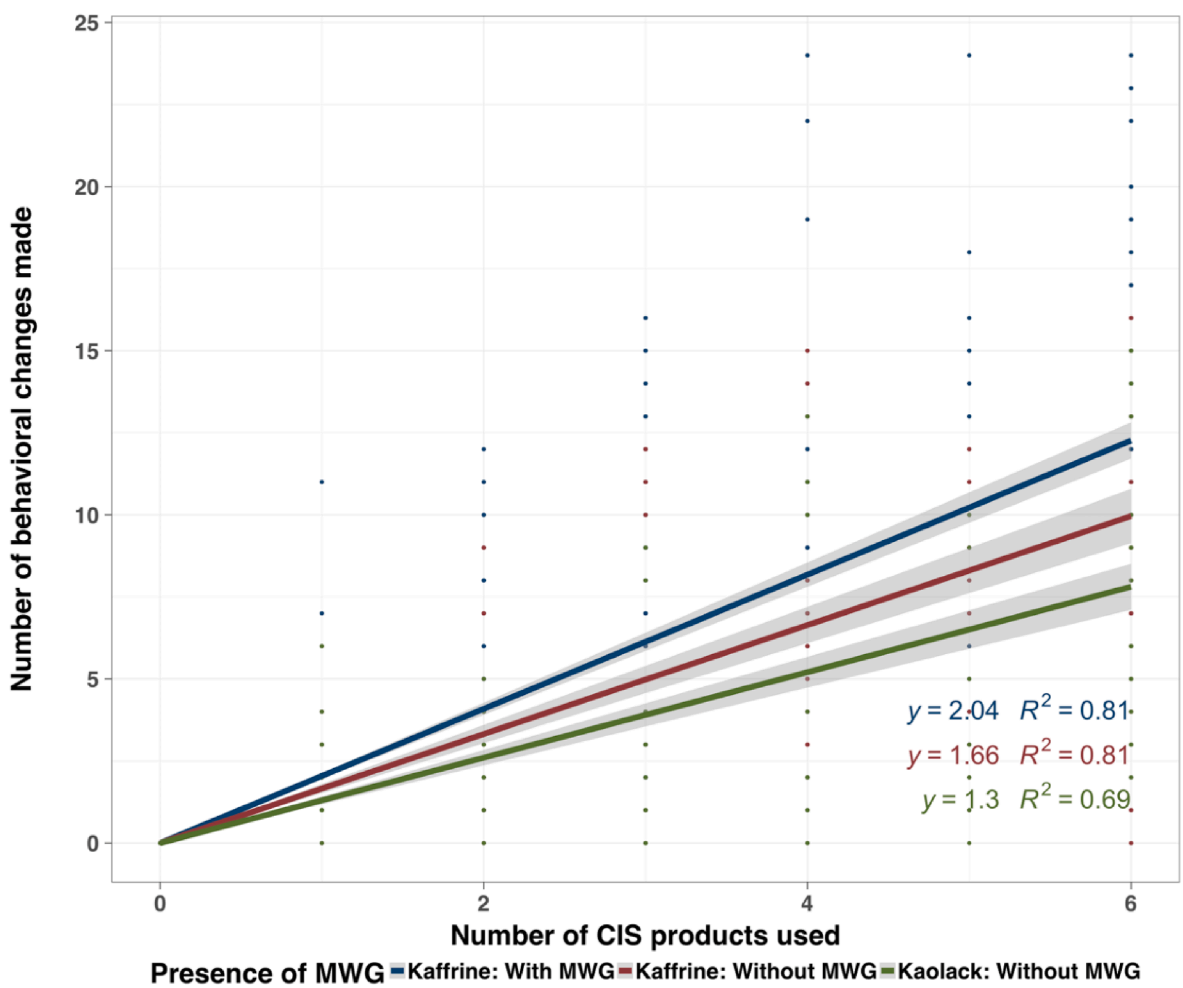


Fig. 7. Correlation between use of WCI and number of behaviour changes made.

5. Econometric results and discussion

5.1. The effectiveness of the MWG model in influencing farmers' awareness, access and use of WCI

In this section, we present the causal impacts of access to the MWGs on awareness, access, and uptake of different WCI based on the

Table 3
Treatments effects estimates of the impact of existence of an MWG and use of WCI on farmer's awareness, access and use of WCI.

Variables	Whole population (ATE)		With MWG (ATT)		Without MWG (ATU)	
	Estimate	Std. error	Estimate	Std. error	Estimate	Std. error
Awareness of WCI						
Awareness of any one type of WCI (dummy)	0.155***	0.0035	0.173***	0.0046	0.133***	0.0051
Awareness of all 6 types of WCI	0.176***	0.0006	0.174***	0.0007	0.179***	0.0010
Awareness of seasonal forecasts	0.230***	0.0027	0.237***	0.0030	0.223***	0.0048
Awareness of daily forecasts	0.191***	0.0030	0.223***	0.0033	0.152***	0.0043
Awareness of EWS	0.266***	0.0020	0.283***	0.0019	0.244***	0.0034
Access to different types of WCI						
Access to any one type of WCI (dummy)	0.147***	0.0034	0.162***	0.0046	0.127***	0.0047
Access to all 6 types of WCI	0.116***	0.0007	0.114***	0.0009	0.118***	0.0012
Access to seasonal forecasts	0.149***	0.0029	0.160***	0.0039	0.136***	0.0041
Access to daily forecasts	0.158***	0.0024	0.180***	0.0030	0.130***	0.0031
Access to EWS	0.107***	0.0016	0.109***	0.0021	0.105***	0.0024
Use of different types of WCI						
Use of any one type of WCI (dummy)	0.104***	0.0048	0.089***	0.0057	0.125***	0.0079
Use of all 6 types of WCI	0.091***	0.0010	0.093***	0.0013	0.088***	0.0015
Use of seasonal forecasts	0.053***	0.0031	0.039***	0.0036	0.074***	0.0048
Use of daily forecasts	0.177***	0.0052	0.176***	0.0065	0.179***	0.0085
Use of EWS	0.245***	0.0011	0.249***	0.0012	0.240***	0.0018
Observations	795		438		357	

Notes: n = 795; Std. error: Standard error; *, **, *** denotes significance level at 10%, 5% & 1%, respectively. The observed behaviour changes are modelled using a two-stage least squares regression approach, starting with a probit specification that generates a predicted probability for each farmer with and without access to the MWG.

Table 4
Treatments effects estimates of the impact of existence of an MWG and use of WCI in informing farmer's management responses.

Farm management responses from use of:	Whole population (ATE)		With MWG (ATT)		Without MWG (ATU)	
	Estimate	Std. error	Estimate	Std. error	Estimate	Std. error
Seasonal forecast: Total amount of rainfall						
Type of crop variety to grow	0.248***	0.0009	0.251***	0.0011	0.246***	0.0015
Field location to plant crops	0.220***	0.0017	0.218***	0.0023	0.223***	0.0024
Decision on intercropping	0.129***	0.0009	0.132***	0.0012	0.125***	0.0014
Type of crop to grow	0.124***	0.0006	0.126***	0.0007	0.122***	0.0009
Crop mix (proportion)	0.128***	0.0004	0.127***	0.0006	0.129***	0.0006
Soil and water conservation	0.102***	0.0018	0.105***	0.0025	0.099***	0.0026
Seasonal forecast: onset of rains						
Timing of planting	0.225***	0.0009	0.229***	0.0010	0.221***	0.0016
Timing of land preparation	0.187***	0.0017	0.199***	0.0016	0.173***	0.0031
Seasonal forecast: cessation of rainfall						
Timing of crop sales	0.219***	0.0033	0.214***	0.0039	0.225***	0.0054
Timing of harvesting	0.089***	0.0011	0.084***	0.0015	0.095***	0.0016
Weather forecast: for 2–3 days						
Application of inorganic/chemical fertilizer	0.302***	0.0028	0.305***	0.0035	0.298***	0.0044
Timing of weeding	0.217***	0.0011	0.218***	0.0014	0.216***	0.0017
Timing of harvesting	0.152***	0.0015	0.151***	0.0021	0.153***	−0.0022
Use of organic fertilizer (manure/compost/mulch)	0.140***	0.0019	0.148***	0.0026	0.130***	0.0028
Weather forecast: for 10 days						
Application of inorganic/chemical fertilizer	0.270***	0.0027	0.276***	0.0034	0.263***	0.0043
Soil and water conservation	0.157***	0.0026	0.154***	0.0036	0.160***	0.0038
Use of organic fertilizer (manure/compost/mulch)	0.041***	0.0040	0.044***	0.0006	0.037***	0.0006
Observations	795		438		357	

Notes: n = 795; Std. error: Standard error; *, **, *** denotes significance level at 10%, 5% & 1%, respectively. The observed behaviour changes are modelled using a two-stage least squares regression approach, starting with a probit specification that generates a predicted probability for each farmer with and without access to the MWG.

potential-outcome ATE framework as outlined in Equations (5), (6) and (7)[11]. For brevity, we suppress the first-stage selection model and only present the impact estimates of the second stage. We start with Table 3, which present the impact estimates of exposure to the MWGs. Columns (1), (2) and (3) present the *ATE*, *ATT* and *ATU*, respectively. The results show that the presence of an MWG has causal impacts on awareness, access, and uptake of different WCI. All the estimates presented are positive and significant at the 1% level, albeit with varying degrees in magnitude.

Starting with the greatest impacts in the awareness model (rows 2–6), results reveal that the presence of MWGs significantly increase farmers' awareness of EWS by 27% for the entire population (*ATE*), 28% for farmers already exposed to the MWG (*ATT*) and 24% for farmers without access to the MWG if they decide to adopt (*ATU*). Similarly, the expected increase in awareness of seasonal forecasts is 23% and 24% for farmers in the whole population and for farmers exposed to the MWGs, respectively. If farmers in the control locations were exposed to the MWG, the predicted increase in awareness of seasonal forecasts is about 22%. We also see that access to the MWGs has very similar effects on

[11] The probabilities for seasonal rainfall are usually presented as tercile probabilities of rainfall falling on the upper (wet), middle (normal), or bottom (dry) categories of the historical distribution in that region

awareness of daily forecasts, which are expected to increase by 19% for the whole population, 22% for farmers exposed to the MWG, and 15% for farmers not exposed to the MWG under the scenario that they got access. Lastly, the presence of an MWG increases the probability that a household is aware of at least one WCI type by between 13% and 17% across the three scenarios: *ATE*, *ATT* and *ATU*.

We now consider the impact of exposure to the MWGs on farmers' access to WCI (rows 8–12), for which we see relatively lower magnitudes compared to the awareness model. The existence of the MWGs show the highest impacts on farmers' access to daily and seasonal forecasts, where access to WCI increase by between 13% and 18% across the *ATE*, *ATT* and *ATU* models. For example, the presence of an MWG is expected to significantly increase farmers' access to seasonal forecasts by 15% for the entire population, 16% for farmers with access to MWG and 14% for farmers without access to the MWG. Interestingly, the least impact of MWG can be seen on the access of EWS, which the results show to be around 11%. This trend is in contrast with that shown in the awareness model. More specifically, the presence of an MWG increases the proportion of farmers with access to seasonal forecasts by approximately; (i) 15% for the whole population, (ii) 16% for the sub-sample of farmers with access to MWG and, (iii) 14% for the counterfactual case of having MWG established in areas where they do not exist.

We now focus on the uptake of WCI displayed in rows (14–18) of Table 3. The presence of an MWG is expected to significantly increase the use of seasonal forecasts by 5% for the whole population, 4% for the sub-sample of farmers exposed to the MWG and a 7% increase for control farmers if they were to be exposed to the MWG. The existence of an MWG is also expected to increase the use of daily forecasts for the three scenarios by about 18%.

Results in this sub-section show that the MWGs can be effective in stimulating awareness access and uptake of WCI.

5.2. The effectiveness of the MWG in influencing farmers' decision making when using WCI

We build on the previous analysis which revealed that MWG improves farmers' awareness, access and use of WCI. Again for brevity, we suppress the first-stage selection model and only present the impact estimates from the second stage. We start by looking at the behavior changes that result from the use of seasonal forecasts on; (i) total accumulated rainfall, (ii) onset of rains, and (iii) cessation of rains. The results in Table 4 of the *ATE, ATT* and *ATU* are all positive and significant, which generally points to the importance of the MWG in farmers use of WCI in informing farm management decisions. A closer look at the results reveal that exposure to the MWGs (*ATT*) among farmers using seasonal information on rainfall total (rows 2–7) increased the use of this information on (i) choice of crop varieties grown (i.e., for groundnuts, maize and millet)[12] by 25%; (ii) the field location to plant different crops by 22%[13]; (iii) whether to intercrop or not by 13%, and (iv) the type of crops to grow and crop mix by about 13%. The model predicts similar trends in terms of impact of the MWGs, for farmers randomly selected in the population (*ATE*) and also in the for farmers in the control locations in case they are exposed to the MWG (ATT). The *ATE* results reveal very similar trends (in terms of proportional increase) to the results of the *ATT*. For example, the presence of an MWG leads to 25% and 22% more farmers in the population using information on total accumulated rainfall to inform the crop variety to grow and the field location to plant crops, respectively. On the counterfactual scenarios (*ATU)*, we also find the same proportional increase in these farming management decisions that would be influenced by introducing MWGs in control areas where they are currently not functional. These results are somewhat in line with some earlier studies that conclude that seasonal forecasts are instrumental in informing farmers to consider the crop type to grow (Tarhule and Lamb, 2003); crop varieties to consider (Maggio et al., 2019), adjust the crop density and crop mix (Luseno et al., 2003; Tarhule and Lamb, 2003; Ziervogel et al., 2005), and change field locations where they grow crops (O'Brien et al., 2000). Hansen et al. (2011) also contend that the accumulated rain for the season, which is predicted by probabilities of whether it will be wet/humid, normal or dry, is one of the most common forecasts parameters for farmers that is forecast in West Africa (WA).

Focusing on results in rows 9 and 10, we find that exposure to the MWGs increased farmers use of rainfall onset in informing timing of planting by 23% and land preparation by 20%. The results of the *ATU* predict that scaling out of MWGs into locations where they are non-existent will increase use of rainfall onset forecasts to inform timing of planting by 22% and land preparation by 23%. A significantly higher proportion of farmers exposed to the MWG used seasonal forecasts on cessation to inform timing of crop sales (21%) and timing of harvesting (8%). The *ATU* results also suggest that in the presence of an MWG, farmers in control locations will increase use of information on cessation of rains to inform farmers' timing of selling their produce to the market by 22% and timing of harvesting by 10%. Our results are in line with other studies like Hassan and Nhemachena (2008), who found that in 11 countries in Africa, farmers tend to use seasonal forecast to vary the harvesting dates, while Ingram et al. (2002) report that farmers in Burkina Faso use the information to decide on whether to sell or store their grain stores. However, the shift in behavior brought about through active consideration of WCIS will then contribute to the realization of the higher order impacts, such as improved yields, food security and nutrition, and better household welfare. The intermediary outcomes that we model in this section are behavior changes as reported by the farmers (and not measured by the researcher) and hence results should be interpreted with some caution due to measurement errors[14].

A closer look at the results in rows 15–22, shows that farmers use weather forecasts, which have shorter lead times, to inform decisions that are very different from those of seasonal forecasts. The ATT results show that a significantly higher proportion of farmers already exposed to the MWG use 2–3 days weather forecasts to make informed decisions on application of inorganic fertilizers (31%), timing of weeding (22%), timing of harvesting (15%) and use of inorganic fertilizers (15%) such as manure, compost or mulch. Similarly, there are 28%, and 15% more farmers exposed to the MWGs that use 10-day forecasts to inform decisions on application of inorganic fertilizers and on the choice of soil and water conservation practices. Considering the counterfactual scenario of introducing MWG into locations where they are non-existent would lead to proportionally similar percentage increases in the use of 2–3 days and 10-day weather forecasts. In addition, there is also a significantly higher proportion of farmers in MWG locations that use information on cessation of rains to inform the timing of crop sales (21.4%) and timing of harvesting (8.4%) compared to those without an MWG. These results are also consistent with findings in Moeletsi et al. (2013), who observed that distributing daily weather forecasts, three times a week influenced farmers in Limpopo Province of South Africa to adjust decisions on timing of weeding and application of chemicals such as pesticides and nitrogen fertilizer.

5.3. Impact of use of seasonal forecasts on observed farm management responses by MWGs

The previous analysis focused on the impact of MWGs in influencing

[12] These are the main crops grown in the study area.

[13] Change crop locations (for example, depending on forecast, farmers can chose to grow the less drought tolerant crops on parts of their fields which retain moisture better like down slopes or crops that require more nutrients to be grown on fields that are more fertile.)

[14] Measurement error is then the difference between the value of a response provided by the respondent and the true (but unknown) value of that response.

Table 5
LATE estimates of the impact of presence of MWGs on use of seasonal forecasts on farm management responses.

Farm management responses	All seasonal forecasts		Both seasonal and weather forecasts	
	Estimate	Std. error	Estimate	Std. error
Use of improved seed (dummy)	0.217***	0.002	0.234***	0.002
Use of manure (dummy)	0.114***	0.002	0.157***	0.002
Use of chemical fertilizers (dummy)	0.092***	0.002	0.237***	0.002
Crop diversification[a]	−0.004***	0.002	−0.006***	0.002
Observations	795		795	

Notes: n = 795; Std. error: Standard error; Bootstrapped standard errors in parenthesis (300 replications) *, **, *** denotes significance level at 10%, 5% & 1%, respectively. The observed behaviour changes for dummy variables are modelled using a probit specification, and a linear regression for crop diversification.
[a] Measured as the Margalef Index.

the behavior of farmers with respect to farm management responses based on the type of WCI received. In this sub-section, we extend this analysis to model the impact of access to the MWGs on farmer's management responses when they use WCI, based on plot level data as reported by farmers during the 2016 agricultural season. More specifically, we model the link between the use of WCI and exposure to the MWGs with use of improved seeds, chemical fertilizers, manure use, and crop diversification as outlined in Equation (8)[15]. According to records from ANACIM, probabilistic forecasts for the Central region (which includes the Departments of Kaolack and Kaffrine for the year 2016 was that of a dry tercile (i.e., below normal) at the beginning of the season to wet tercile (above normal) towards the end of the season.

We again suppress the first-stage selection model and only present the impact estimates from the second stage. Table A1 in the appendix shows the impacts disaggregated by each of the individual seasonal forecasts. We will however focus our attention on Table 5, which presents the LATE estimates for seasonal forecasts on observed farm management responses using joint access and awareness as instrumental variables. First, we start by considering farmers that jointly used all three seasonal forecasts (column 2 and 3) to prepare their farming season in 2016 (i.e. total amount, onset and cessation of rainfall). The results reveal that farmers that were exposed to the MWGs and using all three seasonal forecasts had a 22% higher probability that they used improved seed, 11% higher probability of using manure and a 9% higher probability of using chemical fertilizers than users in non-MWG locations. Second, we consider farmers that combined the use of both seasonal and weather forecasts (column 3 and 4). Results show that farmers with access to the MWGs had a 23% higher chance of also using improved seed varieties, a 16% higher chance of using manure and a 24% higher chance of using chemical fertilizers. Interestingly though, we find use of WCI for the two categories we consider above, to be negatively and significantly associated with crop diversification. This implies that farmers in MWG locations that used all three seasonal forecasts or both seasonal and weather forecasts had a 0.4% and 0.6% chance of having lower crop diversity compared to farmers in the locations without MWGs. Given that the seasonal forecast for 2016 indicated a relatively bad year, reducing the number of crops and focusing resources on a few crops is a plausible adaptation strategy that farmers exposed to the MWGs may choose to undertake. Similarly, diversifying to more crops can also be a reasonable adaptation strategy that farmers may consider to spread out the risk of crop failure. As expected, there was a uniform trend in the impact of forecasts on the total amount of rainfall and onset of rainfall since farmers receive both set of information simultaneously at the beginning of the planting season. Zougmoré et al. (2016) recently showed that the use of climate information resulted in increased yield of crops as farmers used seasonal forecasts to make strategic decisions such as the timing of land preparation, planting, selection of crop varieties, and timing of application of manure or chemical fertilizer.

6. Conclusions and policy recommendations

The provision of tailored WCIS is increasingly gaining importance and has been widely touted as a vital adaptation and mitigation strategy against the adverse effects of climate change and variability. This is particularly true in SSA, where risk and insurance systems are not well developed and inaccessible to the majority of farmers. Tailoring WCIS ensures that information disseminated to users, meets their needs in three criteria: saliency, credibility, and legitimacy. While there have been many participatory initiatives that have been used to tailor WCI in different parts of the world, there is hardly any rigorous evidence testing the effectiveness of these models. A key challenge in evaluating the benefits of WCIS is trying to establish the link between an individual receiving and using WCI and the effects it has on behaviour changes due to the complex decision-making process farmers go through. This evaluation uses data generated from an innovative survey design approach collected from 795 households in Senegal and applies contemporary impact evaluation techniques that account for selection bias to establish causal links between WCI use and their impacts. The survey approach capitalized on the unique sampling design that enables us to reconstruct the counterfactual scenario and apply the *ATE* framework, but this time using an instrumental variable approach. Based on the econometric results, we highlight two main findings from this case study and draw some evidence-based recommendations for policy and the design and development of WCIS. We also highlight some methodological limitations with our study and lessons for future evaluations of WCIS.

In general, results of this study have shown that the existence of the MWGs have a positive effect on farmers' awareness, access and use of different WCI products, as well as behaviour changes in terms of farm management responses. This suggests that participatory approaches in the provision of tailored WCI and advisory services can lead to higher uptake and use among farmers in informing farm management responses for better adaptation to climate change. Our findings also corroborate Ndiaye et al., (2013)'s assertion on the MWGs:

> *'Our project explaining seasonal forecasting to farmers in central Senegal built common ground between scientific forecasting and traditional knowledge. It helped farmers understand and use seasonal forecasts to improve crop strategies, and let farmers explain to meteorologists what seasonal climate information they most needed, in turn improving the forecasts' usefulness.'*

Our contribution to the existing literature is twofold. First, we provide rigorous evidence on the potential benefits of WCIS programs that prioritize sustained and iterative collaborations that blend knowledge and perceptions of multiple actors (producers, purveyors and users). Second, we provide some methodological insights based on the novel survey methods and rigorous analytical approaches in evaluating the benefits of WCI with respect to users. These contributions offer some lessons to researchers and development practitioners involved in the design, implementation, monitoring and evaluation, and scaling of similar initiatives to the rest of the Sahel and other regions SSA and beyond.

While we have used a rigorous ex-post evaluation design to assess the effectiveness of the MWGs, we highlight four main limitations of our study. First, our analysis is built on cross-sectional data implying that we

[15] We purposely focus on these types of WCI based on the results of the descriptive statistics and hypothesized were instrumental in affecting decisions on the four management practices that we explore in this analysis.

Table A1
LATE estimates of the impact of presence of MWGs on use of individual seasonal forecasts on farm management responses.

	Total amount of rainfall		Start of the rains (onset)		Cessation of rainfall	
Farm management responses	Estimate	Std. error	Estimate	Std. error	Estimate	Std. error
Use of improved seed (dummy)	0.095***	0.001	0.081***	0.001	0.096***	0.001
Use of manure (dummy)	0.038***	0.001	0.03***	0.001	0.074***	0.001
Use of chemical fertilizers (dummy)	0.056***	0.001	0.048***	0.001	0.088***	0.001
Crop diversification[a]	0.006***	0.001	0.017***	0.001	−0.026***	0.001
Observations	795		795		795	

Notes: n = 795; Std. error: Standard error; Bootstrapped standard errors in parenthesis (300 replications) *, **, *** denotes significance level at 10%, 5% & 1%, respectively. The observed behaviour changes for dummy variables are modelled using a probit specification, and a linear regression for crop diversification.
[a] Measured as the Margalef Index.

could only observe a snapshot of household decision making on use of WCI based on the 2016 agricultural season, which limits the generalizability of our findings especially given the stochastic nature of weather conditions. Second, farmers in the control group may have directly or indirectly been exposed to downscaled WCI and agricultural advisories from the MWG program, something referred to in impact evaluation as spill-over effect or contamination effects. This could have emanated from the fact that WCI and other climate related knowledge exhibit characteristics of public goods, thus are more often disseminated through public means such as national radio, television and extension services making it unrestricted when it comes to access for all potential users. Furthermore, WCI can easily be passed between individuals, through informal channels such as social and family networks, making it difficult to completely isolate intended beneficiaries of the MWGs from non-beneficiaries. In this case, spill-over effects will actually diminish or deflate the size of the estimated treatment effects thereby threatening significance and/or internal validity of our findings. Third, observational studies like ours , generally suffer from respondent bias i.e., errors in data recorded resulting from respondents' inability or unwillingness to provide accurate and objective answers to questions. For example, the fact that the MWG model in Kaffrine is a well-known and publicized program within the communities they operate, one might argue that respondents might not provide honest answers. In responding to questions on WCI, a respondent may choose to either understate, overstate or honestly answer about their awareness, access, and use of WCI, depending on how the respondents perceive the objectives of the study. This is a common problem which is not unique to this study. We have minimized this type of bias through careful selection and training of enumerators. Based on these shortcomings, we do not claim to provide conclusive evidence, but rather offer some preliminary insights based on innovative methods for assessing the benefits of WCIS. Fourth, interviews in this study were administered with the main decision makers and/or their spouses, who answered all household related information on behalf of other members, thereby evoking Becker's unitary approach model also known as the common preference model (Becker, 1976). Under this model, a household is assumed to be a single unit that pools all its productive resources under a well-defined uniform welfare function headed by an altruistic or benevolent head. Yet several studies have shown that household members neither pool resources (Haddad and Hoddinott, 1995; Quisumbing and Maluccio, 2003) nor do they behave as single unit and that individual preferences differ (Chiappori et al., 1993; Doss, 1999) supporting the idea that a household is a more complex unit made up of individuals with differences in preferences. Consequently, our findings should be interpreted with some degree of caution.

In-light of the above shortcomings, follow-up research with long-term seasonal data may help capture and track farmer's uptake of WCI in informing farm management decision making, under variable weather patterns may help in improving the robustness and external validity of estimates. This point has been emphasized previously in Hansen et al. (2011), Patt et al. (2005) and Tall et al. (2018). In addition, a useful extension that may benefit future assessments would be to use mixed-methods research designs that blend quantitative approaches with more specialized qualitative approaches such as the Livelihoods as Intimate Government (LIG) approach that develops ethnographic understandings of livelihood decision-making (Carr, 2013; Carr et al., 2019; 2015); outcome harvesting approaches that elicit impact pathways of complex system-wide initiatives such as the MWGs (Douthwaite et al., 2003; Faure et al., 2018). Ensuring that all information e.g., uptake of WCI, plot level agricultural information and asset ownership are gender disaggregated (see Doss, 2013; Doss and Morris, 2000) may be useful in considering households not as unitary in decision making, but rather diverse depending on individual preferences of each member. Incorporating these extensions in future research, will contribute in building a more nuanced and comprehensive evidence base for understanding the benefits of WCIS.

CRediT authorship contribution statement

Brian Chiputwa: Conceptualization, Methodology, Investigation, Formal analysis, Writing - original draft, Writing - review & editing. **Priscilla Wainaina:** Writing - review & editing. **Tebila Nakelse:** Formal analysis. **Parmutia Makui:** Data curation. **Robert B. Zougmoré:** Writing - review & editing. **Ousmane Ndiaye:** Writing - review & editing. **Peter A. Minang:** Supervision, Writing - review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Annex

References

Abadie, A., 2003. Semiparametric instrumental variable estimation of treatment response models. J. Econom. 113, 231–263. https://doi.org/10.1016/S0304-4076(02)00201-4.

Adegbola, P., Gardebroek, C., 2007. The effect of information sources on technology adoption and modification decisions. Agric. Econ. 37, 55–65. https://doi.org/10.1111/j.1574-0862.2007.00222.x.

Angrist, J.D., Imbens, G.W., 1995. Two-stage least squares estimation of average causal effects in models with variable treatment intensity. J. Am. Stat. Assoc. 431–442.

Anuga, S.W., Gordon, C., 2016. Adoption of climate-smart weather practices among smallholder food crop farmers in the Techiman municipal: Implication for crop yield. Res. J. Agric. Environ. Manag. 5, 279–286.

Becker, G.S., 1976. Altruism, egoism, genetic fitness: and sociobiology economics. J. Econ. Lit. 14, 817–826.

Bremer, S., Wardekker, A., Dessai, S., Sobolowski, S., Slaattelid, R., van der Sluijs, J., 2019. Toward a multi-faceted conception of co-production of climate services. Clim. Serv. 13, 42–50. https://doi.org/10.1016/j.cliser.2019.01.003.

Briley, L., Brown, D., Kalafatis, S.E., 2015. Overcoming barriers during the co-production of climate information for decision-making. Clim. Risk Manag. 9, 41–49. https://doi.org/10.1016/j.crm.2015.04.004.

Carr, E.R., 2013. Livelihoods as Intimate Government: reframing the logic of livelihoods for development. Third World Q. 34, 77–108. https://doi.org/10.1080/01436597.2012.755012.

Carr, E.R., Fleming, G., Kalala, T., 2015. Assessing Climate Service Needs in Kaffrine, Senegal: Livelihoods, Identity, and Vulnerability to Climate Variability and Change.

Carr, E.R., Goble, R., Onzere, S.N., Chiputwa, B., 2019. Synthesis Report: Improving the monitoring and evaluation of CIS to facilitate learning and improve outcomes. United States Agency for International Development, Washington D.C.

Carter, S., Steynor, A., Katharine, V., Visman, E., Waagsaether, K.L., 2019. Co-production in African weather and climate services.

Cash, D.W., Clark, W.C., Alcock, F., Dickson, N.M., Eckley, N., Guston, D.H., Jäger, J., Mitchell, R.B., 2003. Knowledge systems for sustainable development. Proc. Natl. Acad. Sci. U.S.A. 100, 8086–8091. https://doi.org/10.1073/pnas.1231332100.

CCAFS, 2015. The impact of climate information services in Senegal (No. 3), CGIAR Research Program on Climate Change, Agriculture and Food Security (CCAFS), Copenhagen, Denmark, CCAFS Outcome Study. CGIAR Research Program on Climate Change, Agriculture and Food Security (CCAFS), Copenhagen, Denmark.

Chiappori, P., Haddad, L., Hoddinott, J., Kanbur, R., 1993. Unitary versus collective models of the household: Time to shift the burden of proof?, World Bank. World Bank, Washington, D.C.

Chiputwa, B., Wainaina, P., Makui, P., Nakelse, T., Zougmoré, R., Ndiaye, O., 2019. Evaluating the Impact of the Multidisciplinary Working Group Model on Farmers' Use of Climate Information Services in Senegal. United States Agency for International Development, Washington, D.C.. https://www.climatelinks.org/sites/default/files/asset/document/2019_USAID_MercyCorps_Evaluating the Impact of the Multidisciplinary Working Group Model on Farmers%27 Use of CIS in Senegal.pdf.

Clarkson, G., Dorward, P., Osbahr, H., Torgbor, F., Kankam-Boadu, I., 2019. An investigation of the effects of PICSA on smallholder farmers' decision-making and livelihoods when implemented at large scale – The case of Northern Ghana. Clim. Serv. 14, 1–14. https://doi.org/10.1016/j.cliser.2019.02.002.

Dayamba, D.S., Ky-Dembele, C., Bayala, J., Dorward, P., Clarkson, G., Sanogo, D., Diop Mamadou, L., Traoré, I., Diakité, A., Nenkam, A., Binam, J.N., Ouedraogo, M., Zougmore, R., 2018. Assessment of the use of Participatory Integrated Climate Services for Agriculture (PICSA) approach by farmers to manage climate risk in Mali and Senegal. Clim. Serv. doi: 10.1016/j.cliser.2018.07.003.

Di Falco, S., Chavas, J.-P., 2009. On crop biodiversity, risk exposure, and food security in the highlands of Ethiopia. Am. J. Agric. Econ. 91, 599–611. https://doi.org/http://ajae.oxfordjournals.org/content/by/year.

Dilling, L., Lemos, M.C., 2011. Creating usable science: Opportunities and constraints for climate knowledge use and their implications for science policy. Glob. Environ. Chang. 21, 680–689. https://doi.org/10.1016/j.gloenvcha.2010.11.006.

Dinku, T., Block, P., Sharoff, J., Hailemariam, K., Osgood, D., del Corral, J., Cousin, R., Thomson, M.C., 2014. Bridging critical gaps in climate services and applications in africa. Earth Perspect. 1, 15. https://doi.org/10.1186/2194-6434-1-15.

Dinku, T., Cousin, R., Corral, J., Ceccato, P., Thomson, M.C., Faniriantsoa, R., Khomyakov, I., Vadillo, A., 2016. The ENACTS Approach: Transforming climate services in Africa one country at a time. World Policy Pap. 1–24.

Dinku, T., Thomson, M.C., Cousin, R., del Corral, J., Ceccato, P., Hansen, J., Connor, S.J., 2017. Enhancing National Climate Services (ENACTS) for development in Africa. Clim. Dev. 1–9 https://doi.org/10.1080/17565529.2017.1405784.

Dorward, P., Clarkson, G., Stern, D., 2015. Participatory Integrated Climate Services for Agriculture (PICSA): Field Manual, CGIAR. doi: 10.1007/s13398-014-0173-7.2.

Doss, C., 2013. Data Needs for Gender Analysis in Agriculture. IFPRI Discuss. Pap. 22. https://doi.org/10.1007/978-94-017-8616-4_3.

Doss, C.R., 1999. Twenty-five years of research on women farmers in Africa: Lessons and implications for agricultural research institutions with an annotated bibliography.

Doss, C.R., Morris, M.L., 2000. How does gender affect the adoption of agricultural innovations?: The case of improved maize technology in Ghana. Agric. Econ. (United Kingdom) 25, 27–39. https://doi.org/10.1111/j.1574-0862.2001.tb00233.x.

Douthwaite, B., Kuby, T., Van De Fliert, E., Schulz, S., 2003. Impact pathway evaluation: an approach for achieving and attributing impact in complex systems. Agric. Syst. doi: 10.1016/S0308-521X(03)00128-8.

Faure, G., Barret, D., Blundo-Canto, G., Dabat, M.-H., Devaux-Spatarakis, A., Le Guerroué, J.L., Marquié, C., Mathé, S., Temple, L., Toillier, A., Triomphe, B., Hainzelin, E., 2018. How different agricultural research models contribute to impacts: evidence from 13 case studies in developing countries. Agric. Syst. 165, 128–136. https://doi.org/10.1016/J.AGSY.2018.06.002.

Gunasekera, D., 2010. Use of climate information for socio-economic benefits. Procedia Environ. Sci. 1, 384–386. https://doi.org/10.1016/j.proenv.2010.09.025.

Haddad, L., Hoddinott, J., 1995. Does female income share influence household expenditures? Evidence from Cote D'Ivoire. Oxf. Bull. Econ. Stat. 57, 77–96.

Hansen, J.W., 2005. Integrating seasonal climate prediction and agricultural models for insights into agricultural practice. Philos. Trans. R. Soc. B Biol. Sci. 360, 2037–2047. https://doi.org/10.1098/rstb.2005.1747.

Hansen, J.W., Mason, S.J., Sun, L., Tall, A., 2011. Review of seasonal climate forecasting for agriculture in sub-Saharan Africa. Exp. Agric. doi: 10.1017/S0014479710000876.

Hansen, J.W., Vaughan, C., Kagabo, D.M., Dinku, T., Carr, E.R., Körner, J., Zougmoré, R. B., 2019. Climate services can support African farmers' context-specific adaptation needs at scale. Front. Sustain. Food Syst. 3, 1–16. https://doi.org/10.3389/fsufs.2019.00021.

Hassan, R., Nhemachena, C., 2008. Determinants of African farmers' strategies for adapting to climate change: Multinomial choice analysis. AfJARE 2, 83–104. https://doi.org/10.1007/s00267-008-9197-0.

Ingram, K.T., Roncoli, M.C., Kirshen, P.H., 2002. Opportunities and constraints for farmers of west Africa to use seasonal precipitation forecasts with Burkina Faso as a case study. Agric. Syst. 74, 331–349. https://doi.org/10.1016/S0308-521X(02)00044-6.

Kirchhoff, C.J., Esselman, R., Brown, D., 2015. Boundary organizations to boundary chains: prospects for advancing climate science application. Clim. Risk Manag. doi: 10.1016/j.crm.2015.04.001.

Lemos, M.C., Kirchhoff, C.J., Ramprasad, V., 2012. Narrowing the climate information usability gap. Nat. Clim. Chang. 2, 789–794. https://doi.org/10.1038/nclimate1614.

Lemos, M.C., Morehouse, B.J., 2005. The co-production of science and policy in integrated climate assessments. Glob. Environ. Chang. 15, 57–68. https://doi.org/10.1016/j.gloenvcha.2004.09.004.

Lo, H.M., Dieng, M., 2015. Impact assessment of communicating seasonal climate forecasts in Kaffrine, Diourbel, Louga, Thies and Fatick (Niakhar) regions in Senegal. CGIAR Program on Climate Change, Agriculture and Food Security (CCAFS), Wageningen, the Netherlands.

Luseno, W.K., McPeak, J.G., Barrett, C.B., Little, P.D., Gebru, G., 2003. Assessing the value of climate forecast information for pastoralists: Evidence from Southern Ethiopia and Northern Kenya. World Dev. 31, 1477–1494. https://doi.org/10.1016/S0305-750X(03)00113-X.

Maggio, G., Sitko., N.J., Ignaciuk, A., 2019. mallholder adaptive responses to seasonal weather forecasts. A case study of the 2015/16 El Niño Southern Oscillation in Zambia, FAO Agricultural Development Economics.

Magurran, A.E., 2004. Measuring Biological Diversity. Blackwell Pub, Maldan, MA.

Magurran, A.E., 1988. Ecological diversity and it's measurement / Anne E. Magurran. London : Croom Helm, 1988.

Mauser, W., Klepper, G., Rice, M., Schmalzbauer, B.S., Hackmann, H., Leemans, R., Moore, H., 2013. Transdisciplinary global change research: the co-creation of knowledge for sustainability. Curr. Opin. Environ. Sustain. doi: 10.1016/j.cosust.2013.07.001.

McNie, E.C., 2007. Reconciling the supply of scientific information with user demands: an analysis of the problem and review of the literature. Environ. Sci. Policy 10, 17–38. https://doi.org/10.1016/j.envsci.2006.10.004.

Meadow, A.M., Guido, Z., Ferguson, D.B., Wall, T., Horangic, A., Owen, G., 2015. Moving toward the Deliberate Coproduction of Climate Science Knowledge. Weather. Clim. Soc. 7, 179–191. doi: 10.1175/wcas-d-14-00050.1.

Moeletsi, M.E., Mellaart, E.A.R., Mpandeli, N.S., Hamandawana, H., 2013. The use of rainfall forecasts as a decision guide for small-scale farming in Limpopo Province, South Africa. J. Agric. Educ. Ext. 19, 133–145. https://doi.org/10.1080/1389224X.2012.734253.

Ndiaye, O., Moussa, A.S., Seck, M., Zougmore, R., Hansen, J., 2013. Communicating seasonal forecasts to farmers in Kaffrine, Senegal for better agricultural management. Hunger. Nutr. Clim. justice 4.

O'Brien, K., Sygna, L., Næss, L.O., Kingamkono, R., Hochobeb, B., 2000. Is Information Enough ? User Responses to Seasonal Climate Forecasts in Southern Africa. Oslo, Norway.

Ouedraogo, I., Diouf, N.S., Ouédraogo, M., Ndiaye, O., Zougmoré, R., 2018. Closing the gap between climate information producers and users: assessment of needs and uptake in Senegal. Climate 6, 13. https://doi.org/10.3390/cli6010013.

Pathak, J., Lúcio, F.D.F., 2018. The global framework for climate services adaptation programme in Africa. Resilience 217–226. https://doi.org/10.1016/B978-0-12-811891-7.00017-7.

Patt, A., Suarez, P., Gwata, C., 2005. Effects of seasonal climate forecasts and participatory workshops among subsistence farmers in Zimbabwe. Proc. Natl. Acad. Sci. 102, 12623–12628. https://doi.org/10.1073/pnas.0506125102.

Porter, J.J., Dessai, S., 2017. Mini-me: Why do climate scientists' misunderstand users and their needs? Environ. Sci. Policy 77, 9–14. https://doi.org/10.1016/j.envsci.2017.07.004.

Prokopy, L.S., Carlton, J.S., Haigh, T., Lemos, M.C., Mase, A.S., Widhalm, M., 2017. Useful to usable: developing usable climate science for agriculture. Clim. Risk Manag. 15, 1–7. https://doi.org/10.1016/j.crm.2016.10.004.

Quisumbing, A.R., Maluccio, J.A., 2003. Resources at marriage and intrahousehold allocation: evidence from Bangladesh, Ethiopia, Indonesia, and South Africa. Oxf. Bull. Econ. Stat. 65, 283–328.

Rao, K.P.C., Hansen, J., Njiru, E., Githungo, W.N., Oyoo, A., 2015. Impacts of seasonal climate communication strategies on farm management and livelihoods in Wote, Kenya. CCAFS Work. Pap. 42 pp.

Roncoli, C., Ingram, K., Kirshen, P., 2002. Reading the rains: local knowledge and rainfall forecasting in Burkina Faso. Soc. Nat. Resour. 15, 409–427. https://doi.org/10.1080/08941920252866774.

Roncoli, C., Jost, C., Kirshen, P., Sanon, M., Ingram, K.T., Woodin, M., Somé, L., Ouattara, F., Sanfo, B.J., Sia, C., Yaka, P., Hoogenboom, G., 2009. From accessing to assessing forecasts: An end-to-end study of participatory climate forecast dissemination in Burkina Faso (West Africa). Clim. Change 92, 433–460. https://doi.org/10.1007/s10584-008-9445-6.

Roudier, P., Muller, B., D'Aquino, P., Roncoli, C., Soumaré, M.A., Batté, L., Sultan, B., 2014. The role of climate forecasts in smallholder agriculture: Lessons from participatory research in two communities in Senegal. Clim. Risk Manag. 2, 42–55. https://doi.org/10.1016/j.crm.2014.02.001.

Roudier, P., Sultan, B., Quirion, P., Baron, C., Alhassane, A., Traoré, S.B., Muller, B., 2012. An ex-ante evaluation of the use of seasonal climate forecasts for millet growers in SW Niger. Int. J. Climatol. 32, 759–771. https://doi.org/10.1002/joc.2308.

Rubin, D.B., 1974. Estimating causal effects of treatments in randomized and nonrandomized studies. J. Educ. Psychol. 66, 688.

Stats4SD, 2017. Evaluation of Climate Services Interventions in the GFCS Adaptation Programme for Africa, Beneficiary Assessment Final Evaluation Summary Report.

Tall, A., Coulibaly, J.Y., 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. Clim. Serv. 0–1 https://doi.org/10.1016/j.cliser.2018.06.001.

Tarhule, A., Lamb, P.J., 2003. Climate research and seasonal forecasting for West Africans. Bull. Am. Meteorol. Soc. 84, 1741–1759. https://doi.org/10.1175/BAMS-84-12-1741.

Tesfaye, A., Hansen, J., Radeny, M., Solomon, D., 2018. Estimating the economic benefits of alternative options for investing in agricultural climate services in Africa: Review of methodologies. (No. 223), CCAFS Working Paper. CGIAR Research Program on Climate Change, Agriculture and Food Security (CCAFS), Wageningen, the Netherlands.

Vaughan, C., Dessai, S., 2014. Climate services for society: Origins, institutional arrangements, and design elements for an evaluation framework. Wiley Interdiscip. Rev. Clim. Chang. 5, 587–603. https://doi.org/10.1002/wcc.290.

Vaughan, C., Hansen, J., Roudier, P., Watkiss, P., Carr, E., 2019. Evaluating agricultural weather and climate services in Africa: Evidence, methods, and a learning agenda. Wiley Interdiscip. Rev. Clim. Chang. 586 https://doi.org/10.1002/wcc.586.

Vedeld, T., Mathur, M., Bharti, N., 2019. How can co-creation improve the engagement of farmers in weather and climate services (WCS) in India. Clim. Serv. xxx, xxxx. doi: 10.1016/j.cliser.2019.100103.

Vincent, K., Daly, M., Scannell, C., Leathes, B., 2018. What can climate services learn from theory and practice of co-production? Clim. Serv. doi: 10.1016/j.cliser.2018.11.001.

West, J.J., Daly, M.E., Yanda, P.Z., 2018. Evaluating User Satisfaction with Climate Services in Tanzania 2014-2016. Oslo, Norway.

Ziervogel, G., Bithell, M., Washington, R., Downing, T., 2005. Agent-based social simulation: a method for assessing the impact of seasonal climate forecast applications among smallholder farmers. Agric. Syst. 83, 1–26. https://doi.org/10.1016/j.agsy.2004.02.009.

Zougmoré, R., Partey, S., Ouédraogo, M., Omitoyin, B., Thomas, T., Ayantunde, A., Ericksen, P., Said, M., Jalloh, A., 2016. Toward climate-smart agriculture in West Africa: a review of climate change impacts, adaptation strategies and policy developments for the livestock, fishery and crop production sectors. Agric. Food Secur. 5, 26. https://doi.org/10.1186/s40066-016-0075-3.