EVALUATING THE IMPACT OF THE MULTIDISCIPLINARY WORKING GROUP MODEL ON FARMERS' USE OF CLIMATE INFORMATION SERVICES IN SENEGAL

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Cover Photo: A focus group discussion on CIS in Kaffrine, Senegal. Credit: Jeanne Coulibaly

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Evaluating the Impact of the Multidisciplinary Working Group Model on Farmers' Use of Climate Information Services in Senegal

Climate Information Services Research Initiative: Piloting Quantitative Evaluation Approaches On The Multidisciplinary Working Group in Senegal

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ACRONYMS AND ABBREVIATIONS

ADCMA	Automated Data Collection, Management and Analysis
AGRHYMET	Agriculture, Hydrology and Meteorology
ANACIM	National Meteorological Agency
ANCAR	National Agricultural and Rural Council Agency
ARC	African Risk Capacity
ATE	Average Treatment Effect
ATT	Average Treatment Effect on the Treated
ATU	Average Treatment Effect on the Untreated
AU	African Union
CCAFS	CGIAR Research Program on Climate Change, Agriculture and Food Security
CI	Conditional independence
CIS	Climate information services
CISRI	Climate Information Services Research Initiative
CNAAS	National Agricultural Insurance Company of Senegal
CRS	Catholic Relief Services
CSE	Ecological Monitoring Center
DA	Department of Agriculture
ENACTS	Enhancing National Climate Services
FEWS-NET	Famine Early Warning System Network
GAP	Population Adoption Gap
GFCS-APA	Global Framework for Climate Services Adaptation Program in Africa
GDP	Gross Domestic Product
HURDL	Humanitarian Response and Development Lab

ICRAF	World Agroforestry Centre
ICT	Information and Communication Technologies
IPCC	Intergovernmental Panel on Climate Change
IRI	International Research Institute for Climate and Society
ISRA	Institute of Agricultural Research of Senegal
JEA	joint exposure and adoption
LATE	Local Average Treatment Effect
MLE	Maximum Likelihood Estimation
MWG	Multidisciplinary Working Group
NGO	Non-Governmental Organization
OH	Outcome Harvesting
PICSA	Participatory Integrated Climate Services for Agriculture
PSB	Population Selection Bias
SSA	sub-Saharan Africa
SMS	short message services
ToC	Theory of Change
USAID	United States Agency for International Development
URAC	Union des Radios Associatives et Communautaires du Senegal
WA	West Africa
WRSI	Water Requirement Satisfaction Index

EXECUTIVE SUMMARY

Climate variability and change have been identified as major threats to important sectors that drive economic growth and sustainable development in Africa. The provision of tailor-made climate information services is increasingly gaining importance. It has been widely touted as a vital adaptation and mitigation strategy against the adverse effects of climate change and variability. While various co-design and co-production models have been used to tailor climate information services (CIS) in different parts of the world, there is hardly any rigorous evidence assessing their effectiveness in meeting users' needs.

The main objective of this study is to assess the effectiveness of the Multi-disciplinary Working Group (MWG) — a participatory model that fosters interactions among different actors who produce, translate, transfer and use CIS, to ensure that climate information is appropriately tailored to meet the needs of end-users. The MWG model, illustrated in Figure 3.2, was first piloted in Senegal in 2011. More specifically, we analyze the effectiveness of the MWG in improving farmers' awareness, access and uptake of CIS, as well as how this information is used to inform decision-making by users. This study uses a unique sampling design that aided the categorization of farmers into four broad comparison groups that are not mutually exclusive. These comprise: (i) farmers exposed to the MWG, (ii) farmers not exposed to the MWG, (iii) farmers using CIS and (iv) farmers not using CIS. We consider the use and uptake of different types of CIS, i.e., seasonal forecasts on the total amount of rainfall onset and cessation; weather forecasts for 2-3 days and 10 days; and instant forecasts of extreme weather events. The data, consisting of interviews with 795 smallholder farmers in Senegal, was collected using an innovative automated data collection and management system that is illustrated in Figure 4.1. A more detailed description of the sub-samples is illustrated in Figure 4.4. We complemented this sampling design by using rigorous econometric techniques to account for selection bias, which is a ubiquitous problem in impact evaluation studies that try to establish causal links between an intervention and the resulting impacts on users. More specifically, we used the Average Treatment Effect (ATE) framework (illustrated in the methodology section) to take into account estimation bias that may result from farmers not having equal access to information and knowledge on the different CIS.

The descriptive statistics section generally points to a positive and significant association between farmers exposed to MWG and their awareness, access, and use of CIS using classical estimation approaches. However, we also demonstrate that such classical approaches — which assume all sampled farmers have full information and access to a technology — often leads to biased estimates. It is, therefore, necessary to correct for such bias by using appropriate models that account for selection bias when estimating CIS adoption rates.

Building on the descriptive statistics, the first analytical section uses an econometric model — the counterfactual ATE framework — that corrects for the bias caused by unequal access to CIS information in terms of awareness and access among the sampled households. One main finding is that in locations where the MWG is operational, there were significantly more farmers who were exposed to CIS in terms of awareness and access. The results further show that the presence of an MWG significantly increases farmers' uptake and use of CIS by approximately 30%. The CGIAR Research Program on Climate Change, Agriculture and Food Security (CCAFS) estimates that around 740,000 rural households in Senegal have been exposed to CIS (CCAFS 2015). Using this estimate and results from the adoption model, we predict that if the MWG model were scaled out to all parts of rural Senegal, the 30% increase in CIS uptake would be equivalent to about 205,000 households. Similarly, the population adoption gap for CIS — which measures the unmet demand for CIS resulting from households' lack of awareness and/or access — is estimated to decline from 10% (approximately 81,000 households) to 5% (approximately 41,000 households) when the MWG is introduced. These findings have significant policy implications in that scaling the MWG model has great potential in increasing the uptake and use of CIS in Senegal.

The second analytical section goes deeper into assessing the effectiveness of MWGs in influencing farmers' uptake and use of CIS. It also covers the resulting impact on behavioral outcomes and farm management practices, using an instrumental variable to correct for selection bias. Results indicate that the presence of an MWG influences behavioral changes in farming decisions for the different types of CIS used. For example, in locations where farmers are exposed to MWGs, there is a 25% higher chance that they will use total accumulated rainfall forecast for the season to inform their farming decisions. Farmers revealed that they mostly use seasonal forecasts of total accumulated rainfall to guide them in making decisions such as the crop types and varieties to consider growing for that season. Similarly, farmers exposed to the MWG used seasonal forecast of onset of rains to inform their decisions on timing of planting and land preparation, while the 10-day forecast was used to inform decisions on fertilizer use. When considering the link between use of seasonal forecasts and observed farm management practices, we find that the use of seasonal forecasts was generally associated with a higher proportion of farmers using improved seed, fertilizers and manure, but negatively with crop diversity in MWG locations.

Based on the findings of this case study, we highlight two broad lessons. First, the positive association between the existence of the MWG model and farmers' awareness, access and use of CIS, as well as in influencing farm management decisions is very encouraging. This suggests that participatory approaches in the provision of tailored climate information and advisory services can lead to higher uptake and use among end-users. Second, these results demonstrate that the MWG model may well be instrumental in increased uptake of CIS in Kaffrine, which could offer lessons in the design, implementation, monitoring and evaluation, and scaling of similar initiatives to the rest of Senegal and other countries in Africa and beyond. It is important to highlight that this study does not analyze the impact of CIS use on higher-order welfare outcomes such as household food security, income, or poverty which requires long-term seasonal data collected from the same farms. As our analysis is based on cross-sectional data, exploring these higher-order impacts was beyond the scope of our data.

1
INTRODUCTION AND BACKGROUND INFORMATION

> 'Indeed, while the development of climate services generally occurs in the operational realm, research is needed to advance relevant climate and related science in ways that directly address the persistent challenges that limit use and utility'. .....Vaughan et al. 2016

Climate variability and change has been identified as major threats to key sectors that drive economic growth and sustainable development in Africa. The Intergovernmental Panel on Climate Change (IPCC) forecasts that global mean surface temperatures could increase by about 2.6 - 4.8 °C by the late twenty-first century in addition to seasonal and spatial variations in rainfall patterns with increased incidences of droughts and floods (IPCC 2014). This increasing variability in weather patterns has put profound pressure on agricultural systems particularly in sub-Saharan Africa (SSA), which remains the most important sector in driving economic growth and reducing poverty. The smallholder agricultural sector in SSA is estimated to support almost two-thirds of the population in the region (Rockström et al. 2014), with most of it being rain-fed and characterized by limited use of improved technology. This population is characterized by a high prevalence of poverty and food insecurity, low levels of economic diversification and a general lack of adaptation and mitigation strategies (Hansen 2005; Alfani et al. 2015; Fischer et al. 2005). This makes the agricultural sector one of the most vulnerable to climate change in the region (IPCC 2014), and highlights the inherent need for long-term planning based on climate projections to help reduce risks posed by climate variability (Singh et al. 2017).

Climate information services (CIS) — which involve the production, translation, transfer and integration of scientific information for decision-making — is widely regarded as a potential strategy that could help smallholder farmers in SSA to manage the risks associated with climate variability and change through informed farming decisions (Patt, Suarez, and Gwata 2005; Roncoli et al. 2009; Hansen et al. 2011; Roudier et al. 2014; Collier and Dercon 2014; Vaughan and Dessai 2014). Yet, in reality, despite continuous advances in climate modeling and prediction, and improvements in seasonal lead time (Hansen 2002), Africa's capacity for climate observation is not only insufficient, but marked by 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, knowledge, access and capacity to use 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). Even in cases where farmers are well informed and are willing and able to make the adoption decision, a majority of those with such a positive demand for new technologies may fail to realize the full benefits of the technology due to several other constraints (Shiferaw, Kebede, and You 2008;

Shiferaw et al. 2015; Croppenstedt, Demeke, and Meschi 2003). Some socio-economic factors affecting the uptake of climate information services in Africa include socio-cognitive constraints (cultural components that inhibit an individual's learning and interpretation of a new technology) (Singh et al. 2017; Gunasekera 2010), poor information-dissemination channels between producers of climate information and users (Lemos, Kirchhoff, and Ramprasad 2012; Gunasekera 2010; Singh et al. 2017), and inadequate institutional capacity to effectively deliver and use climate information (Singh et al. 2017; Tall et al. 2014).

In recent years, a lot of attention has been paid to improving the provision of climate information services by ensuring that it is tailored to meet the users' needs. Ngari et al. 2016 illustrate that the value chain of weather and climate services is long and consists of interdependence across multiple actors, such as observers, modelers, forecasters, disseminators and other intermediaries, with farmers on the receiving end of the information spectrum. According to Cash et al. 2003, information is likely to be effective in influencing the evolution of social responses to public issues to the extent that the information is not only perceived as credible by stakeholders but also as salient (relevant) and legitimate. First, *salient* in that the new knowledge is perceived as relevant, as well as important to existing knowledge sources; second, *credible* in that the knowledge is perceived as valid, reliable, trust-worthy and backed by evidence; and third, *legitimate* in that the research considered stakeholders' divergent values, beliefs, knowledge contexts, and interests through an open, transparent, and unbiased process. Carr, Fleming, and Kalala 2016 contend that climate information that lacks credibility and is not tailor-made to suit the users' needs, and hence cannot be acted upon, does not add value to farmers' decision-making, but rather may be counterproductive to existing decision-making processes and reduce the efficacy of existing livelihoods strategies. Patt, Ogallo, and Hellmuth 2007 emphasize that users should have access to local historical data which provides information on the range of actual rainfall each tercile represents. This knowledge should be incorporated into a probabilistic decision-making framework.

A commonly cited approach to ensure that climate information services meet Cash et al. 2003 criteria, and hence is useful to decision-makers, is through highly integrated and iterative methods for co-designing and co-producing CIS. This involves leveraging the expertise of different actors to ensure that climate services are appropriately tailored to meet the needs of end-users (Singh et al. 2017; Lemos and Morehouse 2005; Dilling and Lemos 2011). However, this approach is costly to sustain due to the high financial, human and institutional resources required to sustainably maintain the interactions of the different actors (Lemos and Morehouse 2005). Examples of co-production efforts that enable end-users, like farmers, to integrate CIS into their decision-making include the Enhancing National Climate Services initiative (ENACTS), which was implemented in countries like Ethiopia, Tanzania and Mali (Dinku et al. 2016), the Participatory Integrated Climate Services for Agriculture (PICSA) approach (Dorward, Clarkson, and Stern 2015), which was implemented in countries such as Rwanda and Tanzania, as well as other efforts under the Global Framework for Climate Services Adaptation Program in Africa (GFCS-APA) implemented in various parts of the continent (Pathak and Lúcio 2018).

There is a lack of rigorous evidence on assessment of such co-production models, particularly on influencing uptake of CIS by end-users. The main objective of this study is to

assess the effectiveness of the Multi-disciplinary Working Group (MWG) — a participatory model that fosters interactions among different actors who produce, translate, transfer and use CIS, to ensure that climate information is appropriately tailored to meet the needs of end-users. The MWG model was first piloted in Senegal in 2011. This study will analyze the effectiveness of MWGs in improving farmers' awareness, access and uptake of CIS, as well as how this information is used to inform decision-making by users. This will be done in two ways. The first is to estimate the CIS diffusion and adoption rates and their main determinants — with a focus on the impact of the MWG model — using an Average Treatment Effect (ATE) framework that accounts for selection bias. The second is to assess the effectiveness of the MWG model in influencing farmers' uptake and use of CIS, and the resulting impact on behavioral outcomes and farm management practices using an instrumental variable approach to account for selection bias.

To achieve these objectives, we use a unique dataset collected during the 2017-18 agricultural season, under the USAID Climate Information Services Research Initiative (CISRI)[1]. Within its Learning Agenda on Climate Information Services in Sub-Saharan Africa, USAID has funded CISRI, which has used the following guiding questions in efforts to improve climate information services:

1. What does existing research reveal about factors influencing farmers' access and use of climate information services, and the circumstances under which climate information services benefit livelihood outcomes?
2. What is the range of challenges farmers face in accessing and using climate information services in different socio-economic contexts? Are the interventions currently in use to overcome these challenges effective?
3. What are the best methodologies for evaluating the impact of climate information services?
4. How can learning and evidence be incorporated into processes aimed at improving the design, implementation and evaluation of climate information services efforts in the future?

CISRI consists of four components and this study contributes to Work Stream 3, which involves piloting quantitative methodologies to evaluate the effectiveness of existing climate information services programs in Senegal and Rwanda in improving farmers' awareness, access and uptake. This study adds value to extant literature and the CISRI learning agenda from a methodological and an empirical perspective in assessing the uptake and use of CIS. First, the majority of past studies which focused on adoption of agricultural innovations, particularly on climate information services, relied on descriptive statistics in estimating uptake and use rates (e.g., Bolson and Broad 2013; Coulibaly et al. 2015; Coulibaly et al. 2017a), while others that focused on factors affecting uptake and use mostly use classical adoption models like logit, probit and tobit specifications (e.g., Hassan and Nhemachena 2008; Bryan et al. 2009; Deressa et al. 2009; Fosu-Mensah, Vlek, and MacCarthy 2012; Partey et al. 2018). In both cases, there was an inherent assumption that all farmers in the study population were exposed to complete information about the technology, and could make informed and rational adoption decisions. Yet in most

[1]CISRI draws on the expertise of its consortium partners: Clark University's Humanitarian Response and Development Lab (HURDL); Columbia University's International Research Institute for Climate and Society (IRI); CGIAR Research Program on Climate Change, Agriculture and Food Security (CCAFS); World Agroforestry Centre (ICRAF); Catholic Relief Services (CRS); Practical Action; and Mercy Corps.

instances, particularly in SSA, this assumption does not hold true due to constraints such as limited access to credible information, institutional failures, socio-economic constraints and biophysical factors; all these limit technology adoption among smallholder farmers. There have been very few adoption studies that attempted to appropriately control for the biases that occur when a new technology or innovation is first introduced. For example, biases that prevent all potential users from being able to make informed adoption decisions on a technology include not being aware, not having the ability to access and not having full knowledge of the costs and benefits from use.

Several ex-ante impact evaluation studies have been conducted to estimate the expected value of CIS (Ziervogel et al. 2005; Hansen et al. 2009; Sultan et al. 2010; Roudier et al. 2012; Roudier et al. 2016; Amegnaglo et al. 2017). These studies use different approaches to quantitatively estimate the benefits of CIS such as the general equilibrium model, stated preferences method, contingent valuation techniques, simulations and benefit transfer techniques (Vaughan et al. 2017; Tesfaye et al. 2018; Bruno Soares, Daly, and Dessai 2018). The majority of these methods provide information on expected potential value of CIS and rely on the assumption that climate information services will be delivered without constraints in design, communication and context-relevance.

Beyond focusing on outputs (i.e., awareness, access and use of CIS), one question that has received much less attention in the literature is whether tailor-made climate information models actually influence farmers' decision-making processes (outcomes or intermediate impacts) and subsequently affect their livelihoods through, for example, increased agricultural yields, increased incomes and improved nutrition (higher-order impacts). The evidence base on this, particularly using rigorous evaluation techniques, remains scant and can be attributed to several constraints highlighted in the methodology section.

This study makes two contributions to the existing evidence base on use of climate information services. 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 ex-post evaluation. Empirical evidence in assessing CIS 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 CIS co-production model in the diffusion of CIS, something that is also very rare in existing literature.

The rest of the manuscript is organized as follows: section 2 reviews existing CIS adoption and impact studies; section 3 presents the study context and a description of the MWG co-production model in Senegal, how it was rolled out and the hypothesized impact pathways. Section 4 presents the conceptual and analytical frameworks of the study, sampling strategy and empirical models used in this study. Section 5 focuses on descriptive statistics, while the final two sections are analytical sections. Section 6 focuses on factors that determine farmers' uptake and use of CIS, with special attention to the contribution of MWGs, and while controlling for awareness and access exposure bias. Section 7 focuses more on the effectiveness of MWGs in influencing farmers' uptake and use of CIS, and the resulting impact on behavioral outcomes and farm management practices, while controlling for selection bias using an instrumental variable approach. The

study's concludes with section 8 summarizes the key findings, policy insights for climate change development practitioners and some caveats to consider based on the design and findings.

2
REVIEW OF EMPIRICAL STUDIES ON USE OF CIS AND OTHER AGRICULTURAL INNOVATIONS

> 'Several fundamental challenges complicate the rigorous evaluation of climate service interventions relative to purely agricultural technologies. These challenges have thus far frustrated rigorous assessments of the value of climate services in agriculture.' .....Tall, Coulibaly, and Diop 2018

In this section, we review existing empirical evidence, which we divide into two broad strands in line with the main objectives of this study. The first strand looks at the adoption of agricultural innovations in general. Innovations are defined as new methods, customs or devices used to perform a new task (Sunding et al. 2001). Technology transfer, diffusion and adoption of innovations are the processes through which innovations get to the users for the desired outcome. Diffusion of technology describes how innovation spreads through a population. It may consider factors like time and social pressures to explain the process of how a population adopts, adapts to, or rejects a particular innovation. Diffusion theory takes a macro-perspective on the spread of innovation across time (Rogers 1995; Sunding et al. 2001). The diffusion of new technologies is a key contributor to economic growth, and differences in technology use account for much cross-country inequality (Comin and Hobijn 2010). Adoption of a technology describes the choice an individual makes to either accept or reject a particular innovation. Adoption theory is a micro-perspective on change, focusing on if and when a particular individual will start using an innovation (Sunding et al. 2001). Technology transfer, on the other hand, refers to the application of information into use. In light of this, technology encompasses information, including skills and knowledge (Rogers 1995; Bolson and Broad 2013). Following this definition, climate information can be viewed as a transferable technology in which case awareness and complete knowledge of the information are necessary in order for the innovation to be considered useful.

Over the years, numerous studies on technology adoption have been conducted in developing countries (Feder, Just, and Zilberman 1985; Adesina and Baidu-Forson 1995; Doss and Morris 2000; Marenya and Barrett 2007; Kabunga, Dubois, and Qaim 2012; Arslan et al. 2014). Technology adoption studies mainly focus on estimating adoption rates and understanding the relationship between technology adoption, its intensity and relevant socioeconomic, climatic and policy variables. However, these studies assume that farmers have complete information about these technologies (Shiferaw et al. 2015), and this yields biased estimates of both adoption rates as well as determinants of adoption when applied to a population that is not fully aware of the technology (Simtowe, Asfaw, and Abate 2016). The few studies that control this type of non-random exposure are almost exclusively focused on the adoption of improved crop varieties, for example, the case of

rice in Benin (Diagne and Demont 2007; Dandedjrohoun et al. 2014) and Nigeria (Awotide et al. 2013); bananas in Kenya (Kabunga, Dubois, and Qaim 2012); pigeonpea in Malawi (Simtowe, Asfaw, and Abate 2016); groundnuts in Uganda (Shiferaw et al. 2015); and improved maize storage technologies in Benin (Adegbola and Gardebroek 2007). There are two studies in this strand that do not focus on a specific commodity. One is Ouma et al. 2013, who look into the adoption of soil and fertility management and integrated pest management in Burundi, Democratic Republic of Congo and Rwanda, and the other is Diagne and Cabral 2005 who focus on adoption of improved inputs, modern agricultural practices and modern management using a randomized control trial (RCT) evaluation design. Kabunga, Dubois, and Qaim 2012, whose empirical framework we follow closely in this study, emphasize a need to control for awareness and knowledge exposure bias in their assessment of adoption of tissue culture bananas in Kenya. Awareness exposure means that a user is aware of the technology; knowledge exposure means that in addition to being aware of the technology the user also has more information and knowledge about the use of the technology(Kabunga, Dubois, and Qaim 2012). In this case, being aware of a technology is a necessary condition for adoption, but it is not sufficient in knowing how to use the technology successfully and this may result in knowledge exposure bias (Kabunga, Dubois, and Qaim 2012). This distinction is particularly important when dealing with knowledge-intensive technologies such as CIS in that while most farmers might have the awareness, not all of them will have complete and accurate knowledge to be able to effectively use this information for decision making. For such technologies, knowledge exposure bias may be even higher than awareness bias. All these studies acknowledge that adoption of agricultural innovations is a two-step process; 1) awareness of the technology and 2) uptake and use of the technology. They empirically show that when a technology is new and the target population is not universally exposed to it, the observed sample adoption rate is a biased estimator of the true population adoption rate.

The second strand is around studies that specifically focus on the uptake and use of CIS and factors that enable or inhibit users and the implications on livelihoods (e.g., Luseno et al. 2003; Roncoli et al. 2009; Lemos, Kirchhoff, and Ramprasad 2012; Coulibaly et al. 2015; Coulibaly et al. 2017a; Coulibaly et al. 2017b; Singh et al. 2017; Ouedraogo et al. 2018). Most of this literature uses qualitative or quantitative survey designs or a combination of both. For example, Bolson and Broad 2013 looked at determinants of technology transfer in the case of seasonal climatic forecasts among early adopters in South Florida. They found that in-house climate expertise, innovative agency culture, social networks linking water and climate science researchers, and policy windows were critical in enabling adoption. Similarly, by applying behavioral and experimental economics, Serra and Mckune 2016 went further to show how psychological factors including ideologies and social norms affect the ability of farmers in Senegal to process climate information and evaluate risks. Thus, these factors should be taken in to account when designing any climate information service.

Use of climate information services has been shown to affect farmers' practices and behaviors. Much of the existing literature in sub-Saharan Africa focuses on the effect of seasonal forecasts. Upon receiving and using seasonal forecasts, farmers have been shown to plant early-maturing and drought-tolerant crops or varieties (Ingram, Roncoli, and Kirshen 2002; Hassan and Nhemachena 2008). Hassan and Nhemachena 2008 also observed the following behavioral changes among farmers in 11 African countries classified as arid areas; crop diversification, varying the planting and harvesting dates,

diversifying to non-farm activities, uptake of soil and water conversation techniques and use of irrigation. Other adaption strategies that were observed across different countries in SSA include; increased or reduced use of fertilizers, storing more food, reducing the amount planted and intercropping (O'Brien et al. 2000). Further, Tarhule and Lamb 2003 observed that farmers in West Africa changed crop types, reduced herd sizes, changed planting time and grazing methods, and some even relocated to other places in response to information on seasonal forecasts. According to Ziervogel et al. 2005, some farmers in Lesotho changed their cropping densities. Luseno et al. 2003 studied behaviors among pastoralist communities in Kenya and Ethiopia and observed that some of the farmers adjusted their cultivation choices since the forecast information disseminated was more on crops than on livestock. In addition, Roudier et al. 2012 notes that benefits from seasonal forecasts mostly depend on the type of season, whether it is good or bad. Lo and Dieng 2015 assessed the impact of seasonal climate forecasts on yields in Senegal using test plots. In this case, CIS were used to make decisions regarding a specific plot of land throughout the test plots season, after which yields from the test plot are compared to those of plots where more traditional practices were employed. If well designed, test plots have the advantage of providing a counterfactual, capturing decision-making and potentially overcoming challenges of farmer recall and the elicitation of sensitive economic information (Vaughan et al. 2017). A major challenge with using test plots is that decisions that small-scale farmers make may not compare with those that agronomists make in the test plots.

Patt, Suarez, and Gwata 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. Maini and Rathore 2011 conducted an impact assessment of weather forecast information on yield and profitability following a pilot study of 80 farmers in India. The approach used was to calculate the differences in the outcomes between farmers who received the forecast information and those who did not. The shortcoming with this approach is that it does not control for confounding factors. Coulibaly et al. 2017a assessed perceived impacts of climate information on knowledge, attitudes and practice in Rwanda. Respondents were asked to rank each given statement on CIS with varying intensities based on a Likert scale. Roncoli, Ingram, and Kirshen 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 lack of access to necessary inputs and aversion to risk. Other studies that estimated ex-post impact of CIS using household surveys include (Ouedraogo et al. 2018), which assessed the effects of using seasonal climate forecasts on yields in Burkina Faso; Rao et al. 2015 assessed the effect of climate communication strategies on farmers yields in Kenya; (Anuga and Gordon 2016), which estimated the effects of accessing climate information on yields in Ghana; and (Stats4SD 2017), which estimated the impact of CIS in Malawi and Tanzania. Most of these studies have demonstrated the positive effects of CIS on different livelihood outcomes. However, they do not control for selectivity bias between groups that are exposed to CIS and those not exposed. Additionally, the studies assume a direct link between CIS and livelihood outcomes, but in reality, CIS influences

livelihood outcomes through other pathways such as the adoption of certain seed varieties or different farm management practices.

From this review of literature, we find that there is very limited empirical evidence that appropriately controls for selection bias caused by asymmetries in information and access exposure when assessing the use and uptake of CIS. Second, there is very limited work that investigates the link between farmers' uptake of CIS and the resulting impact on farmers' livelihoods.

3
THE MWG MODEL IN KAFFRINE, SENEGAL

> 'The lesson is that the process of local knowledge learning from science, and science learning from local knowledge, is iterative. It is important to invest time in building trust and a mutually respectful learning.'.....Ndiaye et al. 2013

3.1 Country profile

Senegal is a predominantly rural economy, where rain-fed production systems are the key drivers for economic growth. It is among the fastest growing economies in Africa and had a gross domestic product (GDP) growth rate of 6.7% in 2016 (Loayza, Toure, and Niane 2018). However, in spite of the general decline in poverty levels in Senegal (47% in 2010) due to economic growth, the poverty rate among the rural population was still higher, approximately 51% in the same year (Loayza, Toure, and Niane 2018). Agricultural and livestock production are the main economic activities in Senegal, representing 17.5% of the GDP and employing 69% of the population directly and indirectly (FAO, 2015). Although, the agricultural sector accounts for a relatively smaller share of the Senegalese economy, it is key to poverty reduction as it represents a major source of employment and income for poor households who are mostly located in rural areas. The country's agricultural sector grew at an average rate of 3.2% between 2000 and 2016, but volatility around that average was large (Loayza, Toure, and Niane 2018). The significant fluctuations in agriculture growth were mainly as a result of weather and climatic hazards which heavily affected pastoralism and rain-fed crops. Weather is one of the most important production risks in Senegal due to moisture stress caused either by erratic rainfall, early cessation of rains, delayed onset of rains, extreme events or extended drought. More than 40% of the variation in national crop yields can be attributed simply to the variation in annual rainfall amounts (D'Alessandro et al. 2015). Hence, for Senegal to achieve and maintain high output growth more efforts are needed to protect the agriculture sector against climatic variability and enhance livelihood resilience in rural areas.

In Senegal, rainfall is the key factor that determines agricultural production as more than 95% of land cultivated is under rain-fed conditions. The agricultural economy is characterized by the dominance of smallholder farmers cultivating millet, sorghum, groundnuts, maize and rice for subsistence. To adapt to the weather and climate variability, farmers in West Africa use various indigenous and modern coping strategies such as soil and water conservation practices, water harvesting techniques and, more recently, climate information services. While CIS has the potential to provide farmers with timely weather information to help them make appropriate decisions in risk management, most of the

initiatives on CIS dissemination in West Africa have failed due to a mismatch between what scientists produce as forecasts and what farmers need at the local level (Ouedraogo et al. 2018; Singh et al. 2017).

Senegal is characterized by a hot semi-arid climate with a short rainy season from mid-May to early November, followed by a dry season between November and May. Figure 3.1 presents a summarized assessment of the 2016-2017 and 2017-2018 agricultural seasons (ARC 2017; ARC 2016). The African Risk Capacity (ARC) is a specialized agency of the African Union (AU) with the mandate of developing a risk pooling and transfer instrument designed to improve the capacity of AU Member States to manage extreme weather events and natural disaster risks (e.g. droughts and flooding). The modeling is run using *Africa RiskView* software which uses satellite-based rainfall information to estimate the costs of responding to drought for purposes of insurance payouts.

Season	Rainfall outlook	Drought
2017-2018	**National level**: Comparison of the cumulative rainfall received in 2017 to the long term mean (1983-2016) at the pixel level reveals that most parts of Senegal received between 110% and 150% of their long-term average, implying that most regions of Senegal received above average rainfall during the 2017 season, **Surveyed districts**: Total cumulative rainfall in the central regions of Fatick, Kaolack, Kaffrine and Tambacounda ranged from 600mm to 800mm.	**National level**: The final end of season Water Requirement Satisfaction Index (WRSI) for the 2017 season shows that 95% to 100% of crop water requirements were met for the southern and central regions of Senegal a pointer of adequate precipitation. Comparison of the end of season WRSI with the benchmark (median WRSI for the previous five years) indicates that the final WRSI in 2017 was more than 110% of the median of the previous five years in the central parts and 90%-110% of the median in the western and southern parts of Senegal. The overall performance of the 2017 cropping season was modelled as better than average by Africa RiskView in most parts of Senegal **Surveyed districts**: In the western regions of Thies, Fatick and Diourbel, the final WRSI ranged from mediocre to average based on Africa RiskView modelling.
2016-2017	**National level**: Average to above average cumulative rainfall at national level, with the exception of central Senegal, where rainfall was 20-50% below the 1983-2015 average. Poor spatial and temporal distribution of the 2016 rains, with a late start and early end of the season in most of the country, as well as an erratic distribution of rainfall over the season, **Surveyed districts**: However, central Senegal (Kaffrine and Kaolack regions) experienced a below normal season, with cumulative rainfall totals of 20% below average at regional level, and over 50% below average in localized areas along the Gambian border. 1	**National level**: Optimal planting conditions not reached in most of central and northwestern Senegal, according to Africa RiskView. In areas where the planting threshold was reached, normal WRSI conditions prevailed at the end of the 2016 agricultural season. , **Surveyed districts**: At regional level, the most adverse conditions were recorded in Fatick (25% of normal), Kaffrine (33% of normal), Thies (36% of normal) and Kaolack (52% of normal) regions in central and western Senegal. These were also the areas affected by poor and erratic rains during the 2016 season.

Figure 3.1: Summary assessments of the 2016-2017 and 2017-2018 agricultural seasons in Senegal and surveyed districts

3.2 The MWG model

CCAFS has worked closely with the National Meteorological Agency (ANACIM) to develop locally-relevant climate information services and enhance the capacity of partners to communicate this information to end users. The national MWG mainly comprises 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).

In 2011, CCAFS scientists partnered with ANACIM with the aim of 1) developing CIS that are tailor-made for the users; 2) building the capacity of partners who were tasked to communicate climate information to farmers; and 3) enhancing the transmission of CIS and agricultural advisories for farmers. Under this initiative, the MWGs were set up both at the national and local levels. MWGs constitute decisive and inclusive bodies that facilitate the development of CIS, its interpretation to actionable decisions, diffusion and subsequent uptake by users at the district level. 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).

The Kaffrine region has four departments – Kaffrine, Koungueul, Birkilane and Malem Hodar. However, climate information activities began and focused more extensively in the department of Kaffrine. The Kaffrine climate services project was one of the first local MWGs to be set up. It was implemented in 2011 under the CCAFS flagship 2 program. The objective of the initiative was to provide smallholder farmers with relevant climate information in order to manage the risk posed by climate and weather variability through informed decision-making. In line with this objective, the goal of the Kaffrine project was to provide tailor-made, down-scaled climate information and advisory services to support climate risk management and enhance resilience. Activities included strengthening the capacity of ANACIM to produce down-scaled climate information and agricultural advisories. Several types of climate information have been produced by ANACIM including seasonal forecasts on the onset of the rainfall, total amount of rainfall, cessation of the rains, daily weather forecasts, 10-day weather outlook and early warnings. These climate products were designed to be relevant for specific types of agricultural activities and have been disseminated right down to the district-level . For example, information on onset of rains is used to inform the timing of planting activities (buying seeds, preparing farms, hiring labor, planting seeds); information on total amount of rains will assist farmers to know the types of crops and seed varieties to plant; and daily weather forecasts are used to inform daily operational activities such as weeding and application of chemicals and fertilizers.

The dissemination chain of climate information involves several stakeholders including ANACIM, the MWG, community radios, farmers and some *relais*[1]. Within this setup,

[1]Extension agents selected among lead farmers in their villages

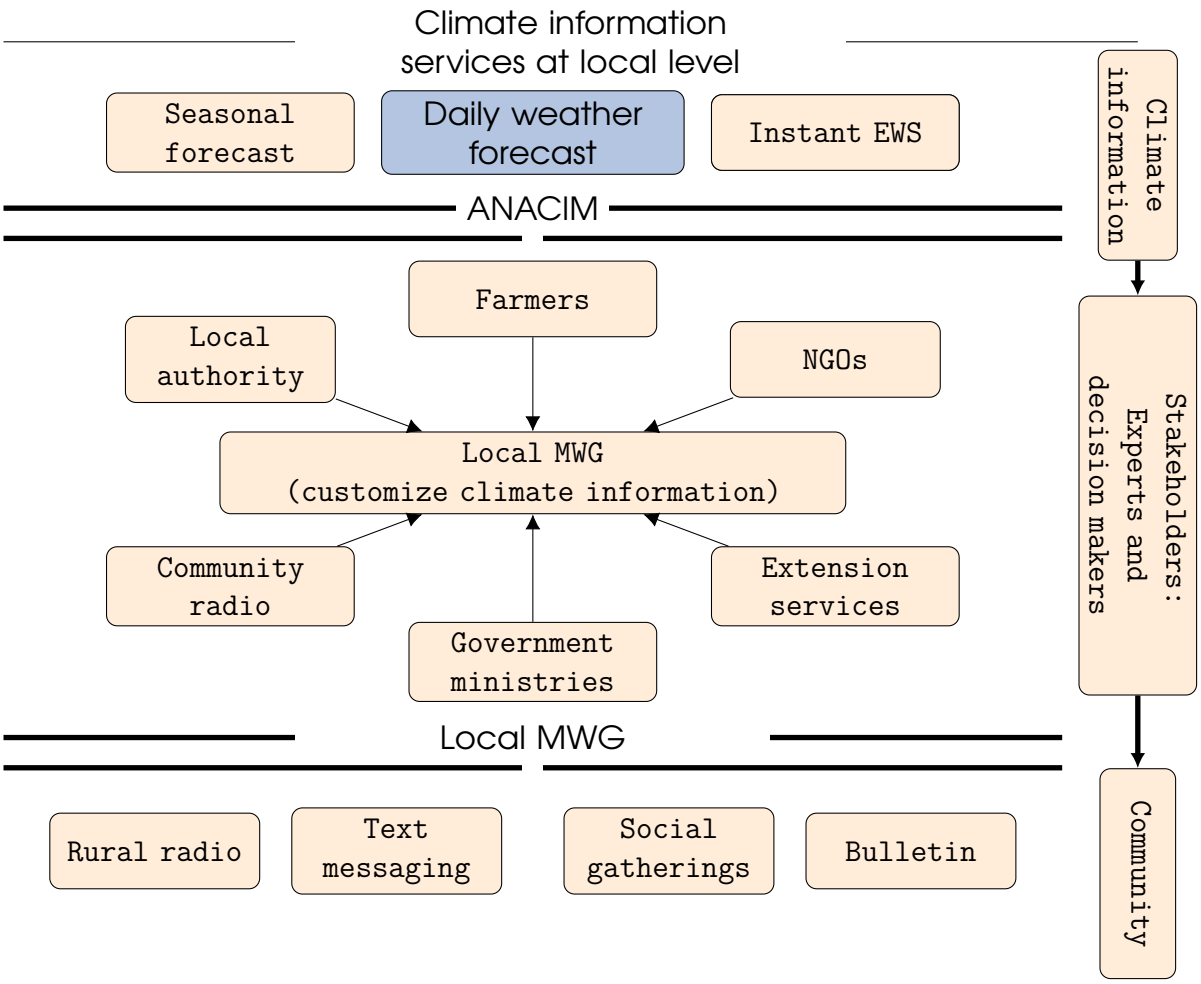
ANACIM is the main provider of scientific climate information and works in close collaboration with members of the MWGs. The technocrats from ANACIM interact with farmers and exchange ideas on how to integrate farmers' indigenous knowledge and forecasting methods with scientific weather forecasts. Farmers are also given the opportunity to indicate their specific climate information needs as well as the way they would like to receive climate information. Such tailoring of climate information to meet the needs of end users can increase uptake and use.

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. In the department of Kaffrine, the MWG includes representatives of the decentralized 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 to discuss 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, leaders of farmers' organizations, or farmers with strong influential power (e.g., religious and 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.

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. The existence of an MWG at the department level and lead farmers in villages to relay information appeared to be instrumental in the peer farmers' access to climate information. For example, in other departments of the Kaffrine region, such as the department of Birkilane, where an MWG had only recently been created, access and use of climate information seem to be limited. This multi-disciplinary partnership in the co-production and dissemination of climate information is summarized in Figure 3.2 below.

> '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.' .....Ndiaye et al. 2013

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.



Adapted from Zougmore and Ndiaye 2015

Figure 3.2: Conceptual schematization of the MWG model

By 2015, the project had partnered with an association of 84 community radios that reached out to a population of 7.4 million rural households in Senegal (CCAFS 2015; Lo and Dieng 2015; Ouedraogo et al. 2018).

CCAFS scientists, in conjunction with ANACIM, produce four broad types of CIS: seasonal forecasts on the total amount of rainfall, onset of rains and cessation of rains; 10-day forecasts; daily weather forecasts (including 2-3 day forecasts); and instant forecasts for extreme weather events. In total, there are six distinct CIS types produced by ANACIM that will be analyzed in this study.

1. **Seasonal forecasts** Seasonal forecasts provide the overall configuration of the rainy season. At the end of May, ANACIM experts observe trends for the coming season and label them: rainy, normal or deficit. If the forecast shows that the season will be in deficit, a warning report is transmitted to government authorities to take appropriate action. The seasonal forecasts are updated in the course of the season at the beginning of June, July and August, and translated into agricultural advice by the MWG. Access to seasonal climate forecasts can benefit farmers by allowing them to make more informed decisions on farming practices such as the type of crop or variety to grow. The onset of rainfall is very crucial to farmers as it can inform those who are involved in off-season work to return to their farms to start land and planting preparations. Under this initiative, ANACIM in partnership with the Agriculture, Hydrology and Meteorology (AGRHYMET), has helped to develop forecast models for the start of the rainy season, particularly in Kaffrine. According to Ndiaye et al. 2013, seasonal forecasting was introduced to farmers and refined through an iterative process that recognizes already existing indigenous knowledge and resonates with their day-to-day life experiences. This way, the new scientific information can be packaged and delivered to farmers in a format that is salient, relevant and legitimate.
2. **10-day forecasts** When the rainy season sets in, ANACIM produces 10-day forecasts that help to identify dry spells and other anomalies in the temporal distribution of rainfall in the project intervention areas. These forecasts are provided to enable the local MWGs, which meet every 10 days, to identify major trends in rainfall and provide appropriate guidance to farmers.
3. **Daily weather forecasts (including 2-3 day forecasts)**
   Two weather reports are produced each day by ANACIM during the rainy season. These forecasts, which indicate the probability of rainfall and the affected regions, are systematically transmitted to community and national radio stations. The first announcement is made at 10 a.m. and conveys the weather conditions for the coming 12 hours, that is between noon and midnight. The evening forecast is made at 4 p.m. and indicates the trends for the next 12 hours. In addition to the daily forecasts, weather forecasts for the next 2-3 days are also provided.
4. **Instant forecasts for extreme events**
   Instant information covers off-season showers or rains, high winds, and especially lightning (during the rainy season) which quite often decimates livestock. At ANACIM, an early warning system has been put in place to provide forecasts on risks of thunderstorm, more than four hours in advance. The EWS has two main objectives: (i) to make arrangements to cope with situations of rainfall deficit, late vegetation growth, decreased yields, showers or floods that may arise, and (ii)

improve and secure agricultural production.

ANACIM organizes a seminar at the beginning of each rainy season with all local partners to inform farmers on major trends during that time. The seminar also provides farmers with an opportunity to share their own forecasts, based on traditional knowledge, with other stakeholders. In all program areas, the major channels for disseminating information are through electronic mail (e-mail), SMS, radio, television and by "word of mouth". To reduce the costs associated with CI dissemination via SMS, the project, in each intervention area, targeted farmer leaders whose contacts could be obtained from the SDDR. The information is sent to the SDDR by ANACIM, and dispatched to the MWG and contact farmers and extension agents disseminate it further to farmers.

3.3 Impact pathways through which CIS can improve the livelihoods of farmers

We have already highlighted in the research methods section4 (see also Vaughan et al. 2017; Tall, Coulibaly, and Diop 2018) that it is empirically challenging to establish causal linkages that connect CIS with improvement in livelihoods. Figure 3.3 conceptualizes the CIS impact pathways for use of CIS under the MWG model in Senegal. We start by distinguishing and highlighting the relationships between activities of the MWG model, the outputs or services generated, the outcomes which result from use of the generated outputs, and the resulting impacts in terms of livelihoods and welfare. In the previous section, we have extensively described how the MWG model is set up and that it produces downscaled CIS of seasonal forecast (total amount of rain, onset and cessation), weather forecasts (daily and 2-3 days), 10 days, and instant EWS. This climate information is disseminated to end-users through various channels that include community radio, SMS, extension and lead farmers. This results in direct outputs such as increased awareness and access to CIS which are instrumental in the uptake and use of climate information. Effective uptake and use of climate services is influenced by farmers' awareness and access to climate information, socio-economic status, assets, and institutional support such as access to credit, seeds and fertilizer. The uptake of climate information with advisory services leads to intermediate outcomes including behavioral change, such as changes in farmers' knowledge, skills and practices. These behavioral changes enable households to buffer their agricultural production and other livelihood activities against climate risks by embracing a number of adaptation strategies. 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 intermediate outcomes lead to reduction in crop failure and livestock losses, as well as reduction in farm income fluctuations which in turn translate into short-term impacts, for example, 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.

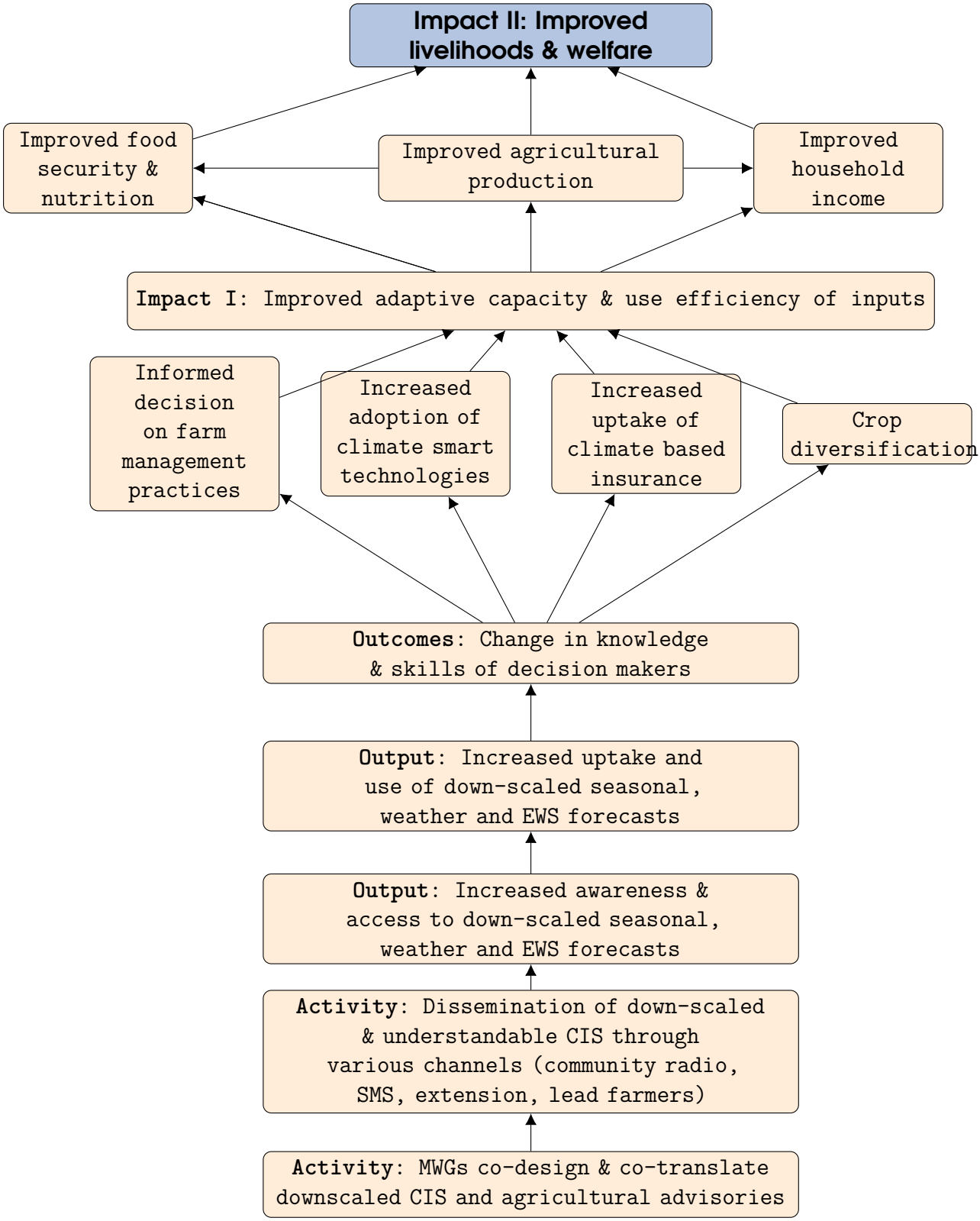


Figure 3.3: Hypothesized impact pathways for CIS use under the MWG model in Senegal

4
METHODOLOGICAL ISSUES IN ASSESSING THE IMPACTS OF CIS

> 'Assessing the value of using seasonal climate services to support decision-making can be practically pursued through a range of methods that span from the quantitative approaches to qualitative methods. .....Bruno Soares, Daly, and Dessai 2018

4.1 Challenges in evaluating the impacts of CIS

Climate information services (CIS) are concerned with the timely provision of tailored climate-related knowledge and information that can be used to reduce losses and enhance profits. Provision of more and better climate services allows vulnerable farmers and communities to fine-tune their planting and marketing strategies, increase farm production, enhance livelihood and food security, and empower end-users to prepare more effectively for climatic and weather variability (Tesfaye et al. 2018; Patt, Suarez, and Gwata 2005).

There are fundamental challenges in trying to evaluate and identify the impacts of using CIS and the pathways that may explain these impacts. First, climate information epitomizes two inherent characteristics of a global public good, that of being non-rivalrous, and non-excludable in consumption (Gunasekera 2010; Vaughan et al. 2017; Tesfaye et al. 2018). The non-rivalrous nature of climate information means that once generated, the marginal or additional cost of replicating and supplying the same information to other users is very low and use by one user does not infringe or diminish use by others. The non-excludable nature of CIS emanates from the fact that once generated, it is practically impossible and potentially expensive to prevent anyone from benefiting from the service (Gunasekera 2010). Put simply, climate information is virtually free in terms of costs and unrestricted when it comes to access to all potential users particularly when disseminated through public means such as national radio, television and extension services.

Second, information and knowledge of CIS can easily be passed along through informal channels such as social and family networks. Rogers 1995 acknowledges the role of social interactions in technology diffusion and contends that the diffusion process consists of interpersonal network exchanges between those individuals who have already adopted an innovation and those who are then influenced to do so. However, the information transferred through informal networks may be incomplete or distorted. This makes it difficult to distinguish between those who receive the service and those who do not, complicating efforts to identify a control sample that does not have access to the information,

as required for an RCT (Vaughan et al. 2017).

Third, the stochastic nature of weather means that the impact of CIS can vary over reasonably small spatial scales within a year or between different years depending on weather changes. This makes it challenging to evaluate the impact of CIS on higher-order livelihood impacts such as household income and food security based on cross-sectional surveys. Hence, for more robust and reliable estimates, longitudinal data may be required (Hansen 2005; Vaughan et al. 2017; Tall, Coulibaly, and Diop 2018). Even with longitudinal data, climatic conditions during project baseline and end-line surveys may be affected by other confounding factors, making it difficult to distinguish between benefits of the service, and the influence of climatic conditions in the baseline and evaluation years (Msangi, Rosegrant, and You 2006). Another challenge in using an RCT design in the assessment of CIS revolves around ethical concerns in that participants that are assigned into the control group are excluded from benefiting from an intervention that could potentially improve their livelihoods. This implies that RCTs may not be the best approach to use in evaluating CIS impacts.

Fourth, as illustrated in Ngari et al. 2016, the value chain of weather and climate services is long and consisting of interdependence across multiple actors such as observers, modelers, forecasters, disseminators, and other intermediaries, with farmers being on the receiving end of the information spectrum. Due to this high interdependency, a weakness in any one link of the chain will have consequences with respect to the usefulness of the information, products, and services provided (Ngari et al. 2016). Ideally, climate services should be able to address real and perceived needs of users, which are often context-specific in terms of content, scale or zone of influence and format (Hansen 2002; Hansen 2005).

Fifth, the link between CIS and livelihood impacts is not a direct one. Climate information in solitary has no intrinsic value, but rather the value comes from improved farm decisions made based on the information received resulting in positive livelihood outcomes (Hammer 2000; Luseno et al. 2003; Hansen 2005; Carr and Owusu-Daaku 2015). Furthermore, even in cases where farmers use CIS to inform decision making, there are other constraints such as biophysical factors, other independent interventions, and institutions and markets that confound livelihood outcomes making it difficult to isolate the effectiveness of adaptation strategies (Gunda et al. 2017). Hence, there is need for research to empirically demonstrate how these impact pathways operate to establish the causal linkages between the use of CIS, farm behavioral changes informed and ultimately the impacts of these changes on farm level impacts, such as income and agricultural production.

4.2 Conceptual and analytical framework

4.2.1 Modeling households' uptake and use of CIS

We model a households' decision to uptake and use CIS using a household decision making under imperfect information and a random utility framework. Under this framework, we assume that a household makes the choice to use CIS 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:

$$MAX\ U = f(X). \tag{4.1}$$

We assume that household i will use one or a combination of CIS j, where j(j=1,...J), if the utility U_{ij} derived is greater than the utility U_{im} of not using CIS. 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:

$$I^* = U_{ij} - U_{im} > 0, for\ all\ j \neq m, \tag{4.2}$$

where I^* represents the benefits of using CIS j as opposed to not using m. While I^* is unobserved, we can observe the type of CIS the household uses. The probability that a farmer uses CIS j can be denoted by $Pr(I = 1)$, otherwise I^* takes a value of zero. The utility maximizing behavior of farmers can then be represented as:

$$U_i = \begin{cases} I^* & if\ I_{ij} \geq 0 \\ 0 & if\ I_{im} < 0. \end{cases} \tag{4.3}$$

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

$$I^*_{ij} = \beta_j X_i + u_{ij}, \tag{4.4}$$

where I^*_{ij} is a latent variable 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}. The households' demand for CIS (adoption decision) is given by

$$I^d_{ij} = \begin{cases} 1 & if\ E(U_{ij} - U_{im}) \geq 0 \Leftrightarrow \beta_j X_i \geq -u_{ij} \\ 0 & if\ E(U_{ij} - U_{im}) \geq 0 \Leftrightarrow \beta_j X_i < -u_{ij}, \end{cases} \tag{4.5}$$

where I^{d*}_{ij} is the expected utility differential of using CIS. The use decision is a function of the expected benefits from the uptake of CIS, which depends on the attributes of the CIS in question such as source and accuracy, as well as other factors that may influence households' uptake behavior under constrained socioeconomic and institutional environments. The fundamental first-step determinants that act as preconditions before a household uptakes CIS are (i) awareness or knowledge and (ii) access to or ability to receive the information. 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). Following the empirical applications of Shiferaw et al. 2015 and Adegbola and Gardebroek 2007, a latent variable I^{a*}_{ij} can be defined as the level of awareness of a household about a particular CIS. This level of awareness is dependent on the level of information or knowledge acquisition K_{ij} that facilitates the household to be aware and have ample knowledge of the innovation, that is above the minimum level of information threshold K_{im} to be able to make the uptake decision. This level of

awareness is also affected by a set of observed household and farm characteristics, and institutional factors Z_i. If a linear relationship is assumed, $I*$ can be written as:

$$I_{ij}^{a} = \begin{cases} 1 & if\ (I_{ij}^{a} - I_{im}^{a}) \geq 0 \Leftrightarrow \alpha_j Z_i \geq -\epsilon_{ij} \\ 0 & if\ (I_{ij}^{a} - I_{im}^{a}) < 0 \Leftrightarrow \alpha_j Z_i < -\epsilon_{ij} \end{cases} \tag{4.6}$$

Similarly, a households' level of access of CIS through various channels such as radio or extension maybe be represented by the latent variable I_{ij}^{r*} and may be presented as:

$$I_{ij}^{r} = \begin{cases} 1 & if\ (I_{ij}^{r} - I_{im}^{r}) \geq 0 \Leftrightarrow \gamma_j M_i \geq -\varepsilon_{ij} \\ 0 & if\ (I_{ij}^{r} - I_{im}^{r}) < 0 \Leftrightarrow \gamma_j M_i < -\varepsilon_{ij} \end{cases} \tag{4.7}$$

In reality, what we observe is the household use of CIS which can be expressed as:

$$I = I^d I^a I^r = \begin{cases} 1 & if\ (I_{ij}^{r} - I_{im}^{r}) \geq 0 \Leftrightarrow \gamma_j M_i \geq -\varepsilon_{ij} \\ 0 & if\ (I_{ij}^{r} - I_{im}^{r}) < 0 \Leftrightarrow \gamma_j M_i < -\varepsilon_{ij} \end{cases} \tag{4.8}$$

The uptake of a particular CIS occurs when several factors hold simultaneously i.e. the household is sufficiently aware of the innovation ($I^a = 1$) ; the expected utility differential has a net positive ($I^d > 0$) and the household is able to receive or access CIS ($I^r = 1$). Therefore, the probability of uptake, P(I), of CIS can be given by:

$$P(I) = P(I^d) * P(I^a) * P(I^r) \tag{4.9}$$

Such a conceptual framework for farm household decision making under information and access exposure illuminates the importance of variables that determine awareness and access to information about innovation, its net benefits and how these influence uptake behavior of smallholder farmers.

4.2.2 Empirical strategy: the counter-factual ATE framework

Program evaluation is the assessment of cause-and-effect with the aim to determine the extent to which the net difference in outcomes between users and non-users of an innovation can be attributed to an intervention. The main concern is threats to internal validity; these threats are external factors affecting outcomes other than the intervention. In other words, the net difference in outcomes could have occurred in the absence of the intervention. The counter-factual approach to impact evaluation pioneered by Rubin consists of measuring what would have happened to users in the absence of the intervention. However, it is not possible to observe the state of nature of users had they not participated in the intervention implying that data collected can only be on the factual. So, this is essentially a missing data issue. A central tenet of the ATE framework is the potential-outcomes model (also known as Rubin's causal model (Rubin 1974)) 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 uses CIS will be different from those of a household that does not use CIS. The treatment is a binary variable I_i that is set to 1 if the farmer is aware, has access and uses CIS to inform farming decisions

and 0, otherwise. The household has two hypothetical potential outcomes, I^0, representing potential outcomes using CIS and I^1, representing potential outcomes for not using CIS.

The potential-outcomes model provides a solution to this missing-data problem and allows us to estimate the distribution of individual-level treatment effects. The econometric estimation of generating counter-factual in non-experimental studies consists of selecting a comparison group with similar characteristics to the treatment group. Any difference that arises between the two groups can, in this case, be attributed to the program rather than to other external factors. However, the empirical challenge is addressing self-selection bias in the estimation of the average treatment effects on the treated. Most approaches assume that the selection into treatment is exogenous after controlling for observed factors (i.e., unconfoundedness of the treatment conditional on a set of observed covariate), or the selection into treatment is endogenous (both observed and unobserved factors matter) (Imbens and Wooldridge 2009; Imbens 2000).

We follow the theoretical framework on technology uptake under heterogeneous information exposure first proposed in Diagne and Demont 2007 building on the seminal work by Rubin 1974 and more recently applied in Kabunga, Dubois, and Qaim 2012; Shiferaw et al. 2015; Simtowe, Asfaw, and Abate 2016. In estimating unbiased adoption estimates, this ATE framework, consists of two stages: (i) the first models heterogeneous information flow within the population as a function of individual characteristics, and (ii) the second models actual adoption controlling for nonrandom selection (Diagne and Demont 2007). The ATE framework, allows both non-parametric and parametric methods to derive consistent estimates under partial population exposure. As outlined above, in our empirical approach we differentiate between two different levels of exposure, namely awareness exposure, and knowledge exposure and assume that some farmers get exposed to both awareness and access to certain types of CIS while others do not.

For observations in N households, we can denote a binary variable w to indicate the observed status of exposure, with $w = 1$ if the farmer is exposed to a particular CIS (treated), and $w = 0$ if the farmer is not exposed (control). Following Diagne and Demont 2007 and Kabunga, Dubois, and Qaim 2012, for a population of N households, we can denote the observed status of exposure to be a binary variable w, which holds when the individual is exposed to both awareness and access i.e. $I^a = I^r = 1$ with the observed status of uptake being $I^1 = I = 1$, implying they are exposed (treatment) and $I^0 = I = 0$, if the farmer is not exposed (control). Thus, from the population of N households, the number of households exposed will be N_e. For each household, we also observe a k-dimensional column vector of covariates, X. At the individual level, we want to explain the adoption status (binary), while at the population level, we want to explain exposure rates N_e/N, uptake rates N_a/N assuming universal exposure, and adoption rates among the exposed N_e/N_a in cases of incomplete exposure.

$$I = wI^1 = I^0(1-w) + I^1 w \begin{cases} I^1 & \textit{if } w = 0, \\ I^0 & \textit{if } w = 1. \end{cases} \tag{4.10}$$

Similarly, a households' level of access of CIS through various channels, such as radio or extension, maybe represented by the latent variable I_{ij}^{r*} and may be presented as:

$$I = wI^1 = I^0(1-w) + I^1 w \tag{4.11}$$

For a population of N households, we can denote the potential uptake of CIS with a binary variable I with the observed status of uptake being I^1, implying they are exposed (treatment) and I^0, if the farmer is not exposed (control). Therefore, under incomplete exposure, the treatment effect for a farmer i can be measured by the difference $I_i^1 - I_i^0$. Similarly, the expected population uptake impact of CIS exposure is expressed as the mean value $E(I^1 - I^0)$, which in principle, is the ATE of exposure. Since it is not possible to simultaneously observe the outcomes of the same individual with and without exposure, $I_i^1 - I_i^0$ cannot be measured. Therefore, since exposure is a necessary precondition for uptake I^0, assumes a value of zero. Thus, the adoption impact of any farmer is given by I^1, hence the mean adoption of uptake of exposure is reduced to $E(I^1)$. Therefore, for the sample of individuals exposed, the mean adoption impact on the exposed sub-population is given by the conditional expected value $E(I^1|w = 1)$, which is the ATE on the treated (ATE_1). Similarly, for the non-exposed sub-sample, the mean adoption impact is given by $E(I^0|w = 0)$, which is the ATE on the untreated (ATE_0).

From equation 4.10, it can be deduced that if $I^0 = 0$, then the expression of the observed adoption outcome reduces to $I = wI^1$, which implies that the observed uptake outcome variable combines both exposure to awareness and access and eventual uptake and use outcome, which is referred to as the population mean joint exposure and adoption (JEA) parameter (Diagne and Demont 2007). The difference between ATE and JEA is that the former measures the potential demand for uptake by the population, while the latter measures the population mean observed adoption outcome.

The difference between the JEA and ATE is the population adoption gap or "non-exposure" bias, $GAP = E(I) - E(I^1)$, which is strictly negative and diminishing with increasing exposure and results due to partial exposure and measures the unfulfilled population demand for the innovation. The disparity between the mean potential adoption outcome in the exposed sub-population and mean potential adoption outcome in the full population is the population selection bias and is derived as: $PSB = ATE_1 - ATE = E(I|X, w = 1) - E(I^1)$.

To consistently estimate the population adoption parameters, we rely on the conditional independence (CI) assumption to identify the ATE involving potential outcomes, which postulates that a set of observed covariates determining exposure, when controlled for, renders the treatment status w independent of the potential outcomes (Imbens and Wooldridge 2009). The CI assumption postulates that a set of observed covariates determining exposure, when controlled for, renders the treatment status w independent of the potential outcomes I^1 and I^0.

The ATE can be non-parametrically identified from the joint distribution of I, X conditional on exposure, $w = 1$ and can be represented as:

$$E(I|X, w = 1) = f(X\beta), \tag{4.12}$$

where f is a known function of the vector of covariates determining adoption, X, and β is the unknown parameter vector which can be estimated by maximum likelihood estimation (MLE) procedures using observations (I, 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, $f(X, \hat{\beta})$, for values $i = 1, 2, ..., n$, to compute ATE for the pooled sample, ATE_1 for the exposed sub-sample and ATE_0 for the non-exposed sub-samples. These can be presented as:

$$\widehat{ATE} = \frac{1}{N} \sum f(X, \hat{\beta}) \tag{4.13}$$

$$\widehat{ATT} = \widehat{ATE_1} = \frac{1}{N_e} \sum w f(X, \hat{\beta}) \tag{4.14}$$

$$\widehat{ATU} = \widehat{ATE_0} = \frac{1}{N - N_e} \sum (w - 1) f(X, \hat{\beta}) \tag{4.15}$$

Since exposure is not random, the application involves controlling appropriately for exposure status using a set of observed covariates. This first stage analyzes the factors that influence exposure, while the second estimates factors determining uptake and use. The covariates in the first and second stage need not be identical since it is plausible in this case that factors that affect exposure to awareness and access may not be the same as those that explain use and uptake.

There are two analytical sections in this manuscript. The first , section 6 will broadly focus on factors that determine farmers' uptake and use of CIS, with special attention to the effectiveness of the MWG, while controlling for awareness and access exposure bias. The second section 7 will dwell more on the effectiveness of MWG in influencing farmers' uptake and use of CIS and the resulting impact on behavioral changes and farm management practices.

4.2.3 Modeling consistent adoption parameters and their determinants

In the second analytical section, 7 we analyze the effectiveness of the MWG on use and uptake of CIS. We use the instrumental variable based method and its local average treatment estimator (LATE) (Imbens and Angrist 1994). From earlier discussion, we have already established that not all individuals that were aware or had access to a particular CIS would actually end up using it to inform farm management decisions. This implies that some farmers complied to satisfy all three conditions of awareness, access, and uptake, while others did not. In such a case, the local average treatment effect "LATE", is a more appropriate estimate of impact to correct the problem of non-compliance. We used the non-parametric LATE model to assess the impacts of CIS (with and without MWG) on behavioral changes and farm management practices. Since the uptake and use of CIS is an endogenous variable, the LATE parameter was estimated with the combined exposure to awareness and access of CIS as instrumental variables. The LATE parameter is estimated as follows:

$$LATE = E(I|X, w = 1) \tag{4.16}$$

Based on econometric literature, the LATE estimator is consistently estimated by the Wald estimator (Imbens and Angrist 1994). Nevertheless, two options appear to be considered in this case: observed heterogeneous impact and unobserved heterogeneous impact (also called essential heterogeneity). If the impact of treatment is constant across the entire population meaning that the outcome response to the treatment is the same for any farmer, the impact of CIS could be estimated using the traditional approach of IV. In this case, estimation is straightforward with the IV command of any Statistical software (e.g. with the *ivregress* command in Stata). However, if the impact varies from one farmer to another due to some unobserved factors, which is likely the case in this study, the impact of CIS is straightforwardly estimated by LATE proposed by Abadie 2003 and defined as follows:

$$LATE_{LARF} = \frac{1}{\hat{P}(t_1-1)} \sum k_i * h\hat{(}y_{1i}, t_{1i}, x_i, \hat{\theta}), \tag{4.17}$$

Under the LATE framework, we estimate the average treatment effect on the treated ATT and 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. This allows measuring the change in the outcome that is attributable to the intervention or treatment. For instance, in the case of climate information services, the causal inference framework assumes that although a household uses CIS at a specific point in time, an alternative scenario of not using CIS could have been taken. We consider two groups of farmers — those that use specific types of CIS (treated) and those that do not (control). The ideal situation would have been to observe both a farmer adoption status of CIS with and without access to MWG, and observe farmers' behavioral status in these two scenarios. However, it is not possible to observe both the with and without the treatment in each case. This situation is known in impact assessment as an evaluation problem. At any given point in time, only one outcome can be observed since the same individual or household cannot be in the two states (uptake and no uptake of CIS, access and no access to MWG) at the same time. Hence, it is not possible to estimate the difference in observed outcomes for the same individual at a given point in time. However, an average difference can be calculated for different households in these two scenarios.

We use the probit specification to model CIS use, the Poisson specification to model the number of crops grown in 2017, and a linear regression approach to model the crop diversity index. A predicted probability of CIS use is generated for each farmer depending on whether they have access to the MWG or not. Based on this, the Margalef index is computed for each farmer. The farmer level ATE, is the difference between the predicted outcome with and without access to MWG. The ATT is, therefore, the average of this difference in the sub-sample of the farmers that have access to MWG, while the ATU measures the difference of farmers without access to MWG.

4.3 Defining awareness, access, and use of CIS

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. For example, the extent of adoption for improved seed can be

expressed in terms of the proportion of area allocated to improved seed. In this study, awareness is expressed as a dummy variable for each CIS and takes a value of 1 if the household has heard of the CIS type in question and 0 if otherwise. Access to CIS is measured as a binary variable that takes the value of 1 for each CIS that the household is able to receive from one or more sources like radio, extension workers, or from fellow farmers, and 0 if otherwise. It is important to emphasize how the questions on awareness and access were phrased. The respondents were asked to provide information on the main types of CIS households are aware of (or have heard of) and have the ability to receive.

The impact of a given CIS is difficult to assess because climate information 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. As stated in an earlier section 3 we consider six distinct types of CIS that were disseminated in the study sites which are forecasts on (i) total amount of rainfall for the season; (ii) onset of rains; (iii) cessation of rains; (iv) daily weather; (v) 10-days weather; and (vi) instant forecasts of extreme events.

First, an individual can only access or receive a particular CIS if they are already aware of it. Therefore, awareness of and having the ability to receive or access a particular CIS 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 CIS if they are simultaneously aware and have the means to access or receive the information. Hence, in this study, we combine uptake and use as one decision, which is defined as a binary variable and for each individual, takes the value of 1 for a household that uses a particular CIS to inform their farm management practices, and 0 if they do not. This implies that for each household, we are able to observe whether they used each of the six CIS types or not. In addition to these six individual CIS use decisions, we also consider an integrated binary measure, which takes the value one, if the household uses at least one of the six CIS, and 0 if not. The farm management practices informed by use of each CIS can be, for example, in terms of crop type, crop variety, and timing of e.g., planting, weeding, or harvesting. It is important that the uptake decision is conditional on (i) the household being aware of the CIS, its attributes and the potential net benefits (utility); and (ii) the household having the means to receive the CIS. Mathematically, this can be shown in equation 4.9. Households are classified as non-users if they decide not to uptake and use any of the six CIS types due to a number of reasons such as lack of awareness, access or knowledge of the value and net benefits derived from using CIS or simply lack resources (e.g., capital or labor) to act upon the information received. Figure 4.4 shows the network of users and type of climate service used for the whole sample and disaggregated by the two surveyed provinces: Kaffrine and Kaolack as well as the existence of the MWG.

The terms CIS 'uptake', 'adoption', 'use', and 'uptake and use', will be used interchangeably throughout this manuscript. Unlike the way awareness and access questions, which were general, the questions related to households' use of different CIS had a very specific reference point and households were prompted to list all the individual CIS that they used during the 2016-17 agricultural season.

4.4 Farm survey design and sampling

4.4.1 Data collection process

Data collection in the sampled sites was conducted through individual household surveys using structured questionnaires and the process is summarized in Figure 4.1. It started off with the design of a structured survey form or questionnaire that captured the main indicators of choice in this study. More specifically, the form captured information on key outcome indicators to assess the first three research questions. Questions included household socio-demographics, asset ownership, awareness, access, and use, farm management decisions, agricultural technologies influenced by climate information, crop production, and risk attitudes.

The data was collected over a period of three weeks, under close supervision from ICRAFs socio-economic team in collaboration with local partners in Senegal. All collected data were then uploaded to the ICRAF server account hosted by ONA (https://ona.io/home/, accessed 7 June, 2018) on a daily basis by the enumerators. In order to remotely monitor and assess the quality of data in real time and ensure that the protocols were being administered correctly and individual measurements recorded accurately, the socio-economic team at ICRAF developed and used automated work-flow scripts and was in constant touch with the enumerators and the field supervisors. The process of good research design and data collection remains an integral part of generating high quality evidence that can be used in answering pertinent research questions in a convincing and credible way in order to inform policy.

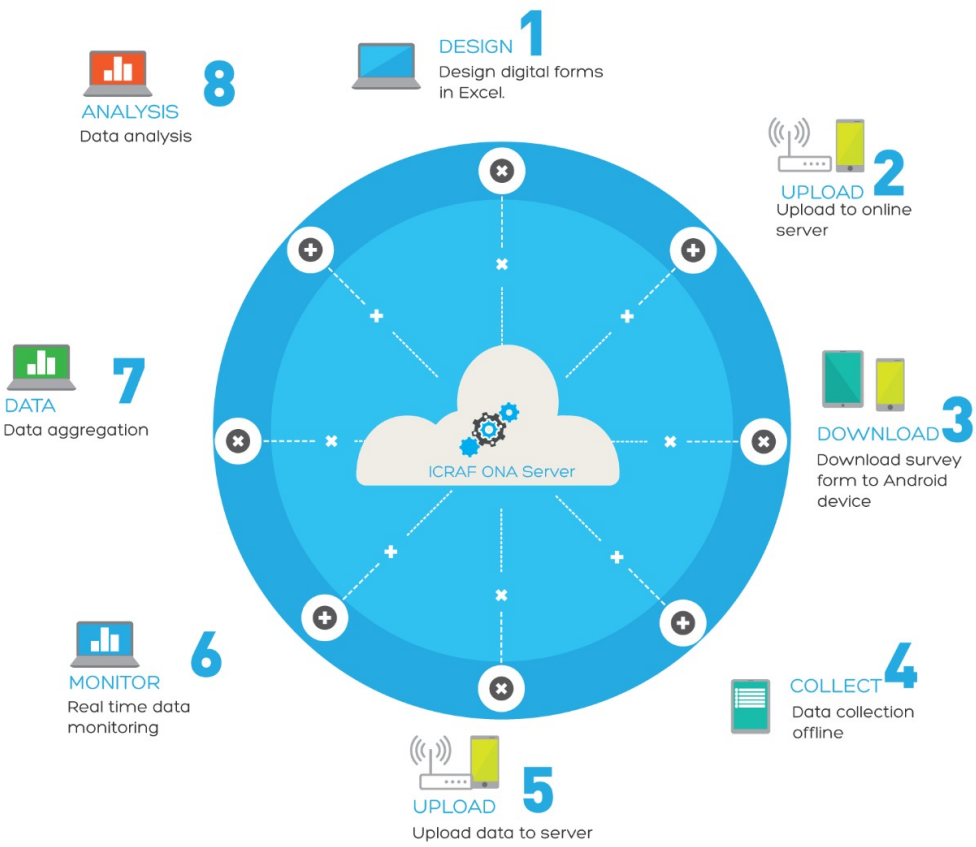
The automated data collection and management (ADCM) system allows for seamless integration of data collection, data entry and data monitoring (Chiputwa, Makui, and Gassner 2018). An ADCM has the potential to transform the way research is delivered by assisting researchers to collect, manage and analyze data in a smart, rapid, efficient and cost-effective way that leads to better quality data and research. Figure 4.1 illustrates eight steps that constitute the ADCM system. The ADCM can be customized to collect data and respective indicators that are linked to a project's specific research questions and hypothesized Theory of Change (ToC).

Implementation of the ADCM under the CISRI Learning Agenda ensured the following principles of good scientific research:

1. **Integrability**: ability to combine digital data collection platforms with statistical programming software like R and Stata and type-setting applications like LaTeXwithin one environment.

2. **Transparency**: the various elements of the research cycle are well-documented, well organized in a logical and clear manner that shows their interconnectedness

3. **Maintainability**: ability to modify and adapt the different elements of the project. Standardized script names and good commenting practices (in the code, as well as things like README files) are key here.
4. **Modularity**: ability to disaggregate different parts of the workflows into components



Source: Chiputwa, Makui, and Gassner 2018

Figure 4.1: Schematic illustration of the data collection process during the farm surveys

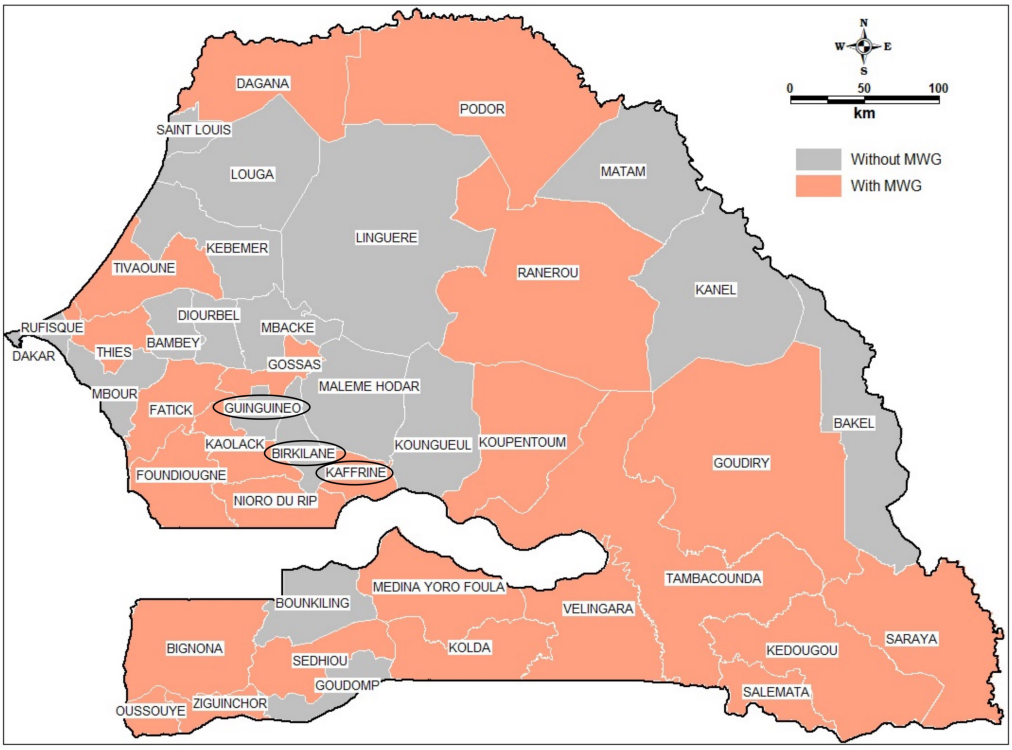
(e.g. all the livelihood modules have individual automated workflows that allow for easy integration).

5. **Adaptability**: ability to modify and customize the workflows to match the needs of individual projects as informed by the Theory of Change (ToC).
6. **Transferability** ability to share the workflows with other users for e.g., for collaborative research environments.
7. **Reproducibility**: ability to program standardized scripts that make research analyses and processes reproducible.
8. **Efficiency**: ability to save time, costs and deliver high-quality research outputs.

4.5 Sampling strategy

The sampling strategy was built on a stratified random sampling design. First, we purposively selected districts that either i) have access to an MWG that had been established and operational since 2011 as well as receiving CIS from a local radio station, or having no access to an MWG but receiving CIS from a local radio station. The two districts of Kaffrine and Birkilane in the Kaffrine region, met the first criteria in that they were one of the first districts to have MWGs established in 2011. The district of Guinguineo in Kaolack region was selected as the comparison district as it met the second criteria of not having access to an existing MWG (see Figure 4.2). Within each of these

communes, two to four villages were randomly selected, and 30 farmers were randomly selected from each village based on a list of households provided by the village head. The Communes are the fourth-level administrative divisions in Senegal (below country, region and department). 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`, accessed on 5 June, 2018). Within Kaffrine district, the rural communes of Kahi, Kathiote and Mbignick were selected on the basis that they had been more exposed to CIS compared to the other communes.



Adapted from Ouedraogo et al. 2018

Figure 4.2: Map of Senegal showing the sampled districts (circled) and presence of MWG

In Guinguineo district, eight villages were randomly selected from Panal Wolof commune, followed by a random selection of 30 households per village. The survey targeted heads of households or the second most important decision makers. In the end, a total of 795 households were selected and interviewed during the survey. Figure 4.3 shows the distribution and geo-referenced locations of some of the sampled households in one of the clusters in Kaffrine district, while figure 4.4 shows the composition of the sampled households disaggregated by province, the existence of an MWG, and households' use of CIS in the 2016-2017 agricultural season.

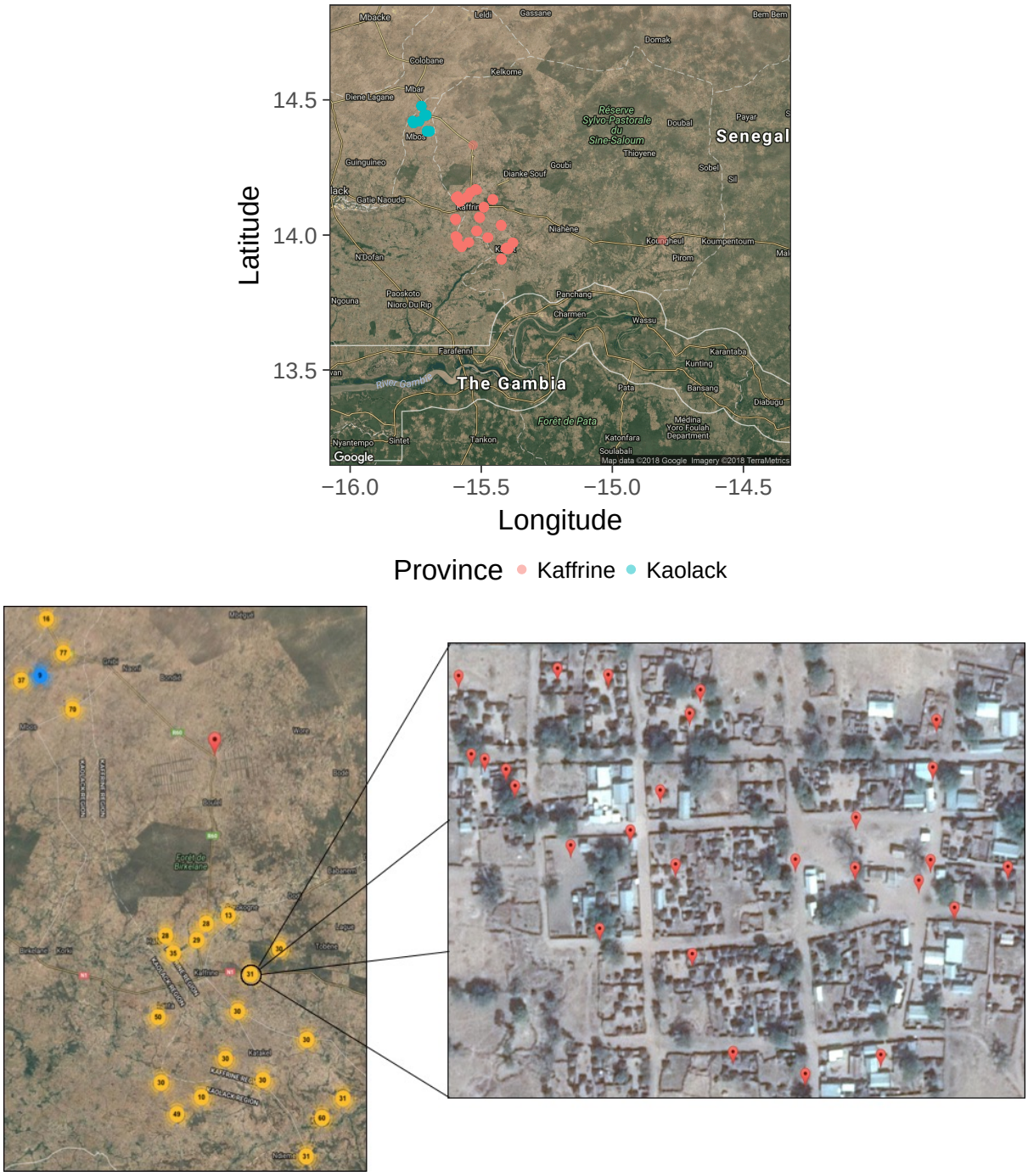


Figure 4.3: Map showing the distribution of sampled households in a specific cluster location within Kaffrine district

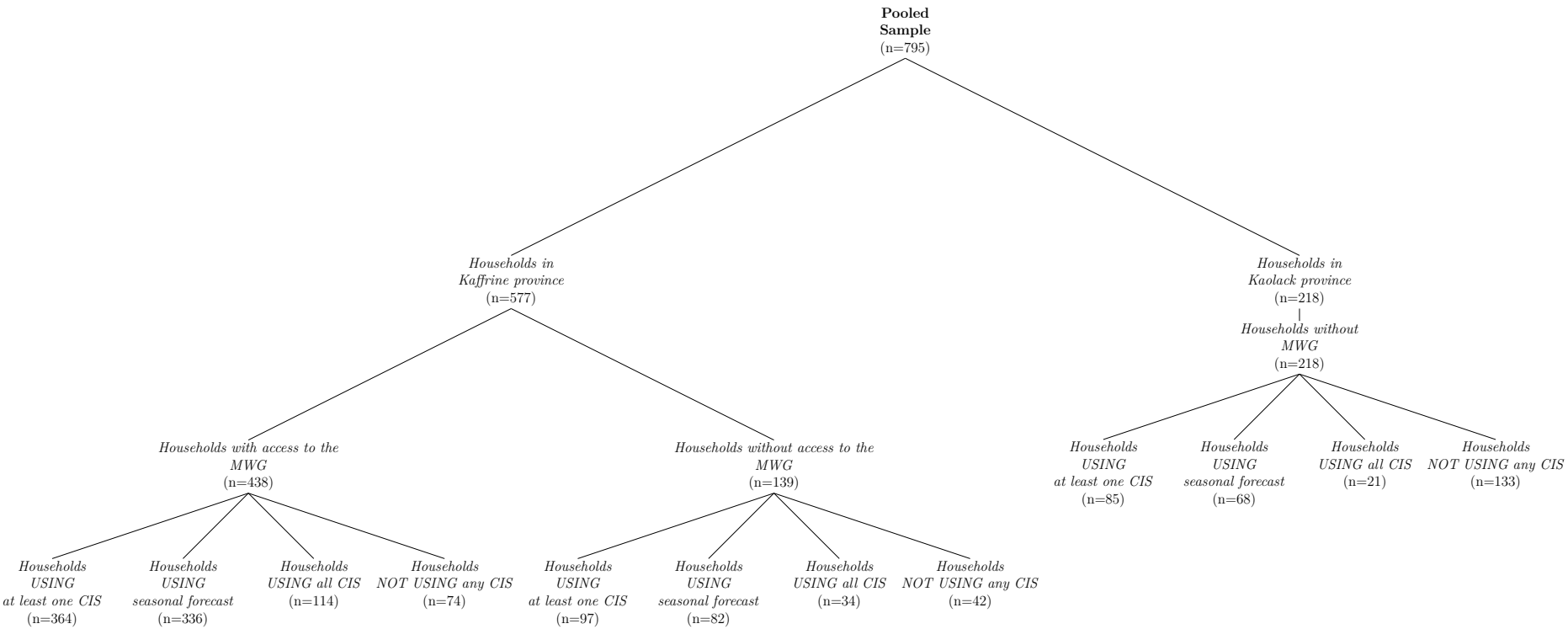


Figure 4.4: Composition of sampled households by MWG and use of CIS

5
DESCRIPTIVE STATISTICS

> 'Seasonal rainfall forecasts can help farmers adapt to climate change and improve their resilience to climate shocks. The adoption level of the farmers is clear – CIS is now regarded as a primary agricultural input.'. .....CCAFS 2015

This section presents summary statistics of surveyed farm households in terms of their household, farm and institutional characteristics as well as awareness, access and use of CIS. We also present differences in characteristics between users and non-users of CIS.

5.1 Farmers' awareness, access and use of different CIS

5.1.1 CIS awareness disaggregated by province and MWG access

Figure 5.1 shows the number and proportion of households that are aware of the different climate information services. Awareness is defined as a dummy variable for each CIS and takes a value of 1 if the household has knowledge of any particular CIS, and 0 if otherwise. Overall, a high proportion of the sampled households are aware of climates services. Two-thirds of all the farmers sampled are aware of four out of the six types of CIS considered (i.e. seasonal forecasts on the onset of rains, cessation of rains and amount of rainfall; daily forecasts; 10 day forecasts; and early warning systems on extreme weather). Overall, there are more farmers in Kaffrine region that are aware of all the six CIS compared to Kaolack region. The most commonly used CIS among sampled households are the 2-3 day weather forecasts with awareness rates of 84% for the whole sample, 90% for farmers in Kaffrine and 72% for farmers in Kaolack. There are, however, relatively few farmers that are aware of 10-day forecasts; approximately 53% in the full sample and about 34% among farmers in Kaolack. Figure 5.2 presents the number and proportion of households that are aware of the different CIS disaggregated by MWGs. A higher proportion of households with access to MWGs were aware of all the six CIS compared to those without access to MWGs.

5.1.2 CIS access disaggregated by province and MWG access

Figure 5.3 shows both the number and proportion of households that are exposed to different CIS. Exposure was measured as a dummy variable that takes the value of 1

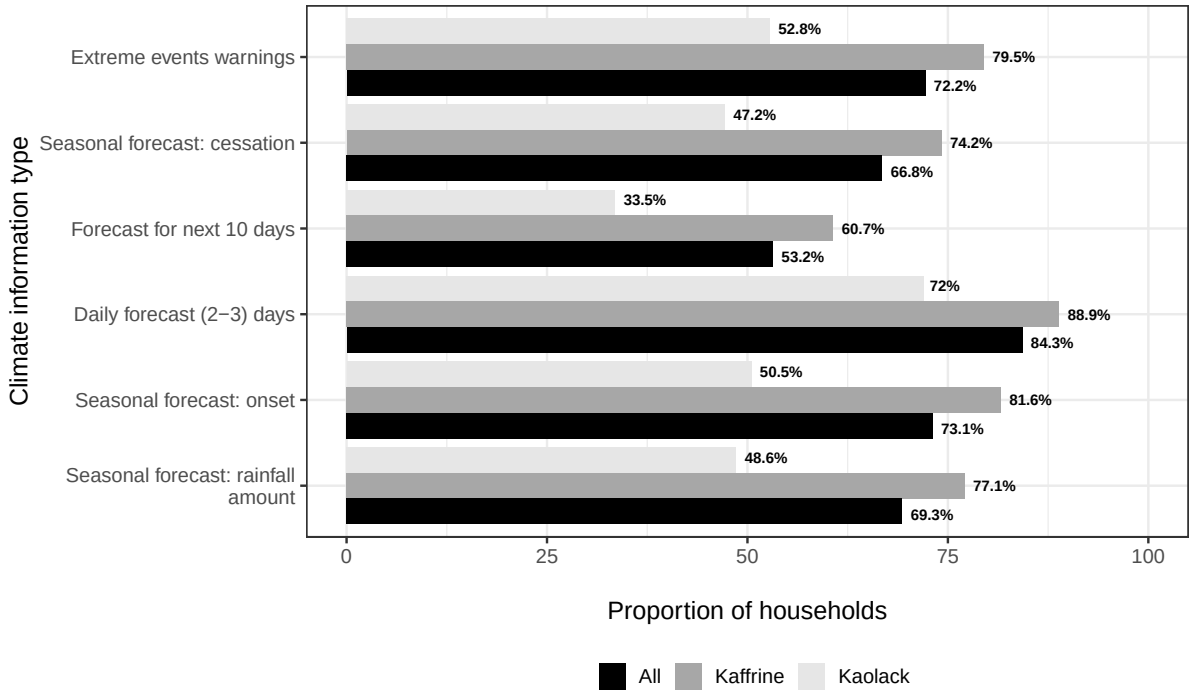


Figure 5.1: Households' awareness to different CIS by province

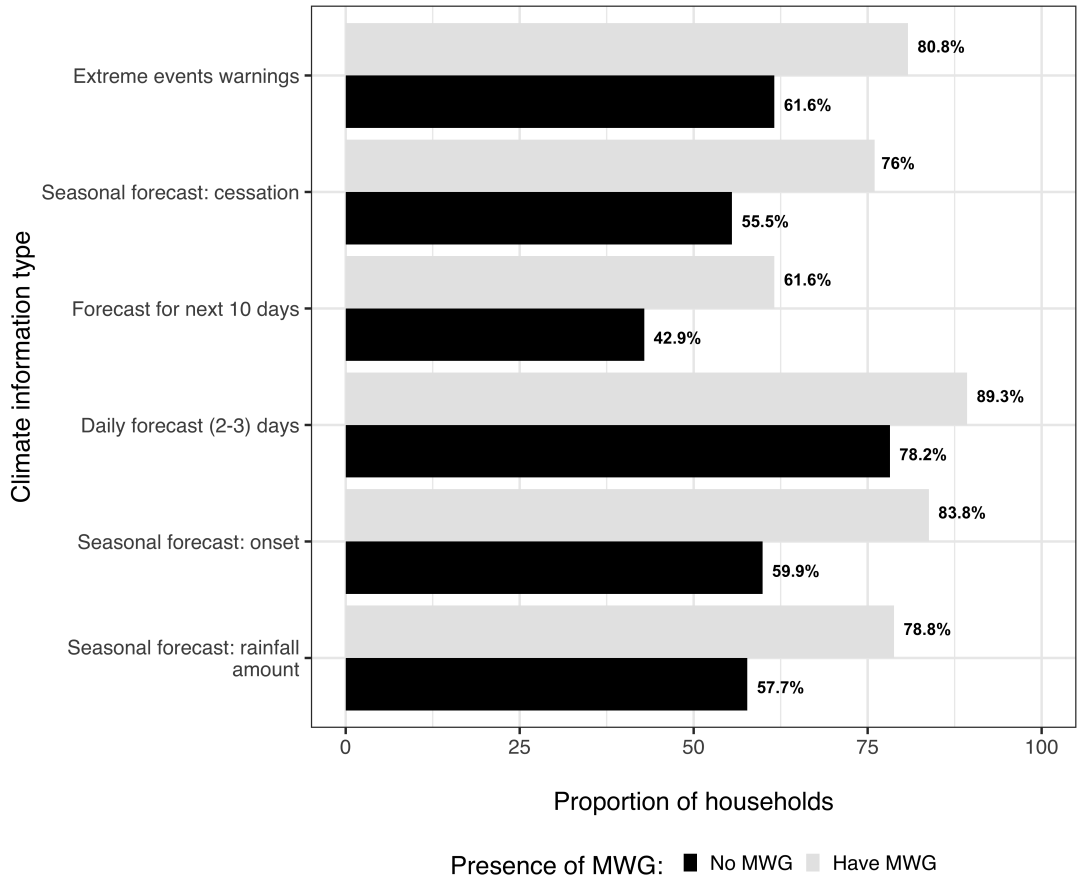


Figure 5.2: Households' awareness to different CIS by MWG

for each CIS that the household receives from one or more sources and 0 if otherwise. We make the assumption that for a household to receive any CIS, it is conditional on them being aware and having enough knowledge to be able to comprehend the costs and benefits of using them. On average, at least 85% of households in Kaffrine acknowledged receiving all the six CIS compared to at about 70% in Kaolack. In Kaffrine region for example, the three most commonly received CIS are the 2-3 days weather forecast (90%), onset of rains (89%) and total amount of rain (88%), while in Kaolack the most received are total amount of rain (82%), 2-3 day weather forecast (78%), and cessation of rains (72%).

Figure 5.4 presents a comparison of CIS access rates for the full sample that was surveyed and the sub-sample that was aware of the CIS disaggregated by the presence of MWGs. The CIS access rates are lower for the full sample compared to the sub-sample that was aware of CIS. The difference is significant among households in areas without MWGs indicating the presence of awareness exposure bias. Thus, estimating CIS access using the full sample will thus under-estimate the actual access rate due to awareness bias since farmers who are not aware of CIS may not be able to access CIS. However, for households in MWG areas, the difference in CIS access rate between the full sample and the exposed sub-sample is not significant mainly because almost all the households in the MWG areas were aware of CIS resulting in minimal awareness exposure bias. A comparison of CIS use by whether or not households are located in areas with MWGs is also presented. The proportion of farmers who had access to climate information for all the six climate information products is higher among households in locations where the MWG exists compared to those without the MWG. Again, this is expected owing to the fact that MWGs are quite fundamental in the flow of climatic information in Senegal.

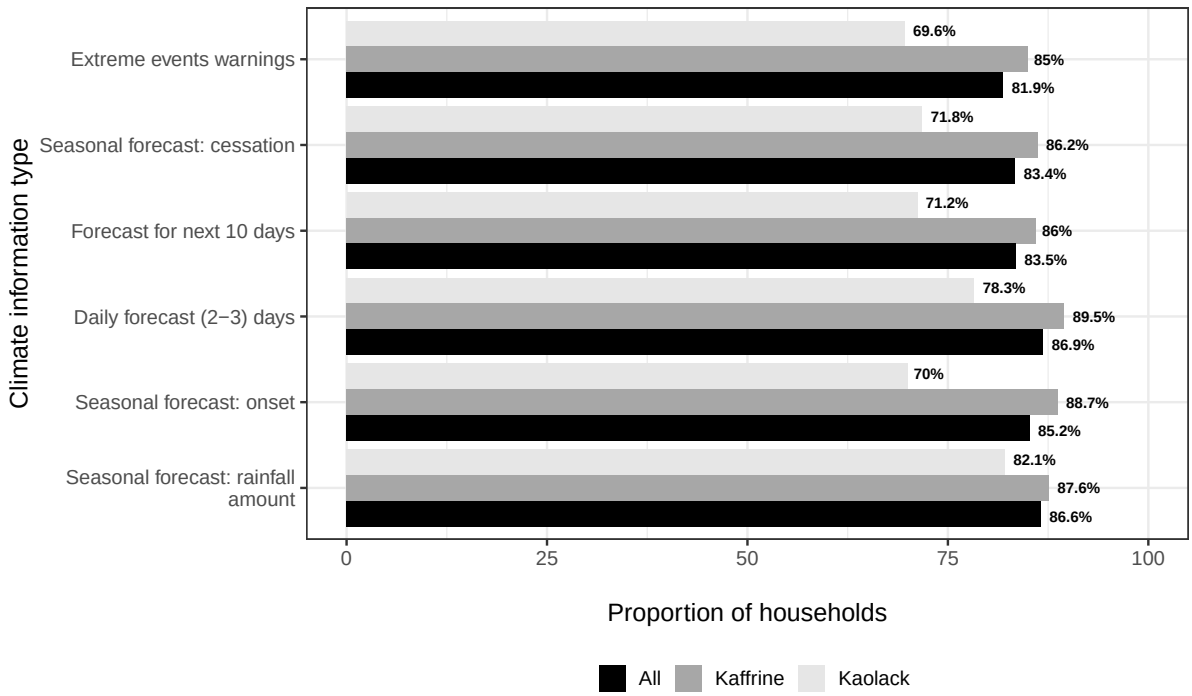


Figure 5.3: Households' access to different CIS by province

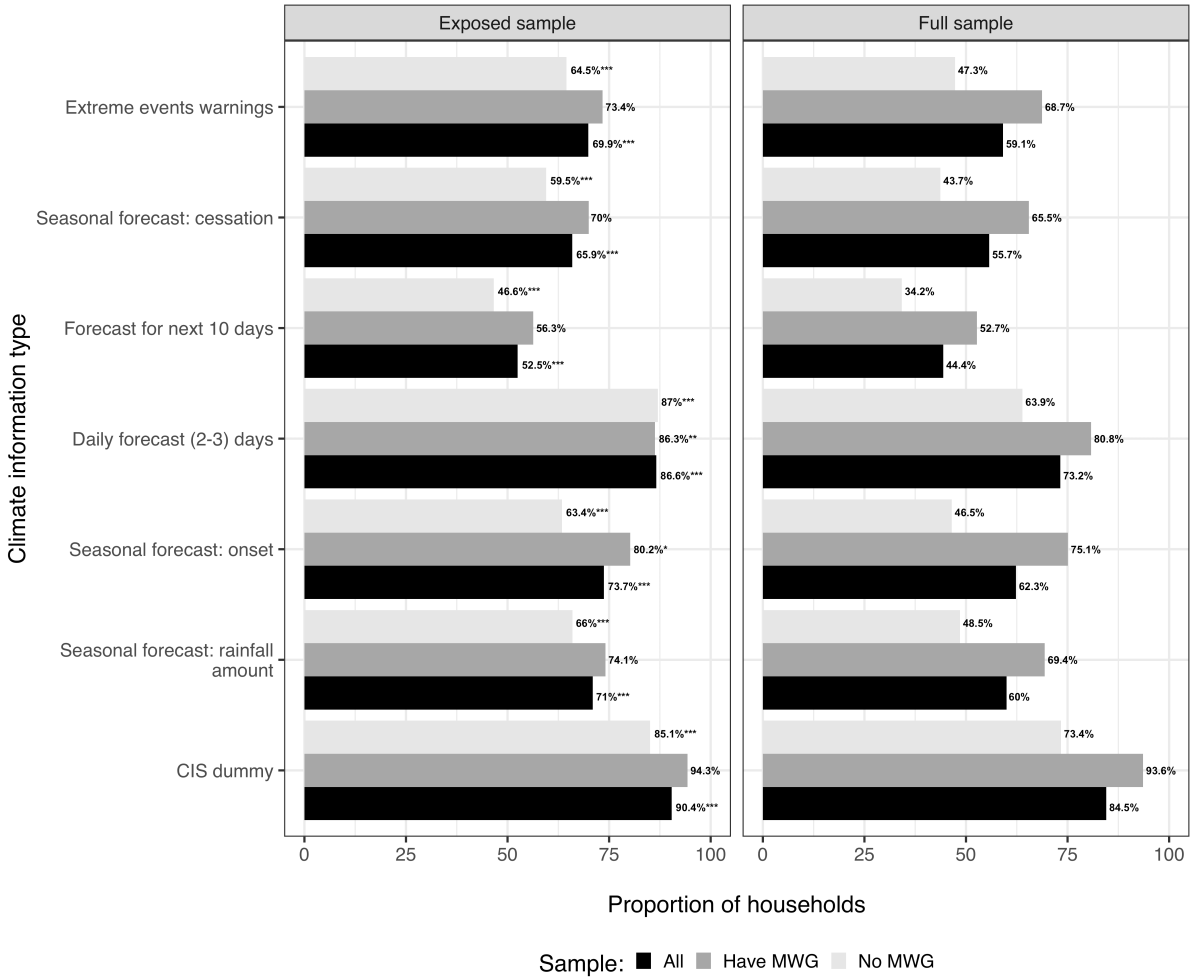


Figure 5.4: Households' access to different CIS disaggregated by presence of MWG

5.1.3 CIS use disaggregated by province and MWG access

Figure 5.5 shows the proportion of households that use each of the six different CIS for the two provinces. Use of CIS is expressed as a dummy variable that takes the value of 1 for each CIS that the household uses from one or more sources and 0 if otherwise. A household ability to use any given CIS is conditional on the household first being aware of the service and receiving the CIS through various sources. The most commonly used CIS in terms of the absolute number of households in Kaffrine are 2-3 day weather forecast, the onset of rains, the total amount of rain, early warning system and cessation of rains in that order. Similarly, in Kaolack, 2-3 day weather forecast, the total amount of rain, early warning system and cessation of rains are the most commonly used CIS. There are more farmers in Kaffrine that used all the six CIS compared to Kaolack. On average, at least 85% of households acknowledged receiving all the six CIS compared to about 70% in Kaolack. In Kaffrine district, for example, the three most commonly received CIS are the 2-3 day weather forecast, onset of rains, and the total amount of rain; while in Kaolack the most received are the total amount of rain, 2-3 day weather forecast, and cessation of rains.

In the previous discussion on CIS use by province, we considered only the exposed sub-sample i.e. households that were aware and had access to CIS. Figure 5.6 presents

a comparison of the CIS use rates for both the full sample and exposed sub-sample, disaggregated by the presence of MWGs. Just as with CIS awareness and exposure, proportionately more households in the MWG areas that used CIS compared to those in locations where the MWG does not operate. In addition, for all the six climatic information services, the use rate was generally lower for the whole sample compared to the sub-sample of those exposed to the MWG. More specifically, the CIS use rates in the full sample were almost half that of the exposed sub-sample for all the six CIS mainly due to the higher rates of farmers that are not aware anddo not have access to CIS. Furthermore, unlike with the CIS access rate, the CIS use rates among households in the MWG areas were significantly different between the full sample and the exposed sub-sample. This points to the presence of access exposure bias among these households; although almost all the households in the MWG areas were aware of the CIS, not all had access. Presence of awareness and access exposure bias implies that, in the adoption estimations, applying classical adoption models on the full sample risks under-estimating the true population adoption rate since farmers who are not exposed to CIS cannot adopt. On the other hand, by using the exposed sub-sample with the classical adoption models, the unexposed sub-sample is omitted. Therefore, we use ATE corrected models to correct for this exposure bias in our econometric analysis in the next section.

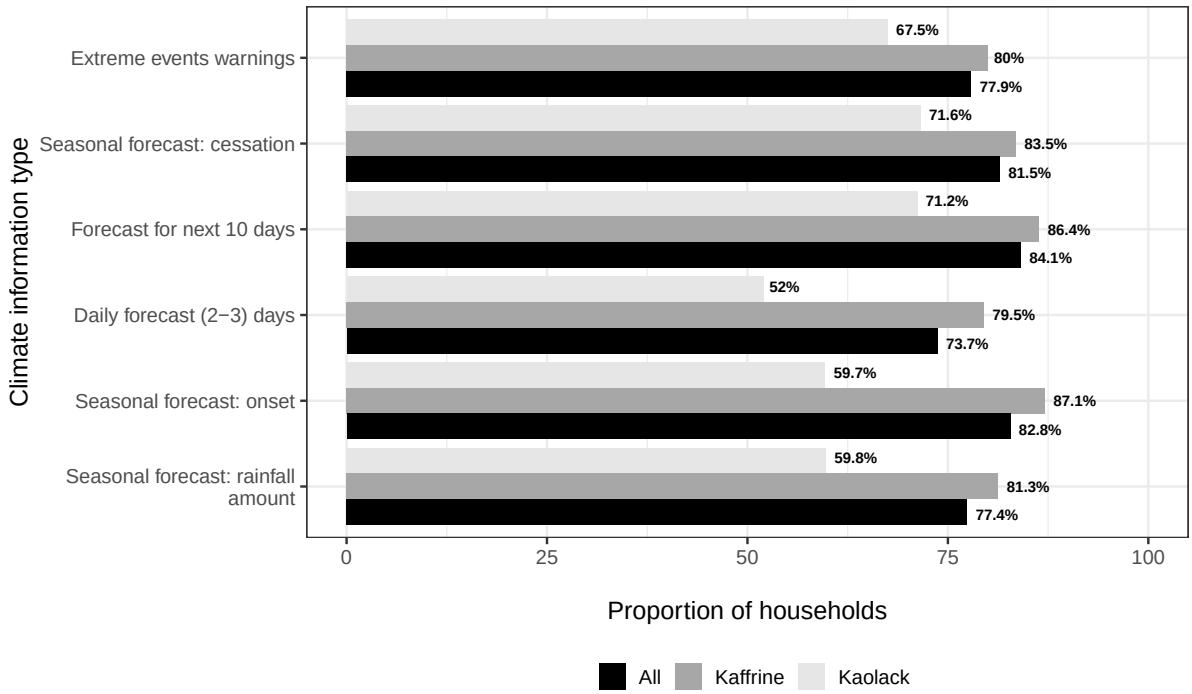


Figure 5.5: Households' use of different CIS by province

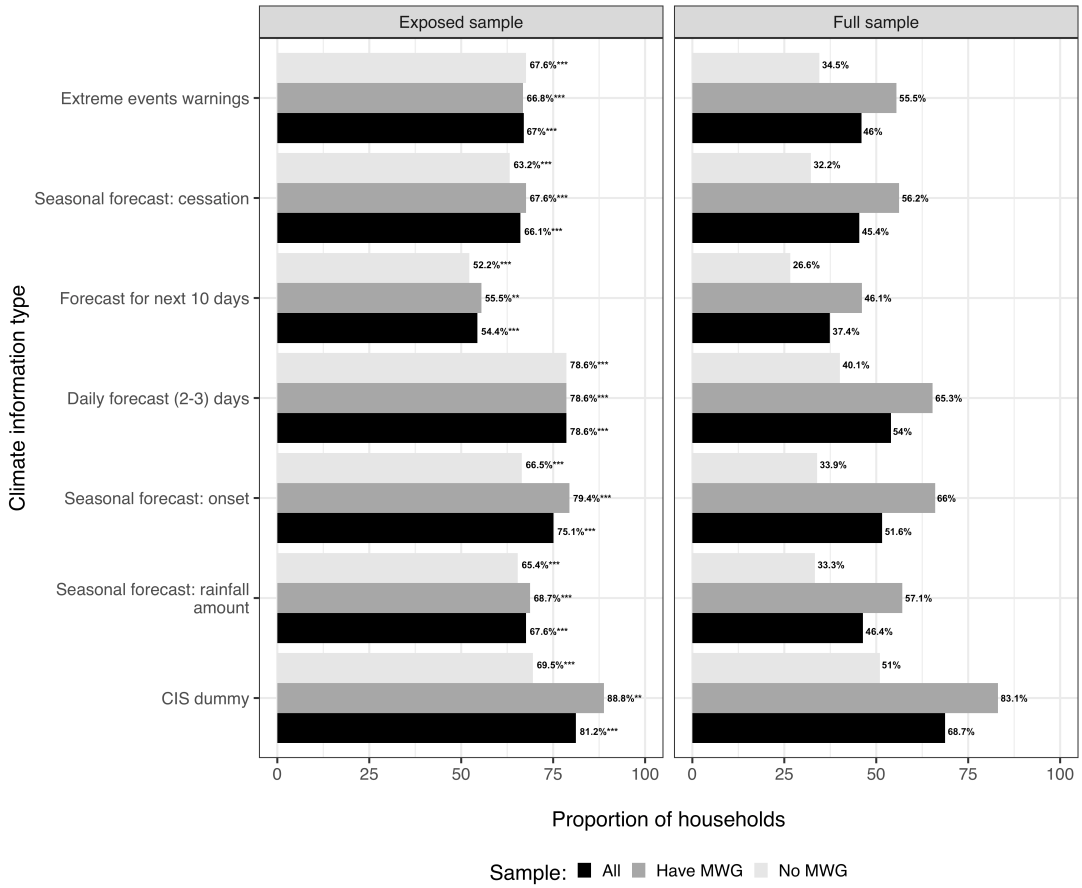


Figure 5.6: Households' use of different CIS disaggregated by presence of MWG

5.2 Sources and extent of use of CIS

We further probed respondents on the extent to which they use CIS to inform on-farm decisions. The perceptions were based on a scale ranging from very large extent to no effect at all as shown in Figure 5.7. For the six climate information products, the majority of farmers that used CIS reported the information as being influential to a very large extent.

We also asked the farmers the level of confidence they have on the climate information they received for the six climate information products. The results presented in Figure 5.8 are based on farmers' perception on the level of confidence they have for each type of CIS based on the following scale: (i) high confidence, (ii) some confidence and (iii) low confidence. For all six CIS, the majority of farmers expressed having high confidence.

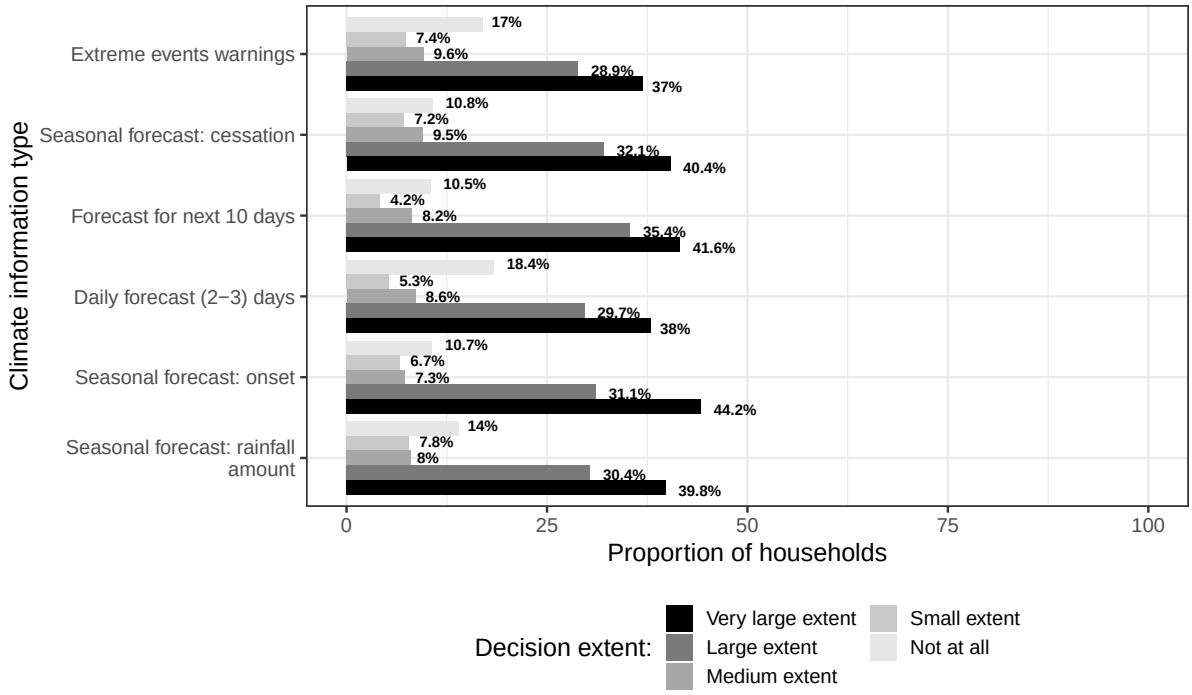


Figure 5.7: Farmers' perceptions on the extent to which CIS influences farming decisions

In addition, Figure 5.9 shows information on the gender of the individual who receives climate information services. It is evident that for the six CIS types, in most of the households the husband is the one who received the climate information. The second most common was where both wife and husband receive the information although it was in relatively few households. However, for all the six CIS, the least popular were households where the wife received climate information alone.

Table 5.1 presents the top five sources for different CIS products in both regions-Kaffrine and Kaolack. National radio is the most common source of climate information for all the six types of information in both districts and community radio is the second most common. This is also the case in Rwanda as indicated by Coulibaly et al. 2017a and in Tanzania as shown by West, Daly, and Yanda 2018. National radio is however more common in Kaolack region where at least 75% of the farmers receive information on all products on national radio compared to 56% in Kaffrine region. In both districts, relatively few farmers reported having received information on climatic products from friends and televisions. None of the farmers in Kaolack region received information from farmer promoters on any of the climatic information services, although it was the third most common source of climate information among farmers in Kaffrine for all the products.

Table 5.1: Top five sources for different CIS products

		Province	
	Full sample	Kaffrine	Kaolack
Seasonal forecast of the total amount of rainfall	(n=477)	(n=390)	(n=87)
National radio	61.4	57.4	79.3
Community Radio	35.8	41.8	9.2
Farmer promoter	20.5	25.1	-
Television	13.0	12.1	17.2
Friends	10.3	11.3	5.7
Seasonal forecast of the start of the rains (onset)	(n=495)	(n=418)	(n=77)
National radio	62.0	58.9	79.2
Community Radio	36.4	41.1	10.4
Farmer promoter	19.2	22.7	-
Television	13.7	12.7	19.5
Friends	10.5	10.8	9.1
Forecast of the weather for today or 2-3next days	(n=582)	(n=459)	(n=123)
National radio	68.9	65.4	82.1
Community Radio	35.6	42.3	10.6
Television	16.2	14.2	23.6
Farmer promoter	12.2	15.5	-
Friends	9.3	10.0	6.5
Forecast for the following 10 days	(n=353)	(n=301)	(n=52)
National radio	62.9	59.5	82.7
Community Radio	38.0	43.2	7.7
Farmer promoter	17.3	20.3	-
Television	11.0	9.0	23.1
Friends	7.4	7.3	7.7
Seasonal forecasts of cessation of rainfall	(n=443)	(n=369)	(n=74)
National radio	59.4	55.6	78.4
Community Radio	39.7	45.5	10.8
Farmer promoter	17.8	21.4	-
Television	12.6	11.1	20.3
Friends	10.2	10.6	8.1
Early warning of an extreme event	(n=470)	(n=390)	(n=80)
National radio	63.6	61.3	75.0
Community Radio	38.1	44.4	7.5
Farmer promoter	15.3	18.5	-
Television	11.5	10.0	18.8
Friends	10.0	10.0	10.0

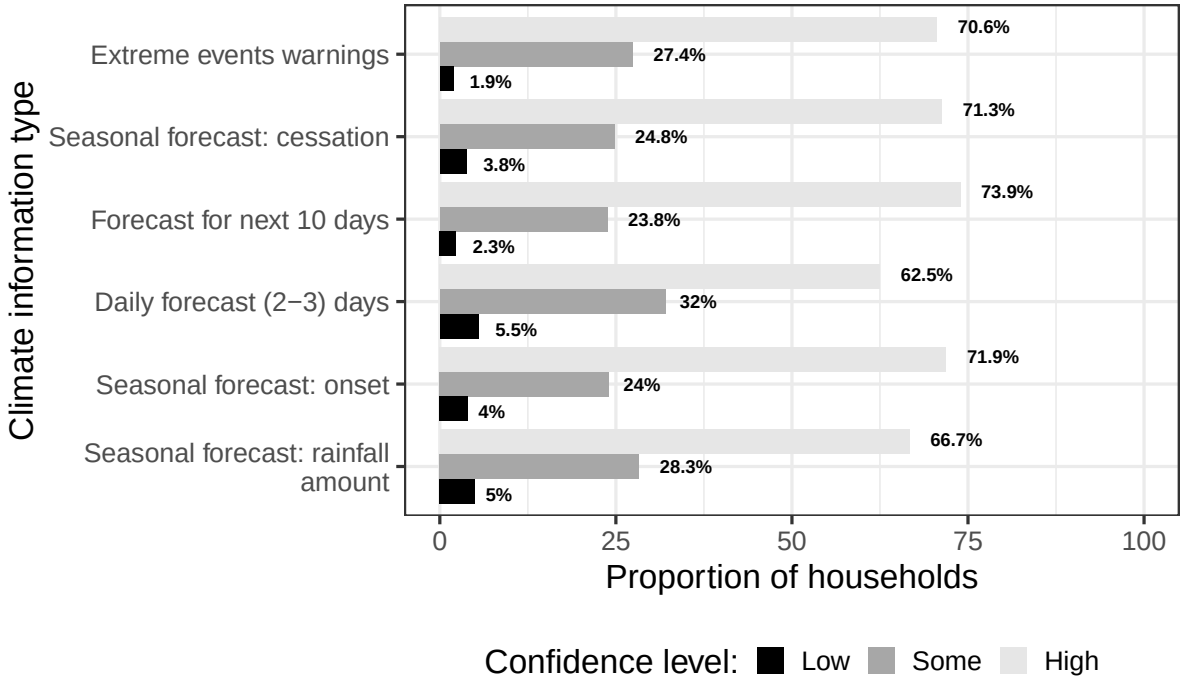


Figure 5.8: Farmer's level of confidence with different CIS types

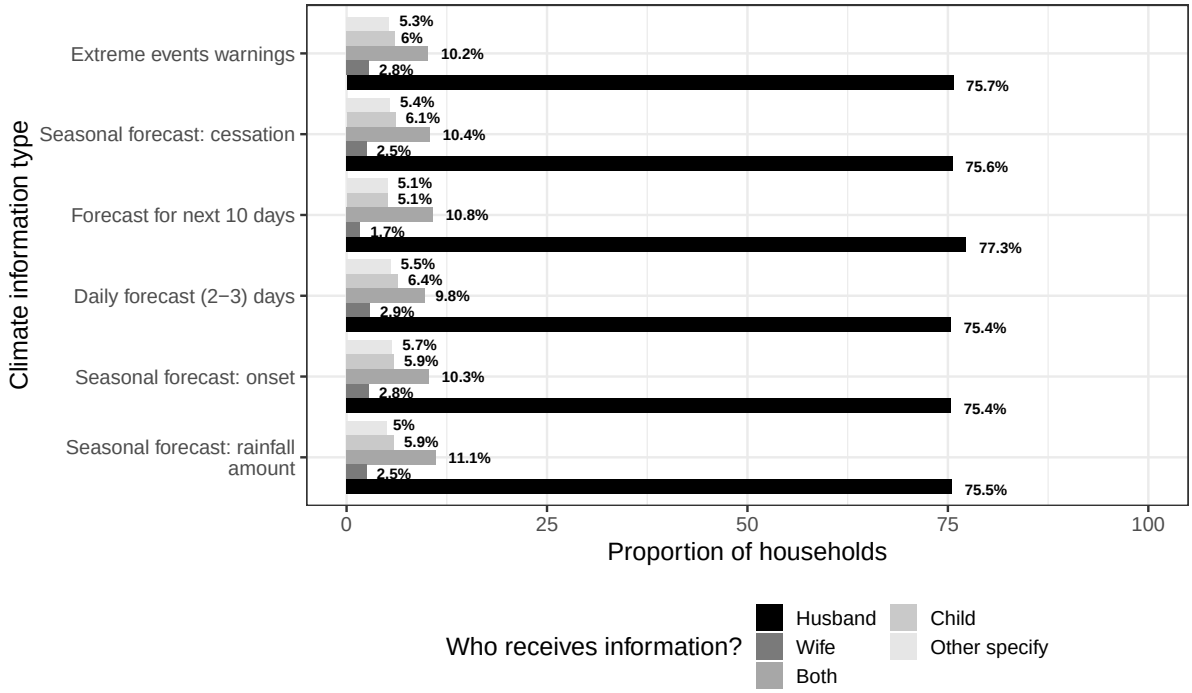


Figure 5.9: Gender of individual receiving information

5.3 Differences between CIS users and non-users

The descriptive summary in Table 5.2 shows the differences between CIS users and non-users in terms of household and farm characteristics; institutional factors; and farm management practices in the two surveyed regions. A household is classified as a CIS

user if in the previous 2016-17 agricultural season used at least one of the six CIS to adjust their on-farm decisions. Non-users, on the other hand, are households that did not use any of the six CIS to inform their farming decisions. This could have been due to a variety of reasons such as lack of awareness, access or knowledge of the value and net benefits derived from using CIS. In Kaffrine region, users of climate services tend to be younger, more educated, with significantly higher labor capacity, higher productive asset index, and higher TLU capacity[1]). To support these finding, there are studies that argue that older farmers are less likely to adopt new technologies because they are less innovative and more risk-averse compared to younger farmers (Feder, Just, and Zilberman 1985; Kabunga, Dubois, and Qaim 2012). Similarly, farmers with more wealth in terms of livestock and productive assets are more likely to have the means to afford assets that enable them to acquire knowledge. Furthermore, it is likely that information flows are biased towards community members of higher social status, which tends to be correlated with wealth and asset ownership (Kabunga, Dubois, and Qaim 2012).

When considering the Poverty Probability Index (PPI)[2], which measures the likelihood that a household falls below a certain poverty threshold (in this case USD 1.25), we do not find any significant differences between CIS users and non-users in the two provinces. In addition, given the fact that climate information products are knowledge-intensive, it is plausible that CIS uptake and use is higher among farmers with higher education. This is consistent with West, Daly, and Yanda 2018 who found low literacy levels to be a constraint in the access and use of CIS in Tanzania. For Kaolack region, there are not many differences between users and non-users of climate services.

In terms of farm characteristics, CIS users in Kaffrine region have bigger farms and cultivate larger pieces of land than non-users. Again, this may be due to the fact that they are wealthier and can afford the cost of knowledge acquisition. In terms of input use, CIS users in both districts tend to use more improved seeds and fertilizers than non-users. When it comes to social capital, a significantly higher proportion of CIS users in both districts receive visits from extension workers than non-users and have a member of the household being part of a farmer group association. This is plausible given the positive role that social capital and access to extension services play in the adoption of technology and access to information (Matuschke and Qaim 2009; Kabunga, Dubois, and Qaim 2012; Abdul-Razak and Kruse 2017).

[1]The Tropical Livestock Unit (TLU) is a common unit that describes livestock numbers across species to produce a single index weighted according to the specie type and age using the "Exchange Ratio" concept. Livestock is considered an important source for the supply of energy, food, and support for agricultural production. Among rural families in different parts of the world, livestock is also a store of wealth. The more livestock a household owns the wealthier they are considered in society (see Njuki et al. 2011 for further details

[2]The PPI is a user-friendly and indirect tool for measuring household poverty developed by the Grameen Foundation and measures consumption-based poverty by considering numerous questions contained in income and expenditure surveys. The PPI is a country-specific poverty measurement tool, available for 60 countries available at https://www.povertyindex.org/ppi-country

Table 5.2: General differences between households with and without access to the MWG and CIS users versus non-users in the surveyed provinces

	Kaffrine (n=577)		Kaffrine (n=577)		Kaolack (n=218)	
	No MWG	MWG	Non-users	Users	Non-users	Users
Household and farm characteristics						
Male household head (dummy)	0.97	0.95	0.93	0.97*	0.96	0.95
	(0.17)	(0.21)	(0.25)	(0.18)	(0.19)	(0.21)
Age of the household head (years)	50.83	49.54	51.76	49.38*	50.41	53.31
	(13.07)	(13.55)	(13.01)	(13.52)	(13.07)	(13.44)
Education level of hhold (years)	1.12	1.87**	0.94	1.88**	2.31	1.15**
	(3.43)	(3.93)	(2.86)	(4.01)	(3.95)	(3.52)
Farm altitude (metres)	39.97	32.17	28.13	35.54	34.99	34.89
	(35.11)	(57.49)	(74.07)	(46.26)	(38.76)	(43.48)
Cultivated area (Ha)	8.01	8.38	6.79	8.66**	8.47	9.71
	(5.74)	(8.15)	(4.74)	(8.16)	(8.22)	(10.08)
Members fully engaged in farming	0.23	0.38	0.26	0.36	0.15	0.25
	(0.75)	(1.07)	(0.91)	(1.03)	(0.60)	(0.67)
Full time farming (dummy)	0.88	0.89	0.89	0.89	0.84	0.76
	(0.33)	(0.31)	(0.32)	(0.31)	(0.37)	(0.43)
Group membership (dummy)	0.65	0.68	0.54	0.71***	0.47	0.62**
	(0.48)	(0.47)	(0.50)	(0.45)	(0.50)	(0.49)
Productive asset index	22.49	24.12	20.69	24.49**	21.34	24.98
	(16.38)	(19.33)	(15.97)	(19.22)	(14.35)	(20.57)
Total livestock unit	3.63	4.17	2.76	4.36	3.74	4.89
	(5.62)	(11.73)	(4.71)	(11.58)	(6.13)	(9.62)
Poverty Probability Index (PPI) score	18.77	22.41**	16.81	22.72***	21.74	23.53
	(11.87)	(16.87)	(12.89)	(16.34)	(16.54)	(16.61)
Access to radio	0.86	0.85	0.75	0.88***	0.83	0.88
	(0.34)	(0.36)	(0.43)	(0.33)	(0.37)	(0.32)
Male access to cellphone	0.24	0.30	0.29	0.28	0.20	0.18
	(0.43)	(0.46)	(0.46)	(0.45)	(0.40)	(0.38)
Institutional factors						
Access to extension (dummy)	0.31	0.28	0.11	0.33***	0.05	0.15***
	(0.46)	(0.45)	(0.32)	(0.47)	(0.21)	(0.36)
Presence of a MWG	0.00	1.00	0.64	0.79***	0.00	0.00
	(0.00)	(0.00)	(0.48)	(0.41)	(0.00)	(0.00)
Distance to extension (km)	9.24	8.37	7.52	8.85	16.23	23.06**
	(7.05)	(12.41)	(8.33)	(11.99)	(18.17)	(21.44)
Distance to all weather road (km)	4.48	3.37	1.90	4.07	3.49	3.43
	(21.61)	(8.10)	(2.76)	(14.14)	(10.98)	(3.94)
CIS awareness and use						
Number of CIS aware	4.36	4.70**	3.38	4.93***	2.15	4.45***
	(1.91)	(1.47)	(1.86)	(1.35)	(2.13)	(1.74)
Number of CIS accessed	3.75	4.12**	2.05	4.53***	1.08	4.11***
	(2.18)	(1.84)	(2.07)	(1.54)	(1.72)	(1.80)
Number of CIS used	2.95	3.46**	0.00	4.18***	0.00	3.60***
	(2.46)	(2.15)	(0.00)	(1.65)	(0.00)	(1.88)
Number of adaptive strategies implemented	5.06	7.30***	0.00	8.46***	0.00	4.74***
	(4.99)	(5.65)	(0.00)	(4.95)	(0.00)	(4.25)
Farm management practices						
Number of crops grown in 2016	3.45	3.21*	3.05	3.33**	3.07	3.22
	(1.25)	(1.24)	(0.99)	(1.29)	(1.37)	(1.47)
Margalef index	2.06	2.05	2.00	2.06*	2.12	2.18
	(0.34)	(0.32)	(0.27)	(0.34)	(0.36)	(0.42)
Use of improved seed (dummy)	0.16	0.34***	0.18	0.33***	0.07	0.25***
	(0.37)	(0.48)	(0.39)	(0.47)	(0.25)	(0.43)
Use of manure (dummy)	0.34	0.35	0.32	0.36	0.21	0.52***
	(0.47)	(0.48)	(0.47)	(0.48)	(0.41)	(0.50)
Use of chemical fertilizers (dummy)	0.73	0.68	0.60	0.72**	0.23	0.34*
	(0.44)	(0.47)	(0.49)	(0.45)	(0.42)	(0.48)
No. of cases	139	438	116	461	133	85

Notes: Mean values are shown with standard deviations in parenthesis;
*, **, *** denotes significance level at 10%, 5% & 1%, respectively.

5.4 Differences in CIS use and farm management practices disaggregated by MWG and province

Table 5.3 presents differences in CIS awareness and use as well as farm management practices between farmers in areas with MWGs versus those without. We also present differences between farmers in Kaolack and Kaffrine regions. Farmers in areas with MWGs were more aware of and had access to and even uptake and use a significantly higher number of CIS in making farming decisions than those in areas without MWGs. However, the use of manure was more common among farmers without access to the MWGs. We use the Margalef index[3] as a proxy for crop diversity and find that farmers that used CIS and had access to the MWGs are less likely to diversify crops compared to those using CIS but with no access to MWGs.

Figure 5.10, shows the correlation between the number of CIS used by farmers and the behavioral changes made in the 2016-17 agricultural season. The trend shows that farmers that used CIS in MWG locations used more CIS and implemented more adaptive strategies, on average, than those in locations where the MWG does not exist. In addition, farmers in Kaffrine province were more likely to use chemical fertilizers and improved seeds compared to those in Kaolack district. Comparing the two provinces, farmers in Kaffrine that used CIS implemented significantly more adaptive strategies compared to CIS users in Kaolack.

Table 5.3: Differences in CIS exposure and use and farm management practices disaggregated by MWG and province

	Sampled farmers by province			
	Without MWG	With MWG	Kaolack	Kaffrine
CIS awareness and use				
Number of CIS aware	4.45	4.93***	4.77	4.90
	(1.74)	(1.35)	(1.55)	(1.36)
Number of CIS accessed	4.11	4.53**	4.36	4.52
	(1.80)	(1.54)	(1.72)	(1.52)
Number of CIS used	3.60	4.18***	3.93	4.16
	(1.88)	(1.65)	(1.86)	(1.62)
Number of adaptive strategies implemented	4.74	8.46***	6.08	8.79***
	(4.25)	(4.95)	(4.52)	(5.03)
Farm management practices				
Number of crops grown in 2016	3.22	3.33	3.38	3.27
	(1.47)	(1.29)	(1.42)	(1.27)
Margalef index	2.18	2.06***	2.12	2.06**
	(0.42)	(0.34)	(0.39)	(0.33)
Use of improved seed (dummy)	0.25	0.33	0.23	0.36***
	(0.43)	(0.47)	(0.42)	(0.48)
Use of manure (dummy)	0.52	0.36***	0.43	0.36
	(0.50)	(0.48)	(0.50)	(0.48)
Use of chemical fertilizers (dummy)	0.34	0.72***	0.57	0.71***
	(0.48)	(0.45)	(0.50)	(0.46)
No. of cases	357	438	461	85

Notes: Mean values are shown with standard deviations in parenthesis; *, **, *** denotes significance level at 10%, 5% & 1%, respectively.

[3]The Margalef index measures the species richness of biodiversity by simply counting the number of different plant species in a given area (Donfouet et al. 2017).

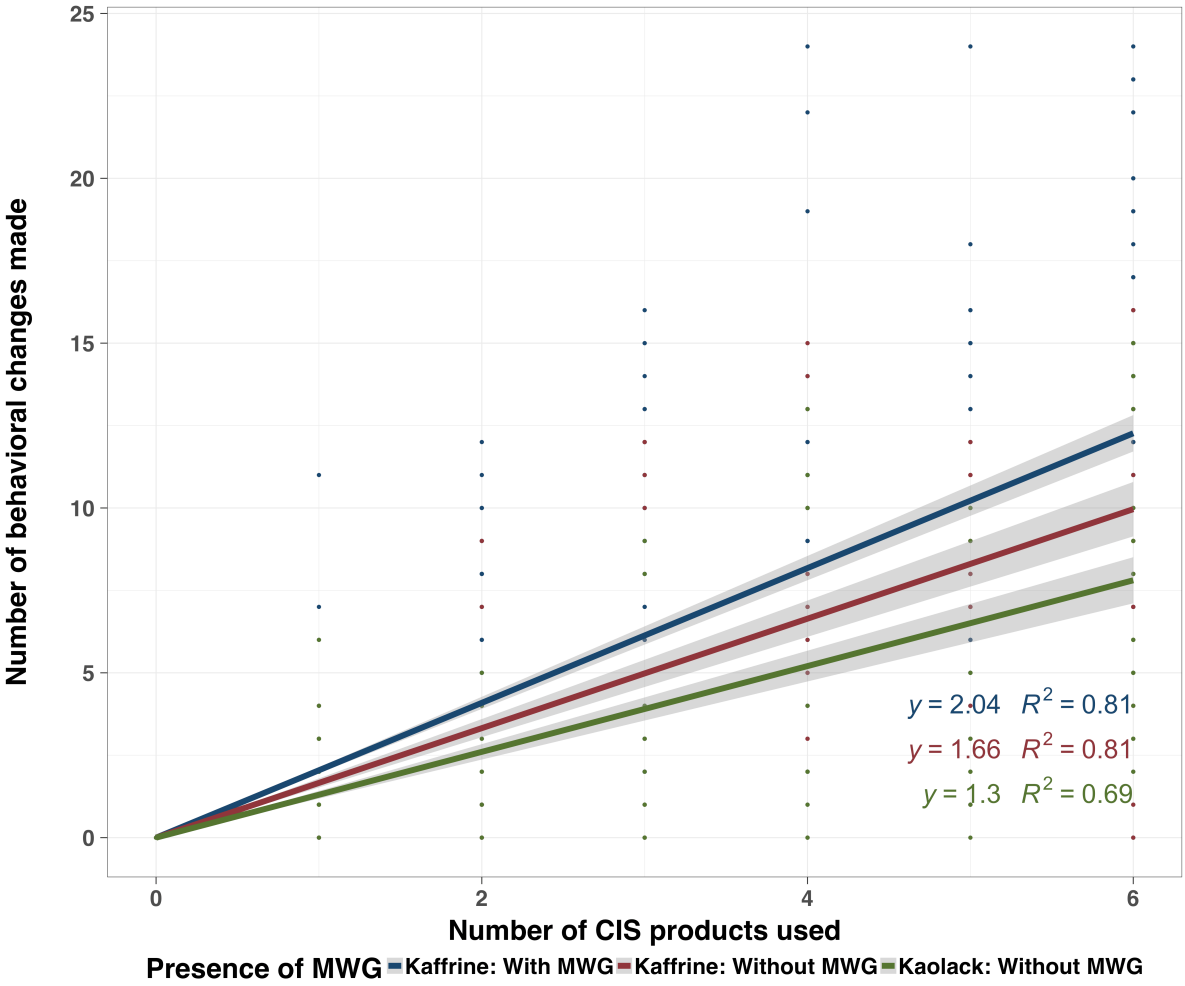


Figure 5.10: Correlation between CIS use and farmers' behavioral changes

5.5 Differences in farm management decisions disaggregated by MWG

We briefly discuss observed patterns in the use of farm management practices by the presence or absence of MWGs. We considered three farm management practices; use of improved seeds, chemical fertilizers and manure on the three most commonly grown crops in the study regions (groundnuts, maize, and millet). Figure 5.11 presents a comparison of the use of improved seeds by exposure to the MWGs. Use of improved seeds in general is higher among households in Kaffrine with access to MWG (38%) compared to those in Kaffrine without MWG (21%) and those in Kaolack without MWG (24%). A similar trend is also observed for maize with households within MWG areas having higher use of improved seed than those in non-MWG areas. Of the three crops, use of improved seeds is highest for groundnuts among households in MWG areas (31%) and lowest for maize (6%). These results seem to suggest that access to MWG seems to be associated with higher of improved seed particularly for maize and and groundnuts. However, the same trend is not prevalent when considering millet where use seems very uniform across farmers, regardless of the location and whether or not they have access to the MWG.

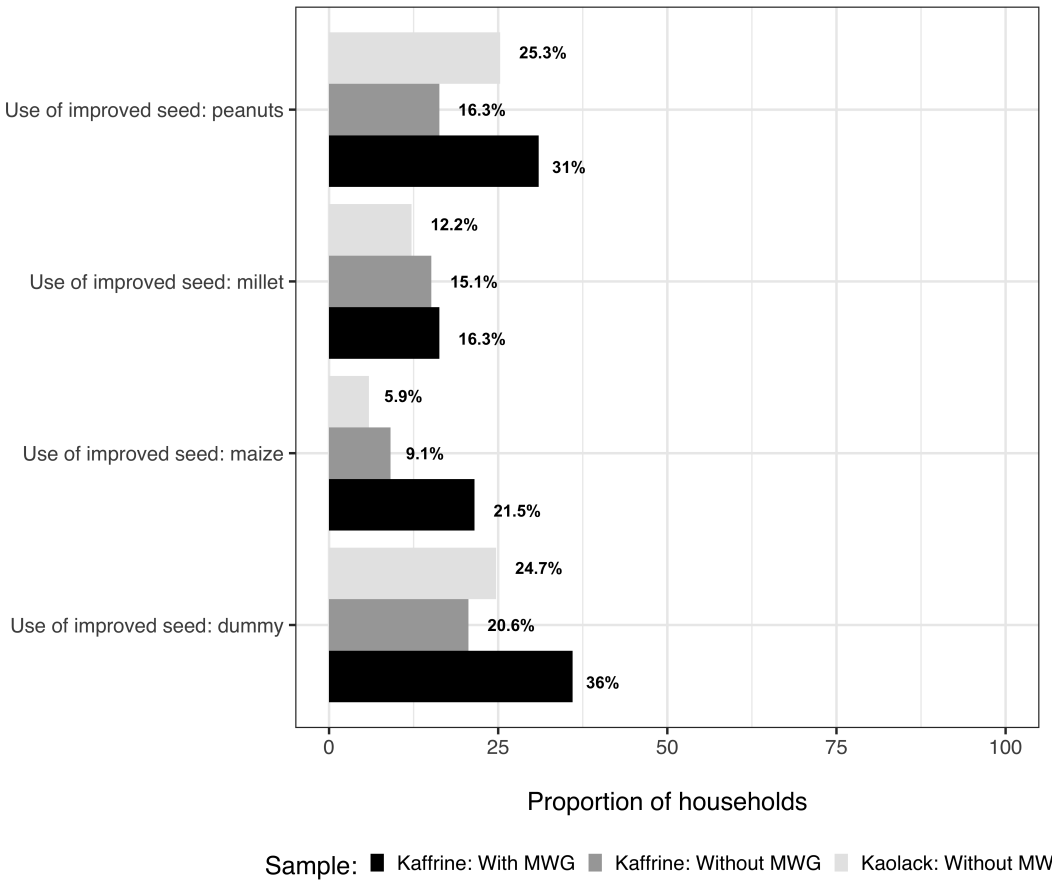


Figure 5.11: Reported rates of use of improved seed disaggregated by MWG access

The trends for chemical fertilizer a bit different. As shown in Figure 5.12, use is significantly higher among farmers in Kaffrine (71% with access to the MWG) and (77% with no access to the MWG) compared to households in Kaolack without access to MWG

(34%). The same trend is also observed when the analyses is dissagregated by type of crop, with higher use rates observed among farmers in Kaffrine compared to Kaolack. The use of chemical fertilizer is generally higher for farmers in Kaffrine compared to those in Kaolack but MWG access to MWG does not seem to be associated with use. In terms of manure use, Figure 5.13 shows that there are proportionately more farmers that use manure in Kaolack compared to those in Kaffrine. For example, just over half of the farmers in Kaolack generally use Manure compared to only about 36% of farmers in Kaffrine. There is no discernible difference between use of manure between households with access to MWG and those without access in Kaffrine. The contrasting patterns observed in Figures 5.12 and 5.13 between manure and fertilizer use in Kaolack and Kaffrine make sense considering that the two are commonly used as substitutes.

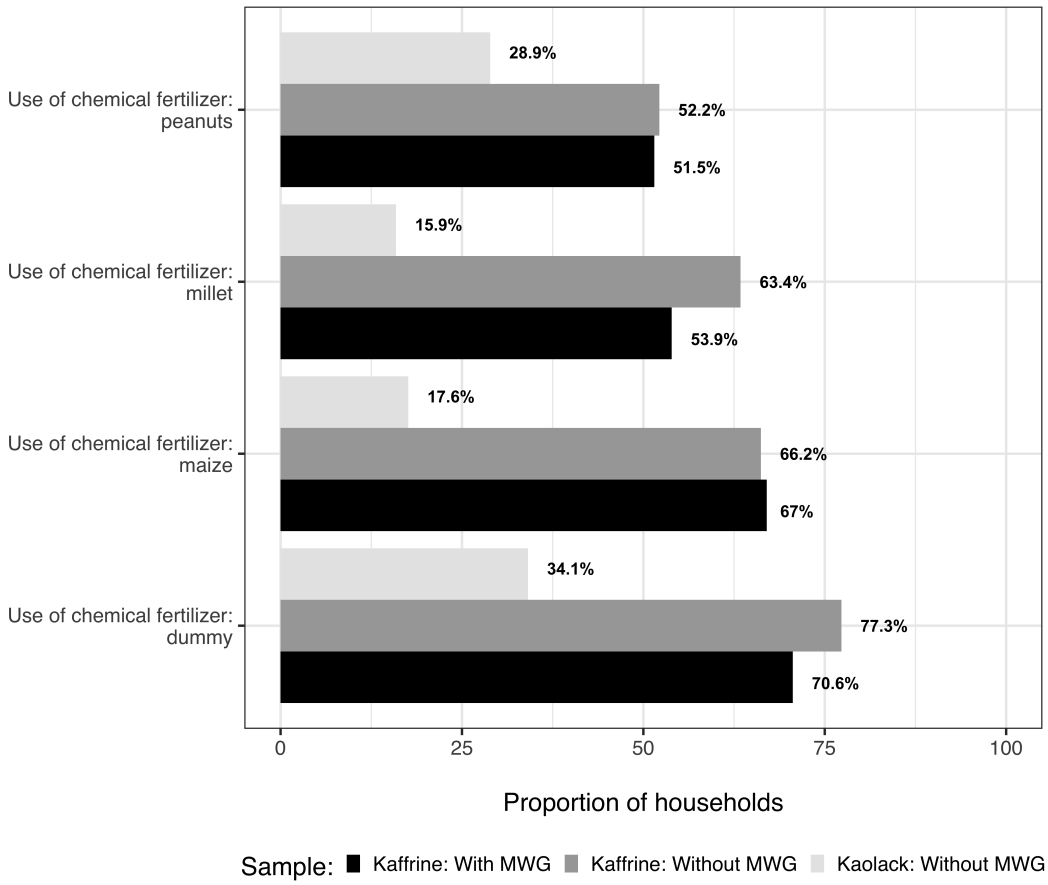


Figure 5.12: Reported rates of use of chemical fertilizer disaggregated by MWG access

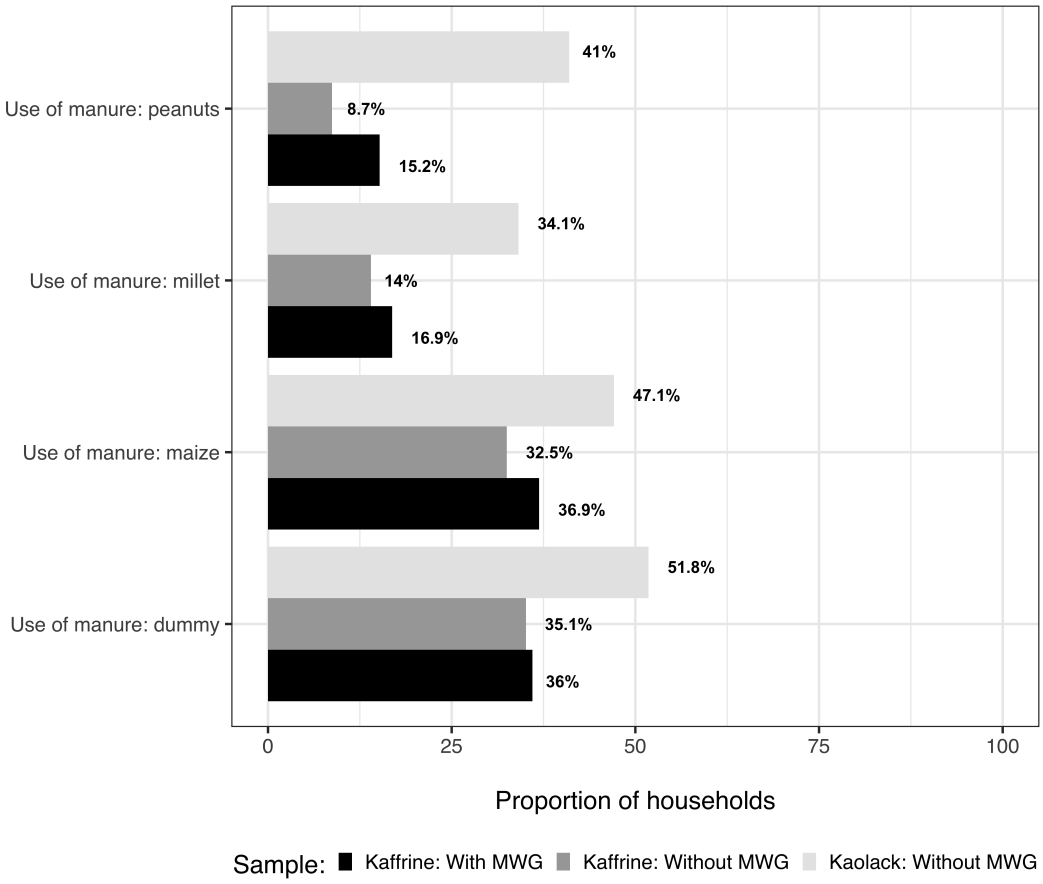


Figure 5.13: Reported rates of use of manure disaggregated by MWG access

5.6 Conclusions from the descriptive statistics

In the descriptive statistics section 5, we have characterized the sampled households' use of the different CIS depending on whether they have access to the MWG and their location. The descriptive statistics seem to point out some systematic differences between CIS users and non-users when disaggregated by access to MWG. Several insights can be drawn from these descriptive statistics. First, we find that there are clear differences in awareness, access, and use of the different CIS between farmers in Kaffrine and Kaolack and between farmers with and without access to MWG. Farmers in Kaffrine (with MWG) tend to be more aware, have better access and use of the different CIS than their counterparts in Kaolack (without MWG). We also observe some systematic differences in terms of household and farm characteristics and institutional factors between users and non-users in the two provinces.

Second, we have demonstrated that estimated adoption rates for CIS vary greatly depending on the approach used. Using a classical approach, which is assumes that all sampled farmers were universally exposed and had full information about CIS, tends to bias the estimated access and use rates of CIS downwards. The results are in the right pane labeled full sample statistics in Figures 5.4 and 5.6. Similarly, we have also shown that estimating access and adoption rates of CIS by only considering farmers that are aware and have access to CIS biases the estimates upwards. The assumption in such a

scenario is that farmers not exposed to CIS, in terms of awareness and/or access, are erroneously treated as if they were indifferent to CIS. If either method is extended in modeling the factors that determine CIS awareness, access, and use, the results from these models will also be biased. In order to account for such exposure bias in awareness and access, the counterfactual ATE framework will be used in the next analytical section6 to properly estimate sample and population awareness, access and use rates of CIS and the factors that affect them.

Third, the descriptive statistics also point to a positive association between farmers' use of CIS in locations where the MWG exists and use of adaptation strategies in making farm management practices. However, due to systematic differences that are apparent between CIS users and non-users, this association cannot be interpreted as a causal one. In order to properly analyze the link between CIS use, the presence of an MWG and implications on behavioral outcomes, we will use the treatment effects model that accounts for the observed and unobserved differences among sampled farmers in the second analytical section 7.

6
THE IMPACT OF THE MWG MODEL ON CIS UPTAKE AND USE UNDER IMPERFECT INFORMATION

> 'The ANACIM agency in Senegal is highly praised for their effort in providing meaningful and effective climate information services. Evidence from farmers' responses reviewed in the previous section, as well as from similar studies in the Kaffrine region, suggests that CIS reach out to many people, and the messages are positively valued by recipients'. .....Serra and Mckune 2016

Under classical economics, farmers can only adopt a new technology if they are exposed to it (Foster and Rosenzweig 2010). This implies awareness and access to the new technology are necessary and conditions for adoption to occur. However, when a new technology is introduced, it is not possible that every individual in the population is exposed due to information asymmetries. Therefore, using classical approaches in estimating adoption rates when the population is not universally exposed can lead to estimators that are biased and inconsistent relative to the true population (Diagne and Demont 2007). In order to account for such exposure bias in awareness and access, this analytical section applies a non-classical approach to estimating adoption, the counterfactual ATE framework to correct the problems resulting from non-exposure and selection biases. We will analyze the effectiveness of the MWG model in influencing awareness, access, and use of CIS among farmers in the surveyed districts. We use regression analyses that follow two stages. First, probit models are used to analyze the factors that affect awareness, access, and use of CIS, while the Poisson regression are used to analyze CIS use intensities of farmers. Second, the probit and Poisson models that control for information asymmetries in awareness and access exposure are used to estimate unbiased CIS use and intensity of use parameters, respectively.

6.1 Factors affecting farmers' awareness of CIS

Table 6.1 presents the results of the first-stage models that explain the factors that affect households' awareness of CIS expressed in terms of marginal effects at the weighted sample mean values. We present results from four models; model 1 looks at the probability of a household being aware of at least one of the six CIS under consideration, while model 2 looks at the probability of a household being aware of at least one of the seasonal forecasts (i.e. the total amount of rain, onset of rains or cessation of rains). Model 3 considers the probability of a household being aware of daily weather forecasts, while model 4 considers the probability of a household being aware of early warning systems. We start with the first column on the likelihood of households being aware of at least one CIS. Household's membership to an organized group increases the likelihood of being

aware of at least one CIS by approximately 2.3 percentage points. This is in line with findings from previous studies that emphasize the positive role that social networks play in information sharing and social learning on technology awareness (Matuschke and Qaim 2009; Kabunga, Dubois, and Qaim 2012; Simtowe, Asfaw, and Abate 2016). Similarly, access to radio is positively associated with farmers' awareness of at least one CIS. The descriptive statistics section5 revealed that the majority of sampled farmers receive climatic information through radio thus owning a radio is expected to have a positive influence on awareness of CIS. Other empirical studies also conclude that in Kaffrine, community radios were the best medium to disseminate climate information and agricultural advice (Lo and Dieng 2015). Ouedraogo et al. 2018 highlight that in addition to diffusing climate information, community radios also play the role of collecting climate data from the manual rain gauges installed by the CIS diffusion center and communicating these to users. Use of information and communication technologies (ICT), such as radio, in disseminating agro-advisory services has a comparative advantage in that it reaches more farmers at relatively cheaper transactions costs compared to conventional methods like face-to-face interaction and extension services (Zougmoré et al. 2018; Etwire et al. 2017).

Surprisingly, farmers engaged in full-time farming were significantly less likely to be aware of at least one CIS by approximately 1.8 percentage points. One might argue that more on-farm time might mean fewer interactions with outside networks hence a lower likelihood to receive information. This is consistent with the finding by Kabunga, Dubois, and Qaim 2012, who conclude that full-time farmers were less likely to be aware of new banana cultivars in Kenya. Formal education is negatively associated with awareness of at least one CIS - implying that the less formal education farmers received the more likely they would be aware of at least one CIS. Among the institutional variables, presence of an MWG significantly increases the probability of CIS awareness by approximately 5.6 percentage points. Similarly, farmers in Kaffrine region are more likely to be aware of at least one CIS compared to farmers in Kaolack region. This can largely be attributed to the fact that MWGs, which are instrumental in the diffusion of climatic information in Senegal, were only found in Kaffrine in our sample.

Focusing on results that are disaggregated by individual CIS types, we find that group membership increases the likelihood of being aware of seasonal forecasts, daily forecasts and EWS by approximately 6.4, 6.3 and 13.8 percentage points, respectively. Similarly, access to radio is positively associated with farmers' awareness of daily forecasts. Further still, households with access to mobile phones were significantly more likely to be aware of daily weather forecasts. This is plausible in that for weather forecasts which are usually disseminated on a daily basis and at specific times, it is farmers that own or have access to mobile devices like phones and radios that are regularly exposed and more likely to be aware of this information. However, farmers who were engaged in full-time farming were significantly less likely to be aware of daily forecasts by about 3.9 percentage points. Among the institutional factors, access to extension services increased the probability of farmers being aware of daily forecasts and EWS by 9.3 and 13 percentage points respectively. The role of extension information in addressing information asymmetry is highly relevant. As expected, owing to the role of MWGs in Senegal, the presence of an MWG increased the probability of seasonal forecasts awareness by 9.7 percentage points. In addition, distance to the weather station has the expected negative sign on awareness. Farmers who are nearer to the weather station were more likely to be aware of daily

Table 6.1: Factors affecting farmers' awareness of CIS

	(1) Awareness of CIS		(2) Awareness of seasonal forecasts		(3) Awareness of daily forecasts		(4) Awareness of EWS	
	β / SE	Mfx	β / SE	Mfx	β / SE	Mfx	β / SE	Mfx
Household characteristics								
Male household head (dummy)	0.448	0.025	0.196	0.037	0.143	0.017	0.129	0.041
	(0.405)		(0.299)		(0.305)		(0.191)	
Age of the household head (years)	0.022	0.001	-0.027	-0.005	0.005	0.001	0.015	0.005
	(0.034)		(0.024)		(0.028)		(0.025)	
Age of h-hold head squared	-0.000	-0.000	0.000	0.000	-0.000	-0.000	-0.000	-0.000
	(0.000)		(0.000)		(0.000)		(0.000)	
Education level of hhold (years)	-0.046**	-0.003**	0.008	0.001	-0.015	-0.002	0.013	0.004
	(0.023)		(0.015)		(0.019)		(0.012)	
Cultivated area (Ha)	0.006	0.000	0.004	0.001	-0.004	-0.000	-0.004	-0.001
	(0.012)		(0.011)		(0.010)		(0.007)	
Members fully engaged in farming	0.124	0.007	0.036	0.007	0.126	0.015	0.106	0.034
	(0.109)		(0.078)		(0.107)		(0.073)	
Full time farming (dummy)	-0.314**	-0.018**	-0.088	-0.017	-0.328**	-0.039**	-0.294*	-0.094*
	(0.152)		(0.162)		(0.137)		(0.157)	
Group membership (dummy)	0.414***	0.023***	0.339***	0.064***	0.535***	0.063***	0.431***	0.138***
	(0.125)		(0.118)		(0.122)		(0.123)	
Productive asset index	-0.006	-0.000	-0.008	-0.001	0.003	0.000	0.001	0.000
	(0.008)		(0.006)		(0.005)		(0.005)	
Total livestock unit	0.016	0.001	0.005	0.001	0.008	0.001	0.006	0.002
	(0.015)		(0.007)		(0.006)		(0.005)	
Access to radio	0.580***	0.033***	0.255	0.048	0.668***	0.079***	0.207	0.066
	(0.160)		(0.156)		(0.141)		(0.126)	
Male access to cellphone	0.568	0.032	-0.086	-0.016	0.754***	0.089***	0.132	0.042
	(0.422)		(0.134)		(0.233)		(0.119)	
Institutional factors								
Access to extension (dummy)	0.000		0.358	0.068	0.786***	0.093***	0.406***	0.130***
	(.)		(0.225)		(0.222)		(0.104)	
Presence of a MWG	0.993***	0.056***	0.510***	0.097***	-0.121	-0.014	0.163	0.052
	(0.303)		(0.193)		(0.263)		(0.167)	
Distance to extension (km)	0.014*	0.001*	0.004	0.001	0.010*	0.001*	0.002	0.001
	(0.008)		(0.005)		(0.006)		(0.004)	
Distance to all weather road (km)	0.053	0.003	-0.001	-0.000	0.069***	0.008***	0.001	0.000
	(0.035)		(0.004)		(0.024)		(0.004)	
Distance to weather station (km)	-0.059	-0.003	-0.143***	-0.027***	-0.157***	-0.018***	-0.028	-0.009
	(0.062)		(0.036)		(0.045)		(0.043)	
Kaffrine province (dummy)	0.723***	0.041***	0.699***	0.133***	0.850***	0.100***	0.555***	0.177***
	(0.231)		(0.178)		(0.259)		(0.174)	
Constant	-0.928		0.780		-0.400		-0.759	
	(1.028)		(0.782)		(0.839)		(0.601)	
Observations	609		795		795		795	
Pseudo R^2	0.289		0.197		0.253		0.115	
LR chi2	1605.892		259.195		541.152		306.179	
Prob > chi2	0.000		0.000		0.000		0.000	
Baseline predicted probability	0.914		0.840		0.869		0.723	

* p<0.1, ** p<0.05, *** p<0.01. Village clustered standard errors in parentheses.

forecasts and seasonal forecasts. Furthermore, farmers in Kaffrine region are more likely to be aware of daily forecasts, seasonal forecasts, and instant extreme weather events compared to farmers in Kaolack region. Again, this can largely be attributed to the fact that since the MWGs were first piloted in Kaffrine province, there are higher chances that many of the households have been exposed to CIS.

6.2 Factors affecting farmers' access to CIS

Table 6.2 presents the results of the first-stage models that explain the factors that affect households' access to CIS expressed in terms of marginal effects at the weighted sample mean values. The dependent variables used for Models 1 to 4 are defined the same as

in the awareness models presented in Table 6.1. Similar to the awareness model, group membership is associated with the higher likelihood (approximately 7.2 percentage points) of a household having access to at least one CIS. Again, this further emphasizes the positive role that social capital plays in information flow between farmers. Access to radio also significantly increases the likelihood of farmers' access to at least one CIS by approximately 5.4 percentage points. Just as with the awareness model, farmers who are fully engaged in full-time farming were significantly less likely to have access to at least one CIS by about 8 percentage points. Again, this may be because these farmers have less time for outside interactions hence low exposure to climate information. In addition, households with access to extension services had a significantly higher probability of CIS access by about 7.2 percentage points. Contrary to our expectation, while MWG affects awareness, it does not have a significant effect on access to CIS. This could perhaps be explained by the fact that being able to receive climate information is more a function of household level characteristics (e.g., ownership of a radio or cellphone) or other institutional factors (e.g., extension services) that are instrumental in the dissemination of CIS to potential users. Distance from the government extension services is positively associated with access to CIS meaning that farmers nearer to the government extension services were significantly less likely to access CIS. This may be because government extension services are not the most common means of climate information extension in Senegal. MWGs and lead farmers are the most popular CIS extension means and most of them are found in rural areas which may be far from the government extension offices. We also observe the same with distance to the weather stations, households that are nearer to the weather stations are less likely to access CIS. Finally, just as with CIS awareness, farmers in Kaffrine region are more likely to access CIS compared to those in Kaolack. Again, this is partly attributable to the fact that Kaolack region has no MWGs which are instrumental in the promotion of CIS in Senegal.

For the specific CIS, households had membership to farmer groups were more likely to have access to seasonal forecasts and EWS. Membership increased the probability of access to seasonal forecasts by about 6.6 percentage points and EWS by 14.4 percentage points. Households that had access to extension services were also more likely to access seasonal forecasts and EWS. Similarly, the presence of an MWG is significantly positively associated with access to seasonal forecasts. However, farmers who were fully engaged in full-time farming were significantly less likely to access seasonal forecasts and daily forecasts. Access to extension services significantly increased the probability of accessing seasonal forecasts and EWS by about 6.6 and 14.4 percentage points respectively. However, farmers who are near the government extension offices are less likely to access daily forecasts and seasonal forecasts. As a result, the presence of an MWG increases the probability of accessing seasonal forecasts by about 5.5 percentage points. Households that are nearer to weather stations were less likely to access seasonal forecasts, daily forecasts, and EWS. Finally, farmers in Kaffrine were more likely to access seasonal forecasts, daily forecasts, and EWS compared to farmers in Kaolack region.

Table 6.2: Model for factors affecting CIS **access**

	(1) Access of CIS		(2) Access of seasonal forecasts		(3) Access of daily forecasts		(4) Access of EWS	
	β / SE	Mfx	β / SE	Mfx	β / SE	Mfx	β / SE	Mfx
Household characteristics								
Male household head (dummy)	0.154	0.016	0.361*	0.049*	0.100	0.016	0.450*	0.100*
	(0.284)		(0.218)		(0.316)		(0.261)	
Age of the household head (years)	-0.060	-0.006	-0.071*	-0.010*	-0.028	-0.004	-0.024	-0.005
	(0.054)		(0.037)		(0.041)		(0.030)	
Age of h-hold head squared	0.001	0.000	0.001**	0.000**	0.000	0.000	0.000	0.000
	(0.001)		(0.000)		(0.000)		(0.000)	
Education level of hhold (years)	0.004	0.000	0.003	0.000	0.002	0.000	0.013	0.003
	(0.021)		(0.021)		(0.016)		(0.019)	
Cultivated area (Ha)	-0.005	-0.001	-0.014	-0.002	-0.016	-0.002	-0.005	-0.001
	(0.013)		(0.013)		(0.015)		(0.013)	
Members fully engaged in farming	0.112	0.012	0.197*	0.027*	0.086	0.014	0.189**	0.042**
	(0.114)		(0.119)		(0.076)		(0.077)	
Full time farming (dummy)	-0.766***	-0.080***	-0.679***	-0.092***	-0.362**	-0.057**	-0.153	-0.034
	(0.218)		(0.223)		(0.175)		(0.268)	
Group membership (dummy)	0.704***	0.073***	0.611***	0.083***	0.535***	0.084***	0.505***	0.112***
	(0.163)		(0.161)		(0.154)		(0.152)	
Productive asset index	0.001	0.000	0.003	0.000	0.003	0.000	-0.004	-0.001
	(0.008)		(0.008)		(0.007)		(0.007)	
Total livestock unit	0.006	0.001	0.017**	0.002**	0.022	0.004	0.032**	0.007**
	(0.006)		(0.009)		(0.014)		(0.014)	
Access to radio	0.515**	0.054**	0.321	0.043	0.536***	0.085***	0.200	0.044
	(0.201)		(0.217)		(0.195)		(0.208)	
Male access to cellphone	0.005	0.001	-0.021	-0.003	0.044	0.007	0.015	0.003
	(0.147)		(0.161)		(0.134)		(0.172)	
Institutional factors								
Access to extension (dummy)	0.689***	0.072***	0.491**	0.066**	0.260	0.041	0.651***	0.144***
	(0.263)		(0.241)		(0.227)		(0.156)	
Presence of a MWG	0.220	0.023	0.404**	0.055**	0.187	0.029	0.042	0.009
	(0.229)		(0.192)		(0.192)		(0.215)	
Distance to extension (km)	0.014**	0.002**	0.008	0.001	0.012**	0.002**	0.011*	0.003*
	(0.007)		(0.005)		(0.005)		(0.006)	
Distance to all weather road (km)	-0.002	-0.000	0.003	0.000	-0.003	-0.000	0.012	0.003
	(0.005)		(0.005)		(0.004)		(0.013)	
Distance to weather station (km)	0.144***	0.015***	0.136***	0.018***	0.099**	0.016**	0.154***	0.034***
	(0.051)		(0.048)		(0.050)		(0.047)	
Kaffrine province (dummy)	0.682***	0.071***	0.417***	0.056***	0.525***	0.083***	0.527**	0.117**
	(0.173)		(0.150)		(0.165)		(0.226)	
Constant	1.179		1.297		0.132		-0.657	
	(1.350)		(0.828)		(1.036)		(0.920)	
Observations	743		668		690		574	
Pseudo R^2	0.208		0.170		0.130		0.145	
LR chi2	399.915		198.077		135.408		147.342	
Prob > chi2	0.000		0.000		0.000		0.000	
Baseline predicted probability	0.892		0.871		0.866		0.790	

* p<0.1, ** p<0.05, *** p<0.01. Village clustered standard errors in parentheses.

6.3 Factors affecting farmers' use and use intensity of CIS

Table 6.3 presents results from the second-stage models showing factors affecting the use and intensity of use of CIS. The first two columns present the results from a probit model showing factors affecting CIS use without accounting for CIS awareness and access exposure bias. The next two columns show results from the second-stage probit models showing factors affecting CIS use after correcting for awareness and access exposure bias. The last two columns present results from Poisson models showing factors affecting CIS use intensity after correcting for CIS awareness and access exposure bias.

For the classical model, we only interpret the marginal effects. The results reveal that while for most of the variables, the direction and significance of the effect on CIS use was the same in both the uncorrected model and the ATE-corrected models there are some exceptions. Consistent with both the awareness and access models, group membership had a significantly positive influence on the use of CIS as well as the number of climate information services a farmer used for both the awareness and access exposure corrected models. This is also true for the uncorrected model, where participating in a group increases the probability of CIS use by approximately 7.2 percentage points. This further emphasizes the positive role that social capital plays in the adoption of technology through the flow of information which has also been shown in other adoption studies in sub-Saharan Africa (e.g., Bandiera and Rasul 2006; Matuschke and Qaim 2009; Kabunga, Dubois, and Qaim 2012).

In addition, households that had access to radio were significantly more likely to use CIS. Access to a cell phone also had a significantly positive effect on the use of CIS as well as intensity of CIS use. Similarly, just as with the awareness and access models, farmers that had access to extension services and MWGs were more likely to adopt CIS. For the uncorrected model, the presence of an MWG increases the probability of CIS use by approximately 16 percentage points. This further emphasizes the importance of MWGs in the uptake, use, and adoption of CIS. However, for the ATE model correcting for access exposure, the effect of MWG on CIS use and intensity of use is not significant.

The effect of education on CIS use is not significant in the uncorrected model. However, for ATE awareness exposure corrected models, education level of the household had a significantly negative effect on the use as well as the intensity of use of the CIS. This may be because highly skilled small scale farmers are more likely to be involved in other off-farm activities thus agriculture is not their priority hence low adoption of agricultural related technologies (Kabunga, Dubois, and Qaim 2012; Uematsu and Mishra 2010). Similarly, for the ATE corrected models for access exposure, farmers who were involved in full-time farming were less likely to use CIS and also used significantly fewer climate information products. This may be because they have less time for social interactions hence low exposure to climate information products. This is, however, not significant for the uncorrected model. In all the models, farmers in Kaffrine are significantly more likely to use CIS compared to farmers in Kaolack province. The intensity of CIS use is also significantly higher in Kaffrine region compared to Kaolack region. Again, just as with CIS awareness and access, this may be partly attributed to the fact that Kaolack region

does not have MWGs among other factors such as access to markets.

Table 6.3: Factors affecting CIS **use** and intensity of use

			ATE corrected models for CIS use and intensity for exposure to			
	Use of CIS (dummy)		CIS use (dummy)		CIS intensity (number)	
	β / SE	Mfx	Awareness	Access	Awareness	Access
Household characteristics						
Male household head (dummy)	0.231	0.077	0.463	0.169	0.458	0.107
	(0.279)		(0.371)	(0.359)	(0.368)	(0.355)
Age of the household head (years)	-0.042	-0.014	0.0236	-0.0574	0.024	-0.066
	(0.028)		(0.0426)	(0.0433)	(0.042)	(0.043)
Age of h-hold head squared	0.000	0.000	-0.000152	0.000590	-0.000	0.001
	(0.000)		(0.000404)	(0.000414)	(0.000)	(0.000)
Education level of hhold (years)	-0.003	-0.001	-0.0461**	0.00272	-0.045**	-0.002
	(0.014)		(0.0223)	(0.0207)	(0.022)	(0.020)
Cultivated area (Ha)	0.012*	0.004*	0.00623	-0.00497	0.006	-0.003
	(0.007)		(0.0158)	(0.0132)	(0.016)	(0.013)
Members fully engaged in farming	0.028	0.009	0.121	0.109	0.123	0.100
	(0.086)		(0.166)	(0.114)	(0.162)	(0.112)
Full time farming (dummy)	-0.169	-0.056	-0.314	-0.751***	-0.291	-0.786***
	(0.139)		(0.281)	(0.288)	(0.279)	(0.282)
Group membership (dummy)	0.275**	0.091**	0.410**	0.687***	0.407**	0.713***
	(0.123)		(0.184)	(0.150)	(0.183)	(0.148)
Productive asset index	-0.001	-0.000	-0.00640	0.000700	-0.005	-0.001
	(0.004)		(0.00869)	(0.00710)	(0.009)	(0.007)
Total livestock unit	0.009	0.003	0.0163	0.00596	0.014	0.007
	(0.007)		(0.0212)	(0.0125)	(0.021)	(0.012)
Access to radio	0.381***	0.127***	0.581**	0.503***	0.595***	0.458**
	(0.134)		(0.227)	(0.193)	(0.226)	(0.188)
Male access to cellphone	0.010	0.003	0.562**	0.000640	0.564**	0.030
	(0.136)		(0.276)	(0.170)	(0.275)	(0.167)
Farm characteristics						
Access to extension (dummy)	0.695***	0.719***	-	0.231***	-	0.641***
	(0.164)		-	(0.243)	-	(0.241)
Presence of a MWG	0.479**	0.159**	1.027***	0.246	0.996***	0.183
	(0.210)		(0.329)	(0.211)	(0.308)	(0.207)
Distance to extension (km)	0.008**	0.003**	0.0144**	0.0146**	0.015**	0.012**
	(0.003)		(0.00654)	(0.00616)	(0.006)	(0.006)
Distance to all weather road (km)	0.010	0.003	0.0518	-0.00225	0.052	-0.002
	(0.008)		(0.0345)	(0.00483)	(0.035)	(0.005)
Kaffrine province (dummy)	0.793***	0.264***	0.747***	0.741***	0.732***	0.620***
	(0.193)		(0.247)	(0.230)	(0.236)	(0.220)
Constant	-0.131		-0.971	1.135	-1.211	1.919
	(0.742)		(1.227)	(1.226)	(1.179)	(1.176)
Observations	795		606	742	606	743
Pseudo R^2	0.200				0.286	0.192
LR chi2	347.803				101.406	90.095
Prob > chi2	0.000				0.000	0.000
Baseline predicted probability	0.687					

** p<0.1, , ** p<0.05, *** p<0.01. Village clustered standard errors in parenthesis*

6.4 Predicted adoption rates for CIS use and intensity of use for the pooled sample

Table 6.4 presents the predicted CIS diffusion and adoption rates based on results from the ATE framework model that corrects for awareness and access exposure bias for the pooled sample of farmers with and without CIS. We start off with the statistics shown at the bottom half of the table, showing the observed sample adoption rates for both CIS use and intensity of use. The sample adoption rate, as shown at the bottom of the table, is approximately 62% for the model corrected for awareness exposure and 74% for the model corrected for awareness and access exposure. These estimates are identical to the joint exposure and adoption rate (JEA) for both models and this is as expected (Diagne and Demont 2007). However, these two measures do not give the correct adoption rates as they significantly understate the population adoption rate (i.e. the potential adoption rate if the population is universally aware of and have access to CIS) due to exposure

bias (Kabunga, Dubois, and Qaim 2012; Ouma et al. 2013). The sample adoption rates among farmers that are exposed both in awareness of and access to CIS is 68% and 81%, respectively. Looking at the adoption intensity, the sample of farmers that is aware of CIS will use, on average, about two different types of CIS, while in comparison, the sample of farmers with access to CIS will use about three different CIS types. Use intensity here is only counting the number of different CIS used without distinguishing by type. As expected, both the sample adoption rates for use and use intensity are identical to the predicted adoption rates in the exposed population (ATE_1). The ATE_1, on the other hand, shows the predicted adoption rate in the sub-population that is already exposed to CIS and it is higher than that of the full population (ATE) hence the positive population selection bias (PSB). The PSB estimates for both awareness and access bias are positive and all significantly different from zero at least at the 5% level for both CIS use and use intensities. This implies that the probability of using CIS as well as the number of CIS used (intensity) for a farmer belonging to the sub-population of those exposed is significantly different from that of any other farmer randomly selected in the general population. The positive PSB indicates that the farmers exposed to the CIS are significantly more likely to adopt at least one CIS than any farmer randomly selected from the population. This is an indication of the presence of exposure bias and thus a justification for the need to use the ATE model that can account for this bias. On the other hand, the potential adoption rate in the unexposed population (ATE_0) is lower than both ATE and ATE_1 in both the awareness and access exposure corrected models. This is expected since both awareness of and access to a particular CIS are necessary for uptake and use. Again, as illustrated in the descriptive statistics section5, these results tend to overstate the population adoption rates due to positive selection bias (PSB).

The desirable parameter in adoption studies is the full population adoption rate (ATE) which provides an estimate of the potential demand for CIS by the target population. From the results, the potential CIS adoption rates for the whole population is estimated at 66% if all farmers were aware of CIS and 80% if all the farmers had access to CIS. In simple terms this implies that if the whole population i) were universally aware of CIS, the potential adoption rate could have been higher at 66% compared to the observed sample adoption rate or JEA of 62% and (ii) universally had access to CIS, the potential adoption rates for the whole population would be higher at 80% compared to the observed sample adoption rate or JEA of 74%.

For the CIS adoption intensity, as shown by the ATE, the full population potential adoption intensity rate is estimated at 2.5 if all the farmers are aware of the CIS and 3.2 if all the farmers could access CIS. The ATE_1 is also higher than the ATE resulting in a positive and significant PSB which also justifies the use of ATE corrected Poisson model in the adoption intensity model. Similarly, just as with the CIS use rates, the predicted adoption intensity among the unexposed sub-population ATE_0 is lower than the ATE and ATE_1. Finally, the population adoption gap (GAP) which is the difference between ATE and JEA, is approximately 3.7% for awareness and 6.9% for access and is significant indicating that there is potential to increase CIS use rate if all the farmers were aware of or could access at least one climate information service. For the adoption intensity, the population adoption gap (GAP) is also significant indicating that with improved awareness and access there is still potential to increase the number of CIS farmers use within the sample.

Table 6.4: Predicted adoption rates for CIS use and intensity for the pooled sample

	Predicted adoption rates for CIS use and intensity			
	CIS use (dummy)		CIS intensity (number)	
	Awareness	Access	Awareness	Access
ATE-corrected population estimates				
Predicted adoption rate in the full population (ATE)	0.660***	0.804***	2.506**	3.242***
	(0.0188)	(0.0144)	(1.042)	(0.944)
Predicted adoption rate in exposed subpopulation (ATE_1)	0.681***	0.813***	2.597**	3.321***
	(0.0182)	(0.0139)	(1.082)	(0.966)
Predicted adoption rate in unexposed subpopulation (ATE_0)	0.435***	0.720***	1.537**	2.489***
	(0.0367)	(0.0291)	(0.621)	(0.739)
Joint exposure and adoption rate (JEA)	0.622***	0.735***	2.375**	3.004***
	(0.0167)	(0.0126)	(0.989)	(0.874)
Population adoption gap (GAP)	-0.0373***	-0.0689***	-0.132**	-0.238***
	(0.00315)	(0.00278)	(0.0533)	(0.0706)
Population selection bias (PSB)	0.0211***	0.00891***	0.0910**	0.0795***
	(0.00251)	(0.00223)	(0.0414)	(0.0234)
Observed sample estimates				
Exposure rate (N_e/N)	0.914***	0.904***	3.817***	4.088***
	(0.0114)	(0.0108)	(0.0932)	(0.0852)
Adoption rate (N_a/N)	0.622***	0.735***	2.375***	3.004***
	(0.0197)	(0.0162)	(0.150)	(0.116)
Adoption rate among the exposed subsample (N_a/N_e)	0.681***	0.812***	2.597***	3.321***
	(0.0216)	(0.0179)	(0.102)	(0.0942)
Observations	606	742	606	743

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

6.5 Predicted adoption rates for CIS use and intensity of use with and without MWGs

In order to determine how the presence of MWGs influence CIS adoption rates, we disaggregated our analysis into; i) sub-sample of farmers in areas with the presence of an MWG (Table 6.5) and ii) sub-sample of farmers in areas without the presence of an MWG (Table 6.6). Both tables present the observed sample and population predicted adoption rate for CIS use as well as the intensity of use among farmers with access to the MWG and those without access, respectively.

When we consider the model that is corrected for access bias, again we find substantially high disparities between adoption rates for the sub-sample of farmers with MWG and those without MWG. More specifically, the sample adoption rates as shown in the bottom half of the tables are approximately 80% for farmers with access to MWG compared to 44% for farmers without MWG for the models that are corrected for awareness exposure. Similarly, for the model that is corrected for access exposure, the sample adoption rates for farmers with access to MWG is 84% compared to 59% for farmers without MWG. The observed intensity in CIS use is also considerably higher for farmers with access to the MWG for both models compared to those without access to the MWG. Interestingly, the exposure rates in the sample of farmers with access to the MWG are very high, with 99% for the awareness corrected model and 94% for the access corrected model, while in locations without the MWG they are 83% and 85%, respectively. This is an important finding in that presence of MWGs seem to have the desired effect of increasing farmers' exposure to CIS in terms of awareness and access.

Moving to the top half of the table, again we find that the population adoption rates, which is the desired adoption parameter, for farmers with MWG are considerably

higher than those without MWGs. The ATE results reveal that within MWG locations, the potential CIS adoption rate is estimated at 81% if all the farmers were aware of CIS and 88% if all the farmers could have access to CIS. Also important to note that these estimates are exactly the same as the sample adoption rates for the sample of exposed farmers with MWGs. In locations where MWGs do not exist, the potential CIS adoption rate is estimated at 51% if all the farmers were aware of CIS and 69% if all the farmers could access CIS. Similar trends are also observed when comparing the use intensity of CIS between farmers with access to the MWG and those without access.

One important aspect to note from these results is that the sample adoption rates for farmers exposed to CIS in communities with access to MWG are almost identical to the predicted adoption rates for the whole population with MWGs for the awareness corrected model. We see that the adoption rates for both the sample and population are about 80% and that on average a household would be aware of about three CIS. These matching estimates can be explained due to the high awareness and access exposure rates of 99% among farmers with access to MWG, hence the low population adoption gap (GAP) of 0.8%. The GAP measures the unmet demand for CIS resulting from households' lack of awareness and/or access. Similarly, the ATE and ATE_1 for the adoption intensity are equal. This is because almost all the farmers in MWG areas are aware of CIS hence there is minimal awareness exposure bias within this group. This is further supported by the insignificant PSB for both the awareness and access corrected models for CIS use. This again is evidence that the presence of an MWG tends to significantly improve awareness of farmers or individuals that are exposed CIS. Many empirical studies have come to the conclusion that one of the major impediments to adoption of new technologies is the lack of awareness of the existence of the technology by a large proportion of smallholder farming population (Diagne and Demont 2007; Kabunga, Dubois, and Qaim 2012; Simtowe, Asfaw, and Abate 2016). However, when it comes to the access corrected model we find, as expected, that the sample adoption and use intensity of CIS are higher for the population estimates than the sample estimates owing to the exposure bias in awareness and access that limit uptake. The GAP for the access corrected model is also substantially higher at 5% compared to 0.8% in the awareness corrected model. The PSB is also not significant in the CIS use model indicating that access exposure bias is also not present among the farmers in the MWG areas since almost all the farmers in these areas had access to at least one CIS. However, the PSB for adoption intensity in the access exposure corrected model is significant.

Results from Table 6.6 show that approximately 83% and 85% of the households in locations without MWGs, were exposed to awareness and access, respectively. The sample adoption rate among exposed farmers is estimated at 53% among the sub-sample that is aware of CIS and 69% among the sub-sample that had access to CIS. After correcting for awareness exposure, the ATE and ATE_1 are approximately 51% and 53%, respectively. The PSB for the awareness corrected model is however significant indicating that there is awareness exposure bias among farmers in locations without MWGs. For the access exposure corrected model, both the ATE and ATE_1 are about 69%, which as expected, is higher than the awareness corrected model. The PSB is not significant indicating that there is no access exposure bias among farmers in locations without MWGs. Finally, the population adoption gap (GAP) is significant in all four models. This indicates that there is potential to increase the use of CIS as well as the intensity of use within the population

due to the unmet demand for CIS resulting from households' lack of awareness of CIS and/or lack of access to CIS.

It is important to note that the CIS adoption rates (observed or predicted) are higher for farmers in locations where MWGs are present (Table 6.5) compared to those in locations without MWGs (Table 6.6). Similarly, the unmet demand for CIS in the population resulting from households' lack of awareness and/or access to CIS is lower among household with access to MWGs compared to those without.

Table 6.5: Predicted adoption rates for CIS use and intensity for the MWG subsample

	Predicted adoption rates for CIS use & intensity			
	CIS use (dummy)		CIS intensity (number)	
	Awareness	Access	Awareness	Access
ATE-corrected population estimates				
Predicted adoption rate in the full population (ATE)	0.809***	0.887***	3.280***	3.678***
	(0.0228)	(0.0156)	(0.122)	(0.0962)
Predicted adoption rate in exposed subpopulation (ATE_1)	0.810***	0.888***	3.282***	3.698***
	(0.0227)	(0.0154)	(0.122)	(0.0961)
Predicted adoption rate in unexposed subpopulation (ATE_0)	0.793***	0.869***	3.020***	3.357***
	(0.0373)	(0.0211)	(0.184)	(0.115)
Joint exposure and adoption rate (JEA)	0.801***	0.837***	3.249***	3.485***
	(0.0225)	(0.0145)	(0.121)	(0.0906)
Population adoption gap (GAP)	-0.00801***	-0.0499***	-0.0305***	-0.193***
	(0.000377)	(0.00121)	(0.00186)	(0.00662)
Population selection bias (PSB)	0.000168	0.00108	0.00264*	0.0196***
	(0.000285)	(0.000662)	(0.00149)	(0.00356)
Observed sample estimates				
Exposure rate (N_e/N)	0.990***	0.943***	4.055***	4.165***
	(0.00581)	(0.0112)	(0.156)	(0.122)
Adoption rate (N_a/N)	0.801***	0.837***	3.249***	3.485***
	(0.0232)	(0.0177)	(0.125)	(0.102)
Adoption rate among the exposed subsample (N_a/N_e)	0.810***	0.888***	3.282***	3.698***
	(0.0234)	(0.0188)	(0.126)	(0.109)
Observations	297	435	297	435

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 6.6: Predicted adoption rates for CIS use and intensity for the non-MWG subsample

	Predicted adoption rates for CIS use & intensity			
	CIS use (dummy)		CIS intensity (number)	
	Awareness	Access	Awareness	Access
ATE-corrected population estimates				
Predicted adoption rate in the full population (ATE)	0.505***	0.688***	1.804	2.610
	(0.0307)	(0.0279)	(1.856)	(2.130)
Predicted adoption rate in exposed subpopulation (ATE_1)	0.525***	0.694***	1.885	2.712
	(0.0305)	(0.0267)	(1.971)	(2.207)
Predicted adoption rate in unexposed subpopulation (ATE_0)	0.410***	0.655***	1.401	2.041
	(0.0423)	(0.0532)	(1.291)	(1.705)
Joint exposure and adoption rate (JEA)	0.437***	0.589***	1.570	2.300
	(0.0254)	(0.0226)	(1.641)	(1.872)
Population adoption gap (GAP)	-0.0685***	-0.0995***	-0.234	-0.310
	(0.00707)	(0.00808)	(0.216)	(0.259)
Population selection bias (PSB)	0.0192***	0.00583	0.0809	0.102
	(0.00508)	(0.00673)	(0.116)	(0.0804)
Observed sample estimates				
Exposure rate (N_e/N)	0.833***	0.848***	3.594***	3.916***
	(0.0218)	(0.0206)	(0.289)	(0.235)
Adoption rate (N_a/N)	0.437***	0.587***	1.570***	2.300***
	(0.0290)	(0.0283)	(0.126)	(0.138)
Adoption rate among the exposed subsample (N_a/N_e)	0.525***	0.693***	1.885***	2.712***
	(0.0349)	(0.0334)	(0.152)	(0.163)
Observations	293	303	293	303

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

6.6 Projected impact of MWG on CIS adoption in Senegal

In this sub-section, we use the estimated adoption rates from the ATE model in conjunction with real national statistics and the estimated rural population with access to CIS to predict changes CIS use among smallholder farmers in Senegal. The rural population of Senegal is estimated at 8,809,122 people (World Bank, 2018). According to CCAFS 2015, there are approximately 7.4 million rural people (not all of them being farmers), which translates to 740,000 agricultural households that have been exposed to CIS in rural Senegal. However, as alluded to in earlier sections, awareness and access exposure to CIS is a necessary but not sufficient condition for uptake and use. This means that not every individual who receives this climate information is able to actually use it to inform or change their farming decisions.

We use the adoption rates estimated in this study as shown in Tables 6.4, 6.5 and 6.6 in conjunction with CCAFS 2015 estimation of the number of households receiving climate information in rural Senegal to extrapolate the number of households that would use CIS under the hypothetical scenarios that i) MWGs are scaled out and all rural households have access to the MWG and ii) all rural households have no access to the MWG. Results in Table 6.4 reveal that 90.4% of the sampled households had access to CIS. Based on this sample estimate and taking into account CCAFS' estimate of the number of agricultural households that are exposed to CIS, we predict the total number of households using CIS in rural Senegal to be about 602,000 (this is for the case where MWGs exist partially in some locations). Extending this analysis for the hypothetical scenario that the MWG model is scaled out to all rural households, we predict that the number of households that will use CIS to be about 685,000. Similarly, in the absence of the MWG, the projected

number of CIS users in rural Senegal will be 481,000. This implies that if the MWG model were to be scaled out to locations without MWGs, CIS uptake will increase by approximately 29.9% (205,000 households). Similarly, scaling out the MWGs will result in a 9% (approximately 75,000 households) increase in the number of households that are aware of CIS in rural Senegal.

Comparing the predicted population adoption gap (GAP) for the two hypothetical scenarios, is substantially higher in areas without the MWG compared to those with access to the MWG, indicates the existing potential to increase CIS uptake and use within the population. More specifically, the population adoption gap associated in areas where the MWG present is estimated at 41,000 households while in locations without the MWG, it is about 81,000 households. This indicates that CIS adoption gap — which measures the unmet demand for CIS resulting from households' lack of awareness of CIS or lack of access to CIS — is twice as high among households without access to the MWG compared to those with access. This has significant policy implications in that scaling the MWG model has great potential in increasing the uptake and use of CIS among exposed households. A closer look at the projected impacts shows that MWGs effectively increased households that used CIS to influence farming decisions by 22% or over 160,000 households.

Table 6.7: Predicted number of adopters by MWG

	Whole population		With MWG		Without MWG		% Increase with MWGs	
	%	n	%	n	%	n	%	n
Predicted adoption rate in the full population (ATE)	0.804	658,142	0.887	726,084	0.688	563,186	0.224	162,898
Exposure rate (N_e/N)	0.904	740,000	0.940	769,469	0.848	694,159	0.098	75,310
Adoption rate for the whole sample (N_a/N)	0.735	601,659	0.837	685,155	0.587	480,509	0.299	204,646
Adoption rate among the exposed subsample (N_a/N_e)	0.812	664,690	0.888	726,903	0.693	567,279	0.220	159,624
Population adoption gap (GAP)	-0.069	-56,400	-0.050	-40,847	-0.100	-81,449	0.498	40,602

Population estimates from Loayza, Toure, and Niane 2018; CCAFS 2015

6.7 Conclusions from the first analytical section

CIS use rate is considerably higher in Kaffrine region compared to Kaolack. In both regions, the climate information product that had the highest awareness, access, and use rate was the 2-3 days forecast while the least popular was the 10-days forecast. For CIS use, the adoption rates were considerably lower for the full sample compared to the exposed sub-sample which is attributable to information asymmetry resulting in exposure bias. To correct for this bias, we apply the ATE corrected model to account for both awareness and access exposure bias. From our estimated adoption rates, we find positive and significant selection bias implying that without correcting for awareness and access exposure bias the population adoption estimates would have been significantly underestimated.

We also find that social capital mainly group membership plays a key role in the awareness, access, and use of CIS. Receiving extension information is also important in enhancing awareness, access uptake and use of CIS. It is also clear that MWGs play a vital role in promoting CIS. Farmers in MWG areas have higher exposure rates, particularly when it comes to awareness exposure (about 99%). Similarly, farmers with access to the MWG also tend to have high adoption rates in both the use of CIS and the intensity of use (expressed as the number of different CIS used). This supports the notion that

MWGs can be instrumental in the diffusion, uptake, and use of CIS in Senegal and that end-users find the information salient, legitimate, and credible as supported by earlier empirical findings (Ouedraogo et al. 2018; Lo and Dieng 2015).

For most of the variables, the direction and significance of their effect on CIS use is consistent for both the uncorrected model and the ATE corrected model. However, there are a few exceptions; the effect of education on the use of CIS is not significant in the uncorrected model but it is negative and significant in the ATE awareness exposure corrected model. Being a full-time farmer also has no significant effect on CIS use for the uncorrected model but has a significantly negative effect on CIS use for the access exposure corrected model. These matching estimates can be explained by the high awareness and access exposure rates of 99% among farmers with access to an MWG, subsequently leading to a very low population adoption gap (GAP) of 0.8%. This again is evidence that the presence of an MWG tends to significantly improve widespread awareness to farmers or individuals that are exposed CIS. On the other hand, the presence of an MWG has a positive effect on the use of CIS for the uncorrected model but the effect is not significant in the access exposure corrected models. This further supports the need to use ATE corrected models since using classical adoption models may result in biased results. Factors that influence information exposure may vary from those that influence actual adoption, mixing them, as is implicitly done in classical adoption models, can lead to erroneous policy recommendations. The results also emphasize that differentiating between awareness and knowledge is important in adoption studies. A closer look at the projected impacts shows that MWGs effectively increased the number of households that used CIS to influence the farming decision by 22% or over 160,000 households.

7
THE IMPACT OF THE MWG MODEL ON FARMERS' USE OF CIS: IMPLICATIONS ON BEHAVIORAL CHANGES AND FARM MANAGEMENT PRACTICES

> 'Many evaluation efforts limit themselves to measuring access whereas true value stems from the use made of the services received, and decisions and behaviors changed as a result, as well as the impact of these changes on rural livelihood outcomes'.....Tall, Coulibaly, and Diop 2018

This section assesses the effectiveness of MWGs in influencing farmers' uptake and use of CIS. It also evaluates the resulting impact on behavioral outcomes and farm management practices using an instrumental variable approach to account for selection bias. As highlighted in (Tall, Coulibaly, and Diop 2018), the key challenge in evaluating the impact of CIS is trying to establish the link between an individual receiving and using CIS, and the impact it has on behavioral outcomes. This is mainly due to the complex decision-making process farmers go through. In this section, we again capitalize on the unique sampling frame that enables us to reconstruct the counterfactual scenario: what could have happened to a household using CIS, had they not had access to the MWG? Our choice of exploring how CIS is used to inform farm management practices — in light of the complex and simultaneous interactions that affect farmers' decisions — is premised and motivated by (i) earlier empirical studies on farmers' use of seasonal and weather forecasts (Patt, Suarez, and Gwata 2005; Ziervogel et al. 2005; Roncoli 2006; Crane et al. 2010); and (ii) the detailed empirical findings that have been conducted around the production and dissemination of CIS through the MWG to help end-users receive tailored climate information in Senegal (Ndiaye et al. 2013; Ouedraogo et al. 2018; Lo and Dieng 2015).

7.1 The effectiveness of the MWG model in influencing farmers' awareness, access and use of CIS

In this section, we present the impact of MWGs on awareness, access and use of different CIS. As a reminder, the ATE framework is used to estimate the (i) ATE: the expected change in awareness, access and use within the population attributed to MWGs; (ii) ATT: the expected change in awareness, access and use for farmers with MWGs and (iii) ATU: the expected change in awareness, access and among the sub-sample farmers with no access to an MWG under the counterfactual scenario. Columns (1) to (3) in Table 7.1 present the ATE, ATT and ATU, respectively. Results indicate that the presence of an MWG has causal impact on awareness, access and use of CIS. We begin by considering the impact of MWGs on awareness of CIS. All the estimates presented are positive and

significant at the 1% level of error, albeit with varying degrees in magnitude.

Starting with awareness, we see that MWGs had the greatest impact on awareness of EWS followed by seasonal forecasts and then daily forecasts. The presence of an MWG led to a 27% significant increase on the awareness of EWS for the entire population (ATE) and a 28% increase for the sub-sample of farmers with access to MWGs (ATT). In the counterfactual case where MWGs were established in areas where they do not exist, we expect a 24% increase in awareness of EWS. The presence of an MWG increases farmers' awareness of seasonal forecasts by 23% for the whole population and 24% for the sub-sample of farmers with access to MWG. If the MWG model were to be introduced in the control locations (with no MWGs), the predicted increase in awareness of seasonal forecasts would be about 22%. We also see that MWGs have very similar effects on awareness of daily forecasts, which increase by 19% for the whole population, 22% for farmers with MWGs, and 15% for farmers without MWGs under the scenario that they obtain access. Lastly, the presence of an MWG increases the probability that a household is aware of at least one CIS type by between 14% and 16% across the three samples.

When considering the impact of MWGs on farmers' access to CIS, again we see very contrasting trends in the relative magnitudes with those in the awareness models. The impact estimates are much lower for the CIS access model when compared to the awareness model. The existence of an MWG had the highest impact on farmers' access to daily and seasonal forecasts, and results indicate an increase of between 13% and 18%. Interestingly, the MWGs had the least impact in increasing farmers' access to EWS, which the results show to be around 11% for the three sub-samples. This trend is in contrast to that presented 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 MWGs and, iii) 14% for the counterfactual case of establishing MWGs in areas where they do not exist.

As discussed in earlier sections, awareness and access are pre-conditions for farmers' ability to use the information received to influence farming decisions. We now focus on the use and uptake, presented in the lower part of Table 7.1. The presence of an MWG has a positive and significant effect on the uptake and use of the different CIS types. The greatest impacts are observed with the use of EWS where results indicate a 25% increase in use on the whole population and sub-samples of farmers with access to MWGs and those farmers without access to MWG if they are afforded access. The presence of an MWG increases the use of daily forecasts by roughly 18% for all three sub-samples of farmers. Interestingly, the lowest impacts (single-digits) are observed on the use of seasonal forecasts. Results indicate that the presence of an MWG leads to a 5% increase in the use of seasonal forecasts for the whole population, a 4% increase for the sub-sample of farmers with access to MWGs and a 7% increase among control farmers if they had access to MWGs. The significant contrast in magnitude of the impact of MWGs on the use of EWS (which is approximately 25%) versus seasonal forecasts (which is approximately 6%) is not surprising. This can be explained by the lower baseline use rates of EWS among farmers with access to MWGs (66.8%), compared to the relatively higher baseline adoption rates of seasonal forecasts of farmers with MWGs (72%).

Table 7.1: Impact of MWG on awareness, access and use of CIS

	Whole Population (ATE)	With MWG(ATT)	Without MWG (ATU)
Variables	(1)	(2)	(3)
Awareness of CIS			
Awareness of CIS (dummy)	0.155***	0.173***	0.133***
	(0.00348)	(0.00455)	(0.00514)
Awareness of all CIS types	0.176***	0.174***	0.179***
	(0.000619)	(0.000735)	(0.00102)
Awareness of seasonal forecasts	0.230***	0.237***	0.223***
	(0.00271)	(0.00297)	(0.00479)
Awareness of daily forecasts	0.191***	0.223***	0.152***
	(0.00295)	(0.00334)	(0.00433)
Awareness of EWS	0.266***	0.283***	0.244***
	(0.00198)	(0.00194)	(0.00336)
Access to CIS			
Access to CIS (dummy)	0.147***	0.162***	0.127***
	(0.00337)	(0.00464)	(0.00468)
Access of all CIS types	0.116***	0.114***	0.118***
	(0.000740)	(0.000907)	(0.00121)
Access of seasonal forecasts	0.149***	0.160***	0.136***
	(0.00285)	(0.00390)	(0.00407)
Access of daily forecasts	0.158***	0.180***	0.130***
	(0.00236)	(0.00304)	(0.00314)
Access of EWS	0.107***	0.109***	0.105***
	(0.00156)	(0.00207)	(0.00237)
Use of CIS			
Use of CIS (dummy)	0.104***	0.0891***	0.125***
	(0.00481)	(0.00570)	(0.00788)
Use of all CIS types	0.0905***	0.0930***	0.0877***
	(0.000986)	(0.00133)	(0.00145)
Use of seasonal forecasts	0.0534***	0.0389***	0.0738***
	(0.00313)	(0.00361)	(0.00482)
Use of daily forecasts	0.177***	0.176***	0.179***
	(0.00517)	(0.00646)	(0.00851)
Use of EWS	0.245***	0.249***	0.240***
	(0.00106)	(0.00116)	(0.00179)
No. of cases	795	795	795

Notes: Mean values shown with standard errors in parenthesis *, **, *** denotes significance level at 10%, 5% & 1%, respectively.

7.2 The effectiveness of the MWG in influencing farmers' decision making when using CIS

7.2.1 Use of seasonal forecasts

We build on the previous analysis which revealed that MWGs improve farmers' awareness, access and use of CIS. In this section, we extend these findings by taking an in-depth look into how the presence of an MWG influences behavioral change or adaptation strategies for the different types of CIS used. We have already highlighted in earlier sections that CIS only becomes valuable to the farmer if it is acted upon to inform decision-making that results in improved livelihoods. Therefore, it is important to emphasize that within the CIS impact pathway, once a farmer decides to use a particular CIS, one can think of farmers' behavioral changes or adaptation strategies (e.g., mix of crops, choice of varieties, timing of fertilizer and manure input use) as the first line of intermediary outcomes observed. This shift in behavior will then contribute to the realization of higher order impacts, such as improved yields, food security and nutrition, and better household welfare. The intermediary behavioral outcomes that we model in this section are adaptation strategies as reported by farmers (and not measured by the researcher) and hence results should be interpreted carefully. For each of the six CIS, information on behavioral changes was captured if, and only if, the household was aware of, had access to and used climate information received to inform their farming decisions. The question was framed as shown in Box 1 below.

Box 1: Verbatim questions from the questionnaire

This section aims to understand the types of farm decisions that households have taken up, adjusted based on the information received and to assess changes in behavior and perceived impact as a result of using climate information services. If you used any of the climate forecasts received through media or any other source of communication, please tell us any decisions or adjustments that you made [based on climate information you have personally been using during the 2016-2017 agricultural season]:

1. I used information on forecast of total amount of rainfall to inform decisions on.....
2. I used information on forecast of onset of rains to inform decisions on.....
3. I used information on forecast of cessation of rains to inform decisions on .....
4. I used the 2-3 days weather forecasts to inform decisions on .....
5. I used the 10-days weather forecasts to inform decisions on .....
6. I used the instant EWS to inform decisions on .....

We consider the impact of MWGs on the six different CIS and their impact on specific behavioral changes as presented in Table 7.2. The ATE model in this instance is used to measure (i) expected change in adaptation strategies or behavioral outcomes among the whole population that could be attributed to the presence of an MWG (ATE); (ii) expected change in certain behavioral outcomes for farmers with access to an MWG versus those without an MWG (ATT); and (iii) expected change in behavioral outcomes among the sub-sample farmers with no access to MWGs under the counterfactual scenario of having access to an MWG. Columns (1) to (3) in Table 7.2 present the ATE, ATT and

ATU, respectively.

We start by looking at behavioral changes that result from the use of seasonal forecasts on (i) total accumulated rainfall (ii) onset of rains and (iii) cessation of rains. Hansen et al. 2011 contend that accumulated rain for the season, which is predicted by tercile on whether it will be wet/humid, normal or dry, is one of the most common forecast parameters for farmers that in West Africa (WA). According to Ousmane Ndiaye[1] of ANACIM, it was predicted that rainfall during the 2016-2017 agricultural season would start early and was expected to be normal to slightly below normal in the survey districts of Kaffrine and Kaolack. Once the forecast was made, extensive consultations with local MWGs developed agricultural advisories that would detail potential practical actions by farmers. These would then be distributed to farmers[2]. The seasonal forecast is translated from its scientific form and communicated to farmers in an easy-to-understand format that can be interpreted and incorporated into their farm management decisions (Ndiaye et al. 2013). Figure 3.1 summarizes the post-season assessments that were conducted by the ARC for the 2016-2017 and the 2017-2018 agricultural seasons. Consistent with the pre-season forecasts from Ndiaye, the central regions of Senegal, which include Kaffrine and Kaolack, did experience a below normal season, with cumulative rainfall totals that were 20% below the average at the regional level, and over 50% below average in localized areas along the Gambian border.

Results of the ATE and ATT generally indicate that there were significantly more farmers in areas where MWGs are operational who used CIS to inform or adjust their farming decisions compared to those that do not have an MWG. A closer look at the results reveals that for those farmers who received seasonal forecasts on total rainfall for the season, the MWG was more effective (in terms of magnitude) in influencing their decisions on crop variety choice, followed by proportion of area allocated to crops, followed by land area to grow, crop choice and crop mix. The ATE results demonstrate that the presence of an MWG leads to 25% more farmers in the population using information on total accumulated rainfall to influence their decisions on the crop variety to grow. Similarly, the ATT results also reveal a similar effect when comparing farmers with and without MWGs. We find that there were 25% more farmers in locations with MWGs who used information on the total amount of rainfall to inform crop varietal choice compared to farmers without MWGs. The counterfactual scenario, the ATU, indicates that if farmers in locations without an MWG were to be afforded access, then there would be an estimated 24.6% increase in the use of total rainfall in guiding farmers' decisions on crop varietal choice. These results are consistent with that of Ingram, Roncoli, and Kirshen 2002, who observed that farmers adjust their crop varietal choices depending on whether the predicted season is expected to be good (above normal rains), average, or bad (below average rains).

The forecast on the total amount of rainfall is also used to make changes on the location to allocate and plant different crops. The presence of an MWG increases the use of forecasts on the total amount of rainfall to inform farmers' decisions on field location

[1]Personal communication, July 2018

[2]We were unfortunately not able to get exact copies of the advisories farmers in the survey districts received based on the seasonal forecasts at the time of conducting this analysis. Hence, we are not able to link the farmers' decisions to forecasts with certainty

Table 7.2: Impact of MWG on behavioral changes/adaptive strategies for each CIS type

	Whole Population (ATE)	With MWG(ATT)	Without MWG (ATU)
Variables	(1)	(2)	(3)
Seasonal forecast: Total amount of rainfall			
Decision to do intercropping or mono-cropping	0.129***	0.132***	0.125***
	(0.000921)	(0.00121)	(0.00140)
Type of crop to grow	0.124***	0.126***	0.122***
	(0.000557)	(0.000687)	(0.000896)
Type of crop variety to grow	0.248***	0.251***	0.246***
	(0.000909)	(0.00113)	(0.00147)
Land area allocation for crops	0.128***	0.127***	0.129***
	(0.000434)	(0.000582)	(0.000649)
Field location to plant crops	0.220***	0.218***	0.223***
	(0.00167)	(0.00229)	(0.00242)
Soil and water conservation	0.102***	0.105***	0.0990***
	(0.00182)	(0.00252)	(0.00260)
Seasonal forecast of the start of the rains (onset)			
Timing of land preparation	0.187***	0.199***	0.173***
	(0.00170)	(0.00160)	(0.00307)
Timing of planting	0.225***	0.229***	0.221***
	(0.000916)	(0.000954)	(0.00164)
Forecast of the weather for today or 2-3 next days			
Use of organic fertilizer (manure/compost/mulch)	0.140***	0.148***	0.130***
	(0.00191)	(0.00255)	(0.00280)
Use of inorganic fertilizer (chemical fertilizer)	0.302***	0.305***	0.298***
	(0.00276)	(0.00351)	(0.00438)
Timing of weeding	0.217***	0.218***	0.216***
	(0.00106)	(0.00137)	(0.00166)
Timing of harvesting	0.152***	0.151***	0.153***
	(0.00150)	(0.00208)	(0.00215)
Forecast for the following 10 days			
Use of organic fertilizer (manure/compost/mulch)	0.0408***	0.0438***	0.0372***
	(0.000439)	(0.000572)	(0.000627)
Use of inorganic fertilizer (chemical fertilizer)	0.270***	0.276***	0.263***
	(0.00269)	(0.00336)	(0.00434)
Soil and water conservation	0.157***	0.154***	0.160***
	(0.00261)	(0.00359)	(0.00379)
Seasonal forecast of cessation of rainfall			
Timing of harvesting	0.0891***	0.0839***	0.0954***
	(0.00109)	(0.00148)	(0.00156)
Timing of crop sales	0.219***	0.214***	0.225***
	(0.00326)	(0.00392)	(0.00542)
Early warning of an extreme event			
Decision to farm or not	0.0182***	0.0200***	0.0160***
	(0.000356)	(0.000469)	(0.000522)
No. of cases	795	795	795

Notes: Mean values shown with standard errors in parenthesis *, **, *** denotes significance level at 10%, 5% & 1%, respectively.

to plant crops by about 22%, choice of crop to grow and the crop mix by between 12% and 13% and on soil and water conservation by about 10% across the three sub-samples. Similarly, comparing the sub-samples of farmers with and without MWGs, we find that there was a higher proportion of farmers with access to an MWG who used information on total seasonal rainfall to inform decisions on which part of the field to plant certain crops (21.8%); crop choice (12.6%); crop mix (13.2%) and on soil and water conservation (10.5%). 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' decisions on the types of crops to grow (Tarhule and Lamb 2003), adjust the crop density, mix (Ziervogel et al. 2005; Luseno et al. 2003; Tarhule and Lamb 2003), and change field locations where they grow crops (O'Brien et al. 2000).

Focusing on the seasonal forecast on onset of rains, we see that the MWG effect had the highest impact on informing timing decisions of planting and land preparation. Results indicate that MWG increases use of information on the onset of rains on the timing of planting and land preparation by about 22.5% and 18.7%, respectively, in the whole population. Comparing farmers with and without an MWG, we see that there are more farmers in MWG locations who use information on the onset of rains to inform the timing of planting (22.9%) and land preparation (19.9%). Scaling out of MWGs into areas where they are non-existent would lead to proportionally higher percentage of farmers using rainfall onset forecasts to inform their timing decisions. Seasonal forecasts on cessation of rain tend to significantly affect the timing of crop sales and harvesting. Results indicate that the presence of an MWG increases use of information on cessation of rains to inform farmers' timing of selling their produce to the market by 21.9% and timing of harvesting by 8.9% in the whole population. In addition, there is a significantly higher proportion of farmers in MWG locations who 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. Introducing MWGs in areas where they are non-existent would lead to proportionally higher percentage of farmers using onset information to inform their timing decisions. 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, Roncoli, and Kirshen 2002 report that farmers in Burkina Faso use the information to decide on whether to sell or store their grain.

7.2.2 Impact of use of seasonal forecasts on observed farm management practices by MWGs

Previous analysis focused on the impact of MWGs in influencing farmer-pronounced behavioral outcomes based on the CIS information received. In this section, we extend this analysis by comparing actual farm management practices the households undertook during the 2016-2017 agricultural season. According to ANACIM's 2016-2017 seasonal forecast of the Central region (including our sampled provinces of Kaolack and Kaffrine)[3], the agricultural advisories disseminated to farmers were broadly based on the outlook

[3]Which corresponds to the post-seasonal assessments released by ARC (ARC 2016)

that within most of the Central region, which includes our sampled provinces Kaolack and Kaffrine, the 2016-2017 agricultural season was predicted to be a below normal wet year. Ndiaye et al. 2013 assert:

> The aim is to translate and communicate the seasonal forecast, and an indication of its probability, in an easy-to-understand language, giving farmers the capacity to make informed farm management decisions.

Based on intensive interactions with farmers in Kaffrine province, Ndiaye et al. 2013 conclude that farmers use information on whether a season is good or bad to make strategic decisions on the choice of crops to consider growing. While total rainfall is important in making farming decisions, they also point out that the forecasts on onset are equally, if not more important, for farmers to decide on the crop varieties for the season. In this sub-section, we analyze the linkages between farm management practices and CIS use with and without MWGs. This final analysis looks at the impact of the use of seasonal forecasts (i.e., total amount of rainfall and forecast on onset) on observed farm management practices between farmers in locations with access to the MWGs versus those without access.

Table 7.3 presents the local average treatment effect of seasonal forecasts on observed farm management practices using joint access and awareness as instruments. This analysis is disaggregated by those with and without MWGs. We consider four farm management practices: use of improved seeds, chemical fertilizers, manure use and the Margalef crop diversification index. Of the different climate information services, farmers in Senegal were exposed to, we purposively focus on the seasonal which we hypothesize were instrumental in affecting decisions on the four management practices we are exploring.

Table 7.3: Local Average Treatment effect of CIS on observed farm management practices

	Chemical fertilizer use		Improved seed use		Manure use		Margalef index	
Variables	With MWG	Without MWG	With MWG	Without MWG	With MWG	Without MWG	With MWG	Without MWG
Use of seasonal forecast on total rainfall	0.062***	0.062***	0.077***	0.161***	0.038***	0.055***	-0.007***	0.029***
	(0.001)	(0.002)	(0.001)	(0.003)	(0.001)	(0.002)	(0.001)	(0.001)
Use of seasonal forecast of the start of the rains (onset)	0.038***	0.081***	0.039***	0.181***	0.013***	0.082***	-0.015***	0.092***
	(0.001)	(0.002)	(0.001)	(0.003)	(0.001)	(0.003)	(0.001)	(0.001)
No. of cases	357	438	357	438	357	438	357	438

Bootstrap Standard errors in parentheses (300replications)*** p<0.01, ** p<0.05, * p<0.1

As presented in table 7.3, out of the sub-sample of farmers that used seasonal forecasts on the total amount of rainfall[4], a significantly higher proportion of them used improved seed, fertilizer and manure compared to those who did not use forecasts on total rainfall. More specifically, of the farmers (within MWG locations) who used seasonal forecasts on total rainfall, 6% more used chemical fertilizers, 8% more used improved seed, and 4% more used manure, compared to farmers who did not use seasonal forecasts on rainfall. Similarly, farmers who used seasonal forecasts on total rainfall in areas without MWGs used significantly more chemical fertilizers, improved seeds and manure by approximately 6%, 16% and 6%, respectively, compared to those who did not use the forecasts. Switching to the use of seasonal forecast on the onset of rainfall we again see a similar pattern. Farmers in both locations with and without access to an MWG who used seasonal forecasts on onset had a higher probability of using chemical fertilizers, improved seed and manure

[4]which predicted that rainfall for the 2016-2017 agricultural season was going to be below average

compared to those who did not use seasonal forecasts on the onset of rains. Zougmoré et al. 2016 recently demonstrated 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 fertilizers.

Very interestingly though, we find some contrast when comparing the use of seasonal forecast and the Margalef crop diversity index. Our results indicate that there is a negative and significant relationship between farmers in MWG areas who used seasonal forecasts of both rainfall and onset on the Margalef crop diversity index. Simply put, farmers in MWG areas who used seasonal forecasts for the 2016-2017 season had significantly less crop diversity on their farms compared to those who did not make use of seasonal forecasts. However, this is in contrast to the results of the sub-sample of farmers without MWGs who actually maintained higher crop diversity on their farms after receiving forecasts compared to non-users of seasonal forecasts. Owing to the fact that the forecast indicated a relatively bad year, reducing the number of crops and focusing resources on a few crops is a plausible adaptation strategy that farmers in MWG areas may choose to undertake. Similarly, crop diversification may be considered a plausible adaptation strategy which farmers may consider when spreading out the risk of 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 sets of information simultaneously at the beginning of the planting season.

7.3 Conclusions from the second analytical section

The presence of an MWG has a positive and significant effect on the awareness, access and uptake of seasonal forecasts, daily weather forecast, and instant forecasts. In terms of awareness, access and use of different CIS, the results show that the greatest impacts of MWGs were on awareness of EWS, access to daily forecasts and use of EWS.

Results also further indicate that the presence of an MWG influences behavioral changes or adaptation strategies for the different types of CIS used. The forecast on the total amount of rainfall is also used to make changes on the location to allocate and plant different crops. The presence of an MWG increases the use of forecasts on total accumulated rainfall to inform farmers' decisions. For example, in locations where farmers are exposed to MWGs, there is a 25% higher chance that they will use total accumulated rainfall forecast for the season to inform their farming decisions. Similarly, we find that farmers in MWG locations used seasonal forecasts on the onset of rains to inform timing decisions of planting and land preparation, while with the 10-day forecast we see that the MWG influences decisions on whether households use fertilizer or not.

When considering the link between use of seasonal forecasts and observed farm management practices, we find that use of seasonal forecasts was associated with a higher proportion of farmers using improved seed, fertilizers and manure use but negatively with crop diversity in MWG locations. In carrying out this analysis, we do acknowledge that the decision-making process, particularly for smallholder farmers is complex and mired by

multi-faceted factors ranging from social to economic to institutional.

One limitation of our study for this section is that we did not ask farmers the specific type of improved crop varieties they grew upon receiving the forecast information (whether they were drought-tolerant, early-maturing or any other improved traits). Future studies ought to further investigate that. In terms of crop diversification, as indicated by the Margalef crop diversity index, farmers in locations with access to MWGs and locations without MWGs reacted differently to the information on forecast on total rainfall and onset of rains. Farmers with access to an MWG significantly reduced the number of crops (inter-crop diversity) while those without access to an MWG diversified more.

8
CONCLUSIONS AND POLICY RECOMMENDATIONS

> 'Climate services can be defined as decision-making support tools developed based on a process of transforming climate information into relevant advisory services that assist decision-making by individuals and organizations of a society'. .....Tall, Coulibaly, and Diop 2018

The provision of tailored climate information services 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 are inaccessible to the majority of farmers. Tailoring CIS ensures that information disseminated to users meet their needs in three criteria: saliency, credibility and legitimacy. While there are many co-production models that have been used to tailor CIS in different parts of the world, there is hardly any rigorous evidence on the effectiveness of these models. This evaluation is part of parallel projects (Coulibaly et al. 2018; Carr et al. 2018; Onzere et al. 2018) under the CISRI learning agenda, which sought to test existing good practices in the evaluation of CIS and experiment with new assessment tools to better understand their value for CIS assessment. More specifically, this evaluation uses data generated from an innovative survey design approach collected from 795 households in Senegal and applies contemporary impact assessment tools that account for selection bias to establish causal links between CIS use and their impacts.

In the first analytical section, we have specifically looked at the role of MWGs in CIS diffusion and adoption in the presence of information asymmetries (awareness and access). During the process of technology diffusion and dissemination, it is not possible that all potential users with a positive demand for the technology get exposed to full information to be able to make the adoption decision, leading to information asymmetries within the population. Using classical models to estimate adoptions rates leads to biased adoption parameters due to exposure and selection bias. We have accounted for such exposure bias emanating from asymmetries in awareness and access to CIS using Diagne and Demont 2007's ATE framework. Our findings suggest that the MWG model in Senegal is effective in increasing farmers' awareness, access and use of CIS. From the estimated adoption rates, we find positive and significant selection bias. This implies that without correcting for awareness and access exposure bias the population adoption estimates would have been significantly (i) underestimated in the case where unexposed individuals are assumed to be non-adopters and (ii) overestimated in the case where adoption rates are calculated based on the exposed sample. Furthermore, analyzing determinants of awareness or adoption using classical approaches to regression models would also yield inconsistent parameter estimates, which might lead to wrong insights in the development of future CIS programs

or for policy makers. For example, inconsistent estimators on gender or age might lead to project design or policies where targeting might focus on unsuitable beneficiaries or miss out on the relevant groups. It is also worth mentioning there were some peculiar trends that were contrary to our expectations. For example, we found the MWG having a positive and significant effect on awareness, but not on access. This could because being able to receive climate information is more a function of household level characteristics such as owning a radio or cellphone or having contact with extension staff. Also surprising was that we found formal education as having a negative association with awareness of CIS. This provides greater context and points to the need for future research to explore further some of these complexities when it comes to CIS uptake.

The exposure rates in the sample of farmers with MWGs are very high, with 99% for the awareness corrected model and 94% for the access corrected model compared to 83% and 85%, respectively, in locations without the MWGs. This is an important finding for policy in that the MWG model seems to have the desired effect of reducing the exposure bias that is heavily cited as a significant hindrance in the diffusion of new technology (Diagne and Demont 2007; Kabunga, Dubois, and Qaim 2012; Ouma et al. 2013; Shiferaw et al. 2015; Simtowe, Asfaw, and Abate 2016). A closer look at the projected impacts reveals that MWGs effectively increased the number of households that used CIS to influence farming decisions by 22% or over 160,000 households from CCAFS 2015 estimated population of 740,000 rural households that have access to CIS. These results demonstrate that MWGs play a vital role in promoting the diffusion and use of CIS among farmers in Senegal.

A key challenge in evaluating the impact of CIS is trying to establish the link between an individual receiving and using CIS and the effects it has on behavioral changes due to the complex decision-making process farmers go through. In the second analytical section, we again capitalize on the unique sampling design that enables us to reconstruct the counterfactual scenario and apply the ATE framework, but this time using an instrumental approach. The presence of an MWG has a positive and significant effect on the awareness, access and uptake of seasonal, daily weather forecast and instant forecasting. In terms of awareness, access and use of different CIS, the results indicate that the greatest impacts of the MWGs were on awareness of EWS, access to daily forecasts and use of EWS.

Taking a closer look at how the presence of an MWG influences behavioral changes or adaptation strategies for the different types of CIS used, we see that MWGs have a positive and significant effect on the awareness, access and uptake of seasonal, daily weather forecast and instant forecasting. In terms of awareness, access and use of different CIS, the results indicate that the greatest impact of MWGs was on awareness of EWS, access to daily forecasts and use of EWS.

The forecast on total amount of rainfall is also used to make changes on the location to allocate and plant different crops. The presence of an MWG increases the use of forecasts on total accumulated rainfall to inform farmers' decisions. For example, the presence of an MWG increases the probability of farmers using the information on total accumulated rainfall by 25%. Similarly, looking at the seasonal forecast on the onset of rains we see that the MWG effect had the highest impact on informing decisions on timing of planting and land preparation, while with the 10-day forecast we see that the MWG influences decisions on whether household uses fertilizer or not.

There are two broad lessons to be learned from this case study. First, the positive and significant effect of the MWG model on farmers' awareness, access and use of CIS, as well as the positive influence on behavioral outcomes and farm management is very encouraging. This sheds lights on the notion that participatory processes in co-production of complex scientific information may lead to more positive impacts in light of the high costs of investment (capital, time, etc.). Second, the fact that the MWG model seems to be instrumental in increased uptake of CIS in Kaffrine, there are lessons to be learned in the design, implementation, monitoring, and evaluation and scaling of similar initiatives to the rest of Senegal and other geographic areas.

While we have used innovative ways to rigorously assess the effectiveness of MWGs in the diffusion of CIS, we acknowledge some shortcomings in our analysis. First, this study builds on cross-sectional data, in which we observe the household's awareness, access and use of CIS in the real world, and try to link this to changes in behavioral outcomes and farm management practices. However, without longitudinal data and the ability to track how farmers use CIS over time under different scenarios of good, normal and bad seasons, there could be other confounding factors that may affect their behavioral outcomes that were not completely eliminated in this study. This limits the scope of our findings and emphasizes the need to carefully interpret results, a point that has already been underscored by Patt, Suarez, and Gwata 2005; Tall, Coulibaly, and Diop 2018 and Hansen et al. 2011. Hence, because this is a 'snap-shot' analysis, we cannot provide conclusive evidence on the link between CIS use and behavioral outcomes, but rather attempt to provide preliminary insights.

Observational studies, in general, 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 CIS, a respondent may choose to either understate, overstate or honestly answer about their awareness, access, and use of CIS, depending on how they 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 of enumerators and training the enumerators to carefully explain, before the start of each survey, that this was an independent evaluation, therefore not linked to any program. This is important so as not to raise expectations or hopes for assistance or aid, which is a factor that could lead to dishonest responses from respondents.

In light of the challenges in using cross-sectional data for impact evaluation, follow-up research with long-term seasonal data may help to further increase the robustness of the estimates and shed more light on impacts over time. In addition, a useful extension that may benefit future assessments would be to use mixed-methods research designs that blend quantitative approaches that we use in this study with other qualitative approaches, such as ethnographic methods (see Carr 2013); gendered assessment tools (see Doss 2014); or outcome harvesting (OH) methods (see Temple et al. 2018) in a complementary manner. Qualitative approaches are better able to capture context-specific issues to better explain the impact pathways that can support findings from the quantitative approaches.

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Definitions of technical terms used in this evaluation

Access to CIS: is measured as a binary variable that takes the value of 1 for each CIS that the household is able to receive different CIS from one of more sources like radio, extension workers, or from fellow farmers, and 0 if otherwise. It is important to emphasize here how the questions on awareness and access were phrased. The respondents were asked to provide information on the main types of CIS households are aware of (or have heard) and have access to receive. In addition, we prompted respondents to further provide more specific information on the frequency, sources and quality of information, the quality of information communicated and trust that households have in the information awareness and access to climate information.

Average treatment effect (ATE): shows the predicted adoption rate in the full population i.e. the predicted CIS use rate within the whole population in Senegal. For the CIS use dummy, it is the probability that a random household in Senegal will use at least one CIS. For the intensity of CIS use, it shows the number of CIS that a random household in Senegal will be using on average.

Average treatment effect (ATE_1): is the predicted adoption rate in the exposed population. It shows the CIS use rate within the population in Senegal that is aware of CIS or has access to at least one CIS. For the CIS use dummy, it is the probability that a random household that is aware of CIS or has access to CIS will use at least one of the CIS.

Average treatment effect of the unexposed (ATE_0): is the predicted adoption rate in the unexposed population. This shows the CIS use rates within the population in Senegal that is not aware of CIS or does not have access to CIS. For the CIS use dummy, it is the probability that household without access to CIS or is not aware of any CIS will use at least one CIS.

Awareness of CIS: is expressed as a dummy variable for each CIS and takes a value of 1 if the household has heard of the CIS type in question and 0 if otherwise.

CIS use and uptake: CIS has no intrinsic value on its own, but rather the value comes when this information is translated into farming decisions that result in positive benefits or utility for the user. Firstly, an individual can only be able to access or receive a particular CIS if they are already aware of it. Therefore, being aware of and having the ability to receive this type of CIS are only necessary but not not sufficient conditions that the individual will uptake the CIS and use it inform their farming decisions. Second, an individual is only able to uptake and use CIS if they are simultaneously aware and have the means to access or receive the information. Hence, in this study we combine the uptake and use as one decision, which is defined as a binary variable that takes the value

of 1 for each CIS that the household uses to make to make and informed decision on one or more farm management practices such as type of crop or variety to grow, timing of planting, weeding , fertilizing or harvesting. It is important that the uptake decision is conditional on (i) the household being aware of the CIS its attributes and resulting net benefits (utility), and having the means to receive it, having the ability (resources (human, economic and institutional) to consciously use CIS to inform farm management practices.

Climate information services (CIS): CIS are concerned with the timely provision of tailored climate-related knowledge and information that can be used to reduce losses and enhance profits. In this context, they entail the information services offered to households in Senegal by the climate experts.

Daily forecasts: Since weather information is a 'perishable commodity' that can become quickly obsolete, two weather reports are produced each day by ANACIM during the rainy season and downscaled for the project regions.

Exposure rates: Exposure rates are defined in terms of the proportion of households who are aware or have access to at least one CIS. Awareness is defined as a dummy variable and takes a value of 1 if the household has knowledge of at least one CIS, and 0 if otherwise. Hence, awareness exposure rate is the proportion of households that have knowledge of at least one of the six CIS. Access on the other hand is defined as a dummy variable and takes the value of 1 if the household received at least one CIS from any of the climate information sources and 0 otherwise. Thus access exposure rate shows the proportion of households that received at least one CIS.

GAP: This is the population adoption gap. shows the existing potential to increase CIS use within the whole population if all farmers were aware or had access to at least one CIS. In this case, it indicates the proportion by which CIS use rate in Senegal will increase by if all the households were aware or had access to at least one CIS.

Immediate outcome: The initial change in a sequence of changes expected to occur as a result of implementation of a science-based program.

Impact evaluation: A type of outcome evaluation that focuses on the broad, long-term impacts or results of program activities; effects on the conditions described in baseline data.

Intensity of use of CIS: Intensity of use of CIS is defined as the number of climate information services that the household uses in their decision making. The more the number of CIS the household uses, the higher the intensity of CIS use and vice versa.

Intermediate Outcome: The changes that are measured subsequent to immediate change, but prior to the final changes that are measured at program.

Instant forecasts for extreme events: The instant information concerns off-season showers or rains, high winds, and especially lightning (during the rainy season) which quite often decimates livestock. At ANACIM, an early warning system (EWS) has been put in place to give forecasts on risks of thunderstorm, more than 4 hours in advance.

Key informant: Person with background, knowledge, or special skills relevant to topics examined by the evaluation; sometimes an informal leader or spokesperson.

Longitudinal study: A study in which a particular individual or group of individuals is followed over a substantial period of time to discover changes that may be attributable to the influences of an intervention, maturation, or the environment.

Mixed-method evaluation: An evaluation design that includes the use of both quantitative and qualitative methods for data collection and data analysis.

Multidisciplinary working group (MWG): is an inclusive institution/body that was set up in Senegal both at the national and local levels. It was formed following a collaboration between scientists and the National Meterological Agency (ANACIM) in Senegal. It aims to facilitate the development of CIS, interpretation of CIS into actionable decisions, diffusion of CIS and subsequently facilitates the uptake of CIS by users at district level.

Observed adoption rates (use rate): The observed adoption rate indicates the actual (observed) proportion of households within our sample that used at least one of six CIS.

Outcome evaluation: Examines the results of a program's efforts at various points in time during and after implementation of the program's activities. It seeks to answer the question, "what difference did the program make"?

Outcomes: Changes in targeted attitudes, values, behaviors or conditions between baseline measurement and subsequent points of measurement. Changes can be immediate, intermediate or long-term; the results/effects expected by implementing the program's strategies.

Quantitative data: Numeric information, focusing on things that can be counted, scored and categorized; used with close-ended questions, where participants have a limited set of possible answers to a question. Quantitative data analysis utilizes statistical methods.

Random assignment: A process by which the people in a sample to be tested are chose at random from a larger population; a pool of eligible evaluation participants are selected on a random basis.

Sample: A segment of a larger body or population in the targeted population.

Seasonal forecasts: Seasonal forecasts give the overall configuration of the rainy season. At the end of May, experts observe trends for the coming season and label them: rainy, normal or deficit. If the forecast shows that the season will be in deficit, a warning report is transmitted to government authorities to take appropriate action. The seasonal forecasts are updated during the course of the season at the beginning of June, July and August and translated into agricultural advice. Access to seasonal climate forecasts can benefit farmers by allowing them to make more informed decisions on farming practices such as type of crop or variety to grow. The onset of rainfall is very crucial to farmers

as it can inform that are involved in off-season work to return to their farms start land and planting preparations. Seasonal forecasts were introduced to farmers and refined through an iterative process that recognizes already existing indigenous knowledge and resonates with their day to day life experiences. This way, the new scientific information can be packaged and delivered to farmers in a format that is salient, relevant and legitimate.

Ten day forecasts: When the rainy season sets in, National Meterological Agency (ANACIM) produces ten-day outlook forecasts that help to identify dry spells and other anomalies in the temporal distribution of rainfall in the project intervention areas. These 10-day forecasts are provided to enable the local Multidisciplinary working groups (MWGs), which meet every 10 days, to identify major trends in rainfall and provide appropriate guidance to farmers.

Theory of change:A set of assumptions about how and why desired change is most likely to occur as a result of your program, based on past research or existing theories of behavior and development. Defines the evidenced-based strategies or approaches proven to address a particular problem. Forms the basis for logic model planning.

Types of CIS: We considered six types of CIS namely; seasonal forecasts on the amount of rainfall, seasonal forecasts on the onset of rainfall, seasonal forecasts on cessation of rainfall; 10-days forecasts, 2-3 days forecasts and instant forecasts for extreme events. A brief discussion of these climate information services is presented below.

Use and uptake: Use and uptake of CIS is defined as a dummy variable that takes the value of 1 if the households uses at least one of the CIS to make informed farming decision. This is conditional on the farmers being aware and having access to the CIS. CIS use and uptake is sometimes used interchangibly with CIS adoption rate.