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Can Climate Information Salvage Livelihoods in Arid and Semiarid Lands?

An Evaluation of Access, Use and Impact in Namibia

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Can climate information salvage livelihoods in arid and semiarid lands? An evaluation of access, use and impact in Namibia

Abstract

Climate forecasting is a crucial tool for managing risks in climate-sensitive economic sectors like agriculture. Although rainfed farming dominates livelihoods in Africa, information on access, use and impact of improved seasonal climate forecasting remains scanty. This paper addresses this gap using representative data from Northern Namibia. The study employed propensity score matching, with a sensitivity analysis for hidden bias, to evaluate the impact of climate information on adaptive capacity and food security. Although half of the households received climate information, many rated it as insufficient for decision-making and relied on traditional knowledge. Farmers were found to attach high importance to climate information in relation to decisions about sale of livestock, stocking livestock feed, restocking, storing food for consumption smoothing and in making crop choices. Households receiving climate information had more diversified diets, higher food expenditure and engaged in more adaptive strategies. Effective response to climate information for risk mitigation will require enhanced community awareness of available adaptive choices, development of market value chains, institutional support like extension services, and improvement of rural road and communication infrastructure. Working with local leaders and integrating climate information into local knowledge systems can enhance access and utilization in farm decisions.

Keywords: Impact evaluation, Climate information, Namibia, Adaptive strategies, Food security, Dietary diversity

1. Introduction

1.1. Background

The role of climate-information forecasting in an environment where the main economic activity is rain-dependent cannot be overstated. Rain-fed agriculture is the dominant source of livelihood for millions of rural families in Sub-Saharan Africa (Cooper et al., 2008). High rainfall variability is a characteristic of arid and semi-arid agro-ecosystems and adversely affects crop and livestock production; this problem is exacerbated by climate variability. Such agro-ecosystems are mainly located in Sub-Saharan Africa (SSA), where countries have limited financial and technical capacities to deal with the negative impacts of climate variability (Thomas and Twyman, 2005). Barrios et al. (2008) provide evidence that climate change has in the past contributed to poor agricultural performance in Sub-Saharan Africa compared to the rest of the world. This trend will continue to deteriorate, as the most important staple crops in the SSA region, maize, millet, sorghum and cassava, are projected to decline as a result of climate change (Schlenker and Lobell, 2010).

Research has shown that African economies are sensitive to climate variability and more specifically to changes in temperature and precipitation (Acevedo et al., 2018; Dell et al., 2012, 2014; Jury, 2002). This is largely because of the agricultural sector's relatively high share of the total GDP in Africa compared to the rest of the developing world (Barrios et al., 2006; Diao et al., 2007; Jury, 2002; Szirmai, 2012). Over reliance on rain-fed agriculture and on hydroelectric power are two key factors that have curtailed economic growth in Africa following the trend towards declining rainfall since the 1960s (Barrios et al., 2010). Taken together, these factors make Africa the most vulnerable region worldwide to the negative effects of climate change (Challinor et al., 2007).

Given the importance of the agricultural sector for food security and the vital role of energy in social and economic transformation (Wolde-Rufael, 2006), seasonal climate information forecasting and early warning systems are vital to planning and risk mitigation in key economic sectors like agriculture, water, health and transport (Hellmuth et al., 2007). Droughts and variations in rainfall occur commonly in Southern Africa, with frequency of up to four droughts per decade (Mogotsi et al., 2012). Households that rely on farming in these agro-climatic conditions operate under highly risky conditions and providing them with timely climate information forecasts can be a good risk-mitigation strategy (Luseno et al., 2003; Vogel and O'Brien, 2006). This is of significance to Namibia, which despite being the driest country in Sub-Saharan Africa has most of its rural population heavily dependent on agriculture. To underscore the severity of this problem, the President of the Republic of Namibia declared a state of emergency on 6 May 2019 following recurrent droughts since 2013 (see Appendix B.4). Although there is a drought monitoring center in the Southern African region, lack of drought forecasting and of institutional capacity to mitigate droughts hinders the management of drought-related risks in the region (Nhamo et al., 2019).

Past studies have indicated a remarkable improvement in predicting rainfall patterns and major climatic events since the devastating drought in the Southern African region in 1991/1992, but there is little empirical research on how this has been used and what impact it has had on adaptive strategies and the welfare of rural communities. The current level of access to and use of climate information, and its impact on rural communal households in Namibia, is largely unknown.

This paper contributes to the literature by looking at the perceived role of climate forecast information and early warning systems in the production choices made by farmers in the semi-arid regions of Northern Namibia. It provides a better understanding of the level of access to and integration of such information in the production decisions. The paper also considers many adaptive strategies, grouped into five categories which include crop-based, livestock-based,land management-based, water management-based and non-farm-based strategies. The paper then constructs a weighted household adaptive capacity based on these five categories. Lastly, the paper evaluates the impact of climate information on household adaptive capacity, dietary diversity and food security using propensity score matching with a sensitivity analysis for hidden bias.

2. Literature review

2.1. The role of climate information forecasting and early warnings

The use of improved seasonal climate-information forecasting and early warning systems can improve farm earnings by allowing farmers to adjust their management decisions. Savings can be made by the use of timely and reliable long-range climate forecasts (Jury, 2002). Policy makers can also use the information to develop national disaster preparedness plans, advise citizens, and build buffer stocks, while the private sector can use it to prepare for appropriate response to regional food needs (Dilley, 2000; **?**; Patt et al., 2007).

The 1997/1998 forecast by the Southern Africa Regional Climate Outlook Forum (SARCOF) is a good example of an instance where policy makers, humanitarian organizations and lending/financial institutions in the region used forecast information to plan adequate response options for an anticipated drought resulting from an El Niño weather pattern (O'Brien et al., 2000). Ziervogel et al. (2010) discuss how municipalities could utilize seasonal climate forecasting to plan and manage water resources. Recently cases of flooding in major cities have been increasing, leading to the loss of lives and property because of poor planning and a lack of preparedness. Mozambique, having been twice hit by two major tropical cyclones, Idai and Kenneth, in just five weeks between March 14 and April 25, 2019, is a case in point (Boykoff et al., 2019; Devi, 2019; Scully, 2019; Tumwine, 2019).

At the farm level, Amegnaglo et al. (2017) and Roudier et al. (2014) demonstrate how West African farmers use seasonal climate forecasting to adjust planting dates, planting area, crop and crop variety choices, and level of fertilizer application. In the Southern Africa region, improved seasonal climate forecasting could be a risk-management tool for farmers and help to improve food security (O'Brien et al., 2000; Ziervogel et al., 2005; Zinyengere et al., 2011). Increased yield and crop loss reduction have been associated with the effective use of seasonal climate forecasting by farmers in Senegal (Roudier et al., 2014). CGIAR's study for the CCAFS (*Climate Change, Agriculture and Food Security*) program across West and East Africa, and South Asia showed that farmers who received weather information made changes to their farming practices like adopting improved crop varieties, short-cycle and drought-tolerant crops, but that better output prices were a major incentive for these changes.

For seasonal climate forecasting to be meaningful, institutional and infrastructural support is needed. Indeed, Babcock (1990) argues that increased accuracy of weather forecasts does not necessarily translate to increased farmer welfare, especially for those producing commodities with inelastic demand. Other factors, such as credit constraints, lack of working financial markets and socio-cultural beliefs based on experience might limit a farmer's response to such opportunities.

Improved climate information forecasting, if used well, could be an important adaptive and mitigation tool to cushion African agriculture against shocks related to climate variability (Roudier et al., 2014; Weaver et al., 2013).

With the right information about future climate events, the farmer can decide on the number of livestock to keep based on the availability of feed, what composition of livestock to have, and what crop varieties to plant, before extreme climate events. However, climate forecast information remains underutilized as a tool for climate risk management and enhancing food security in southern Africa (Vogel and O'Brien, 2006). The next section explores why this is the case in spite of all the attention given to climate change and its impacts in SSA.

2.2. Climate information forecasting and food security

The 1996 World Food Summit defined food security as a situation in which all people at all times have physical and economic access to sufficient and nutritious food that meets their dietary needs and preferences for an active and healthy life. Livelihoods and food security in the Southern African region are highly vulnerable to adverse effects of climate variability but climate predictions can play an important role in mitigating these impacts (Archer et al., 2007). Seasonal climate information is also an important tool in forecasting yields of major food crops thereby enabling planners to better respond to production shocks and spikes in food prices (Iizumi et al., 2018). Timely provision of seasonal climate information forecasts can enable farmers make smart investment decisions to avoid crop failure and loss of livestock by choosing the right crops and keeping the optimal number of livestock. Planting drought tolerant crops and early maturing varieties in anticipation of dry-spell or reduced precipitation would guarantee some harvest and food security for households. Households can also enhance their food storage for consumption smoothing during the lean periods. If seasonal forecasts predicts a good season, farmers can diversify their production and therefore their diets. Households can also sell some of the stored surplus in anticipation of a good harvest later in the season. Sibhatu and Qaim (2018) find cash income generated through sale of farm produce to have a more significant impact on dietary diversity than diverse subsistence production. Households can use early drought warnings to diversify their income sources and make savings in farm inputs, both capital and labour. Money saved in smart farm decisions can be used to buy food and cushion the households in times of production shocks. Similarly, livestock farmers can sell some of the animals while still in good health as a way of preserving value and use the money to purchase the feeds for the remaining herd and also buy food for their families. Shifting from cattle to goats might ensure continued supply of milk and hence family nutrition in harsh times because goats are more resilient than cattle. Governments and aid agencies can use climate services and early warnings to plan,coordinate and pre-position humanitarian interventions to meet food needs during severe droughts Dilley (2000).

2.3. Access and use of climate information by end-users

There has been great improvement in predicting rainfall patterns and in early warning systems, both in accuracy and lead-time (Hansen, 2002; Kusunose and Mahmood, 2016; O'Brien et al., 2000; Vogel and O'Brien, 2006; Ziervogel and Calder, 2003). However, access and effective response to climate information is likely to be determined by supply-side factors, mostly related to the attributes of the forecast information as perceived by the end-users, and dissemination strategy by relevant agencies. These factors could potentially constitute barriers to the effective utilization of the forecast and include such things as the legitimacy and credibility, scale, technical complexity, and timing of the forecast (Patt and Gwata, 2002). Farmers' lack of capacity to understand and assimilate improved climate forecasting could limit its integration in decision making (Mjelde et al., 1988). While it is important to generate such information, understanding its relevance and ensuring that it is accessible and available to potential users are even more crucial (Dilley, 2000; Haigh et al., 2015). Communicating the uncertainty associated with forecasting and integrating such information in decision making by the end users is key to the successful management of risks to the agricultural sector caused by climate variability (Haigh et al., 2015; Hansen et al., 2004). Legitimacy, trust and credibility issues can arise if the probabilistic nature of the forecast is not well understood by users, thereby reducing its value (Ziervogel and Downing, 2004).

The technical complexities of climate information at the point of dissemination and the mismatch between the released information and farmers' needs are some of the major limitations to effective utilization. For instance, in Southern Africa, farmers indicated that they would prefer to receive a seasonal climate forecast with a lead-time of six months, but that the forecast only came to them two to three months before the onset of the rains (O'Brien et al., 2000; Ziervogel et al., 2005). In some cases, farmers received the information after they had already purchased the seeds (Patt and Gwata, 2002). Less precise climate forecasts received earlier in the season might be more valuable than more accurate predictions that are received close to the start of the season (Mjelde et al., 1988). Research in Senegal has shown that complementing seasonal climate forecasts with technical advice on crop choice and inputs greatly enhances the value of the information to the farmer (Tall et al., 2014).

Many agrarian rural families in Sub-Saharan Africa have no access to climate information forecasts. A study conducted over two decades ago to understand users' perspective on and response to the 1997/1998 El Niño forecast found that more than half of the small-holder farmers in Southern Africa did not receive that information (O'Brien et al., 2000). Luseno et al. (2003) found that only about a fifth of the pastoralists in East Africa had access to scientific climate information and the majority relied on traditional knowledge. Dissemination of climate information to end users remains poor with little contact between farmers and extension staff(Luseno et al., 2003; Vogel and O'Brien, 2006; Ziervogel et al., 2005). Of the few who receive climate information, a high proportion integrate it in their decision-making. Poor access and utilization of climate information could be attributed in large part to lack of proper targeting and inclusion of such groups in preseason climate outlook forums (Archer, 2003; Patt et al., 2007). Other constraints on seasonal climate forecast utilization, such as the credibility and legitimacy of the forecast information, its scale and timing, and farmers' capacity to interpret the forecast information, are discussed in papers by Patt and Gwata (2002), Millner and Washington (2011) and Amegnaglo et al. (2017). Another barrier to effective utilization of seasonal climate forecast is lack of resources. Farmers with low resource endowment are least likely to benefit from the good season that usually follows prolonged dry spells or droughts due to trade-off between investing in yield-enhancing improved inputs for future returns and the immediate need to feed their families. Loss of livestock during a drought means that many farmers have to cultivate less land as they have fewer draft animals available for ploughing O'Brien et al. (2000). Measurement and prediction errors notwithstanding, several studies have found significant yield benefits for farmers who integrate climate forecast information in their production decisions (Patt et al., 2005; Roudier et al., 2014).

2.4. Sources and dissemination of Seasonal Climate forecast and early warning systems in Africa

Following the devastating drought of 1983/84 and subsequent droughts of 1991/1992 and 1994/1995 as a result of El Niño events, interest in and awareness of the important role of climate forecast and early warning systems in the management of climate risk increased in Africa, as well as in the rest of the world. In the light of this increased awareness, a workshop on reducing vulnerability to climate variability in Southern Africa was held in Zimbabwe in 1996, where the idea of having regional climate outlook forums for the different regions in Africa was conceived (Ogallo et al., 2008). The World Meteorological Organization (WMO), national meteorological services, and other stakeholders organized the first regional climate outlook forum (RCOF) to form consensus on a seasonal climate forecast that would be useful to climate-sensitive sectors of the economy (Ogallo et al., 2008; Patt et al., 2007). The three most active RCOFs in Africa include the PRÉvisions Saisonnières en Afrique de l'Ouest (PRESSAO) in West Africa, the Southern Africa Regional Climate Outlook Forum (SARCOF) and the Greater Horn of Africa Outlook Forum (GHACOF) covering East African countries (Kenya, Uganda, Rwanda, Burundi, Ethiopia, Sudan, South Sudan, Djibouti, Eritrea and the United Republic of Tanzania). The drought-monitoring centres (DMCs) in these regions have annually since 1997 brought together climate experts, from Africa and beyond, to form consensus forecasts for the upcoming season. PRESSAO and SARCOF meet once a year and GHACOF meets twice, reflecting the unimodal (one wet season) and bimodal (two wet seasons) climate patterns in the respective regions. Pre-season workshops are also organized to enhance the capacity of national meteorological services (NMS) to produce and to improve the quality of the seasonal climate outlook in their respective countries (Harrison et al., 2007; Ogallo et al., 2008).

Like other countries in the Southern Africa Development Community (SADC) region, Namibia's national meteorological service (NMS) receives the forecast consensus information in both soft and hard copy from SARCOF for further distribution to other users in Namibia. The forecast information is provided in tercile probabilities indicating the likelihood of either receiving below normal, normal, or above normal rainfall but not showing the expected amounts (Harrison et al., 2007). Namibia first received this consensus climate forecast in the 1997/1998 season, but the majority of small-holder farmers did not receive it and only a few of those that received it actually used it. Low confidence in the forecast information, lack of access to draft or tractor services, and alternative seeds were cited as causes of the low utilization of forecast information (O'Brien et al., 2000).

The current paper differs from O'Brien et al. (2000) in a number of ways. First, it uses a large representative sample of 653 respondents, compared to the 112 households in the earlier study. Secondly, it looks at the channels of information flow, and gaps and missed opportunities in the dissemination of forecast information. Thirdly, the previous study was purely qualitative, whereas the current study provides an empirical analysis of the determinants of access to climate forecast information and its impact on household food security and adaptive strategies used to mitigate risks related to climate variability and social shocks. The current study also differs from the previous one in terms of temporal and spatial coverage. The previous study was conducted two decades ago and covered Ohangwena, Caprivi and Okavango regions while the current study covers the three most populous regions in Northern

Namibia, namely Omusati, Oshana and Oshikoto.

The rest of the paper is organized as follows: Section 3 discusses the methodology, followed by data description in section 4. Section 5 discusses the empirical results and section 6 presents conclusion and recommendations.

3. Methodology

3.1. Conceptual framework

Once provided by the meteorological service departments, some climate forecast information is a global public good. The goal of the regional climate outlook forums has been to make the information accessible by as many end-users as possible. The cost of dissemination is in most cases absorbed by the public sector through various government agencies. The producer must then make the economic decision whether to invest time in accessing and using that information in his or her production decisions. The producer elects to use scientific climate information if the expected utility of using it, U_{sc}, exceeds his/her reservation utility U_{tk}, i.e. $U_{sc} > U_{tk}$.

The forecast must include new and relevant information that supplements a farmer's traditional knowledge and helps reduce the uncertainty associated with farming under climate variability. Access to climate information is modelled as a binary choice dummy, taking a value of one for households that have access to climate information and zero otherwise. Social-cultural, demographic, economic and institutional factors determine the likelihood of accessing climate information, as illustrated in Figure 1. One can think of these as demand-side factors affecting the producer's need for climate forecast information. For instance, subsistence farmers operating on a small scale with little access to markets may not see the need to actively seek new information beyond the traditional knowledge that they have access to historically.

The social-cultural factors like religious beliefs and traditional knowledge can constitute barriers to use of seasonal climate forecasts and adoption of climate-smart agricultural practices like early maturing and drought-tolerant crops, and selection of hardy livestock breeds (Davies et al., 2019). This would ensure that households are food secure and can take advantage of favorable seasonal forecasting to diversify their diets through own farm production. Integrating scientific climate information with tradition knowledge and involving traditional and religious leaders in dissemination can enhance access and use because communities trust them. Social networks are likely to increase the access and use of climate information through farmer-to-farmer peer influence. Access to and use of climate information in Namibia is also likely to decline with age given that many rural households are headed by elderly persons. Education is expected to increase the likelihood of accessing, understanding and using climate information because educated people are likely to appreciate the importance of climate information in farm decisions. Size of the household signals availability of family labour and demographic diversity in the household. Larger households with diverse demographics are more likely to have access to climate information from some of its members. These households are likely to cultivate more land, invest more capital and labour inputs and therefore be more sensitive to any potential losses. Most households in Namibia are headed by females and this may have implications on the access to resources that might be required to respond effectively to climate information. The access, need for and use of climate information have been shown to differ significantly between men and women(Diouf et al., 2019; Gumucio et al., 2020)

Other economic factors like wealth endowment and ownership of communication assets, (*radio, television and mobile phones*), are expected to increase access and effective utilization of seasonal climate information forecasts. For instance, a household might need resources to purchase suitable inputs, livestock feeds or repair water wells and rehabilitate water points in anticipation of a dry spell or drought. Migrants can also influence access to and utilization of climate forecasts by sharing information with their rural families and by sending as remittance the resources needed for effective response to such forecasts e.g. early land preparation, purchase of inputs and early planting.

Institutional support through agricultural extension services can increase dissemination and therefore access to and use of climate information in farm decisions. Functioning products and factor markets can increase the demand for and integration of climate and agricultural information in making production decisions. Regular government relief assistance and cash transfers like non-contributory old age pensions (Levine et al., 2011), provide households with social insurance and might reduce their incentive to seek information that would mitigate the risks of crop failure or loss of livestock.

Wide access and integration of climate forecast information in production decision-making has the potential to increase the adaptive capacity and reduce vulnerability to climate variability through strategic farm investments and loss avoidance. The outcome would be the enhanced resilience in the agricultural sector, reduced vulnerability to climate risks, improved food security, and reduced reliance on government emergency relief.

In this paper, the treatment group comprises households that received climate information in general, including early warnings, and the 'control group' as those that did not receive such information. Even though the households' selection into the study sample was random, access to climate forecast information and early warning is not. This could lead to self-selection bias. The next section presents mean comparisons between the treatment and control groups on key covariates used later for impact evaluation. Individuals in the two groups are then matched based on their conditional probability of receiving information and the conclusions tested for sensitivity to hidden bias.

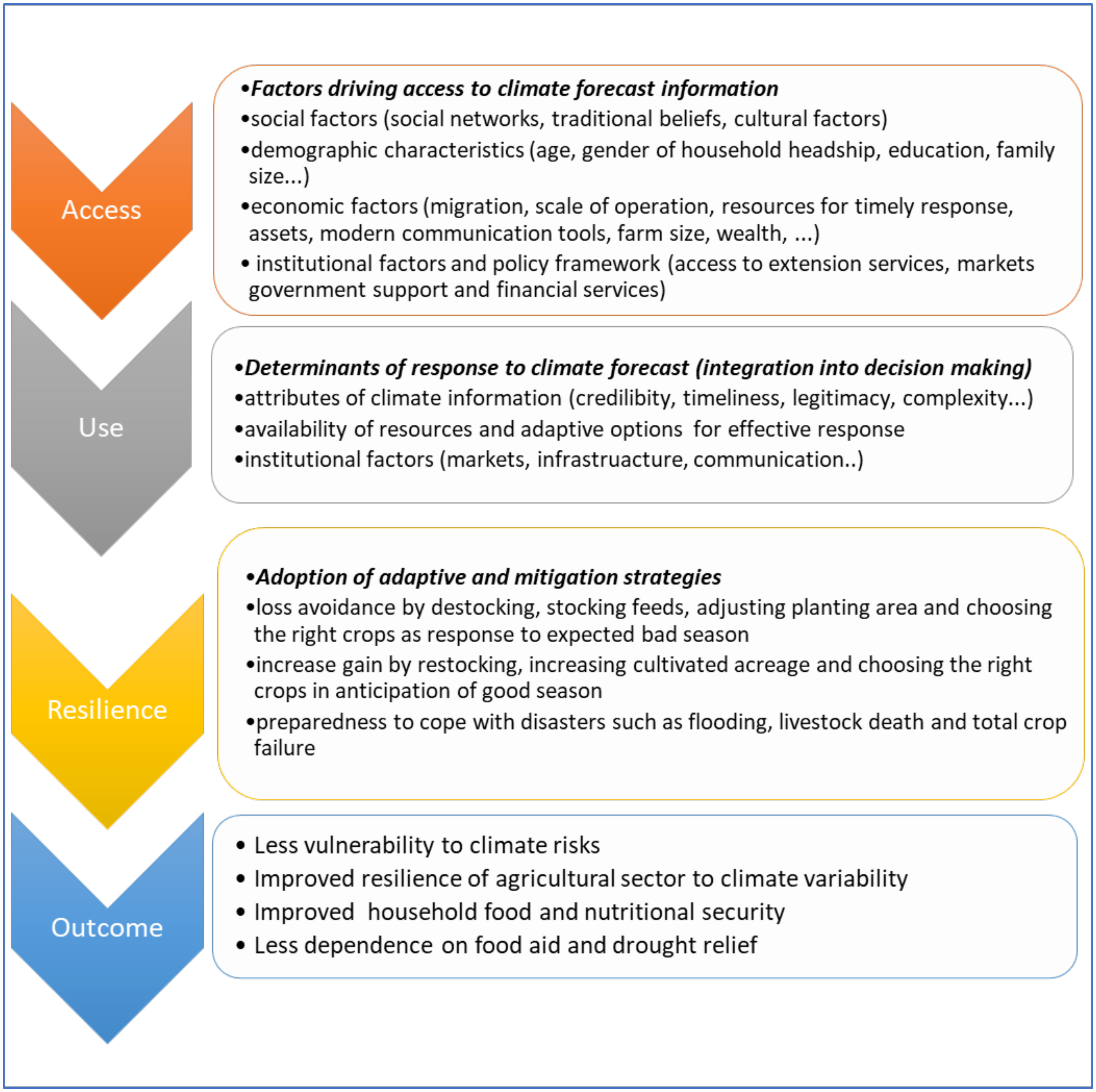

Fig. 1. Drivers of access and use of climate forecast information and impact pathway (source: authors)

3.2. Empirical model

As in other observational studies that do not have the benefit of randomizing the treatment assignment, the main challenge is creating a counterfactual that will allow the attribution of differences in outcomes between the two groups to the treatment. By letting $\tau_i \in [0, 1]$ denote the dummy describing access to climate forecast information, and y_i denote the outcome of interest, (*the number of adaptive strategies and food security indicators*), potential outcomes can be defined following Angrist and Pischke (2008),

$$y_i = \begin{cases} y_{i1}, & if \quad \tau = 1 \\ y_{i0}, & if \quad \tau = 0 \end{cases} \tag{1}$$

Where y_{i1} is the outcome for a household that received climate information and y_{i0} denotes the outcome for the same household had it not had access to climate forecast information. The observed outcomes can then be written as

$$y_{i1} = y_{i0} + (y_{i1} - y_{i0})\tau_i \tag{2}$$

The effect of climate forecast information on the outcome variable of interest, *treatment effect*, is given as $y_{i1} - y_{i0}$. The average treatment effect of the climate information forecast is given in Eq.3.

$$\underbrace{E(y_i)}_{ATE} = \underbrace{E\{y_{i1} - y_{i0}|\tau = 1\}}_{ATT} + \underbrace{E\{(y_{i0}|\tau_i = 1) - E(y_{i0}|\tau_i = 0)\}}_{Selection\ Bias\ (ATENT)} \tag{3}$$

The first term on the right-hand side (RHS) indicates the average effect of receiving climate information on outcomes for the treatment group and the second term shows what the average treatment effect would have been for the control group had the households in that group been treated. Self-selection bias is likely because households that have communication assets, higher resource endowment, and better social networks are more likely to access climate forecast information. To control for self-selection bias, the paper applies the propensity score matching technique proposed by Rosenbaum and Rubin (1983). This is the conditional probability of receiving climate forecast information given a set of observable characteristics (Rosenbaum and Rubin, 1984). Households with similar propensity scores are statistically similar in observed covariates regardless of their treatment status. The conditional independence between treatment assignment and potential outcomes, given the observed covariates ($Y_{i0}, Y_{i1} \perp \tau_i | X_i \quad \forall i$), further allows for an unbiased estimation of the treatment effect (Dehejia and Sadek, 2002; Imai and Van Dyk, 2004; Rosenbaum and Rubin, 1984). X_i is a vector of observable characteristics that affect both the treatment assignment and outcomes. The propensity score is estimated using the probit model (Eq4).

$$Pr(\tau_i = 1|X_i) = Pr(\tau_i^* > 0|X_i) = 1 - \phi(-X\beta) \tag{4}$$

Where $\phi = (2\pi)^{(1/2)} exp(\frac{X\beta^2}{2})$, $0 < Pr(\tau_i = 1|X_i) < 1$, i.e. the overlap condition requires that $\forall X_i$ within the unit interval, there is a positive probability of either participating or not participating (common support condition). It would be difficult to compare the two groups for covariate values whose probability of being treated is one or zero(Hirano and Imbens, 2001). The logit model $Pr(\tau_i = 1|X_i) = \frac{exp(X\beta+\epsilon)}{1-\exp(X\beta+\epsilon)}$ is also commonly used to estimate the propensity scores (Dehejia and Sadek, 2002; Rosenbaum and Rubin, 1984).

3.2.1. Matching algorithms

The study used matching with replacement, which allows a single treatment unit to be matched to multiple units in the control group. This matching technique minimizes the propensity score distance between the treatment unit and the nearest units in the control group, thereby reducing bias Dehejia and Sadek (2002). The paper presents the results of three matching algorithms, namely nearest neighbour matching with a calliper of 0.1, calliper (radius) matching, and kernel matching. Nearest neighbour matching compares the units in the control group with the least difference in propensity score, to a unit in the treatment group. For radius matching, a calliper (maximum propensity score difference or tolerance level) of 0.1 is chosen for this paper to improve the quality of the matches. The paper employs the psmatch2 estimation routine developed by Leuven and Sianesi (2018). The routine performs propensity score matching, common support graphing, and covariate imbalance testing.

3.2.2. Test for hidden bias with Rosenbaum bounds

The object in this section is to test how strong the effect of unobserved variables on access to climate information would have to be for it to undermine the inference of the matching results. Let $\pi_i(X_i, \mu_i) = Pr(\tau_i = 1|X_i, \mu_i)$ where ϕ_i is the conditional probability of receiving climate information for $household_i$ presented as a function of both the observable covariates X_i and unobservable factors μ_i. Similarly, $\phi_j(X_j, \mu_j) = Pr(\tau_j = 1|X_j, \mu_j)$ represents the probability of $household_j$ receiving climate information.

$$\phi_i(X_i, \mu_i) = F(x_i\beta + \gamma u_i) \tag{5}$$

Then, following Becker and Caliendo (2007), the possible effect of the unobserved characteristics can be evaluated by checking if γ in Eq. 5 is significantly different from zero; otherwise, two households with the same set of covariates X_i will have different probabilities of receiving climate information. Empirically, two households with a similar set of covariates ($x_i = x_j$) could differ in the probability of receiving treatment owing to unobserved factors, leading to hidden bias (Rosenbaum, 2005). Assuming the "F" in Eq.5 takes the form of a logistic distribution, then

$$\frac{\pi_i(x_i,\mu_i)}{1-\pi_i(x_i,\mu_i)} / \frac{\pi_j(x_j,\mu_j)}{1-\pi_j(x,\mu_j)} = \Gamma = \frac{exp(x_i\beta+\gamma\mu_i)}{exp(x_j\beta+\gamma\mu_j)} = exp(\gamma(\mu_i-\mu_j)) \tag{6}$$

Sensitivity analysis shows how changing the value of *gamma* could, in the present case, alter the inference about the effect of the climate information on target outcomes (Becker and Caliendo, 2007). The odds of $household_i$ being treated is $\frac{\pi_i(x_i,u_i)}{(1-\pi_i(x_i,u_i))}$ and that of $household_j$ is $\frac{\pi_j(x_j,u_j)}{(1-\pi_j(x_j,u_j))}$

$$(\frac{1}{\Gamma} \leq \frac{\pi_i(x_i,u_i)}{(1-\pi_i(x_i,u_i))} / \frac{\pi_j(x_j,u_j)}{(1-\pi_j(x_j,u_j))} \leq \Gamma) \tag{7}$$

The value of is $\Gamma = 1$ if there are no differences in unobserved factors i.e. $(u_i = u_j)$ between the two groups or there is no hidden bias $(\gamma = 0)$. $\Gamma > 1$ when there is unobserved bias.

4. Data sources and descriptive statistics

4.1. Sampling and data collection

The study used primary survey data collected from a representative sample of 653 rural households in Northern Namibia. A multistage sampling procedure was used to generate a self-weighted probabilistic sample. The study covered seven constituencies in three administrative regions, namely Omusati, Oshana and Oshikoto (Figure 2). The constituencies are Onesi, Oshikuku and Otamanzi in the Omusati region, Okaku and Ongwediva in the Oshana region, and Olukonda and Omuthiya in the Oshikoto region.

Field research involved a preliminary visit to all of the selected study regions to generate sampling frames and to pilot the survey instrument with the local people. A list of all the villages in each constituency was obtained at the constituency office, and the number of villages required for each constituency was randomly selected using probability proportionate to size sampling (PPS). The second step involved visiting the selected villages and listing all the households from each with the help of village headmen or elders. Ten households from each of the villages were then randomly selected, with an additional five for possible replacement. This exercise was carried out in May 2017 and used as the basis for the survey logistics and a revision of the survey instrument. Two trained teams, each consisting of five enumerators and a supervisor, collected the data from 653 households, using Computer-Assisted Personal Interviewing (CAPI), between July and September 2017.

4.2. Definition and measurement of outcome variables

In this section, we provide a brief description of the outcome variables, how they were measured in the survey and how they were constructed during the analysis. These include household food insecurity access scale (HFIAS), months of adequate household food provisioning (MAHFP), household dietary diversity score (HDDS) and adaptive capacity.

4.2.1. Household food insecurity access scale(HFIAS)

This food security outcome indicator was constructed following the Food and Nutrition Technical Assistance III Project (FANTA) guidelines (Coates et al., 2007). The indicator assesses prevalence of food insecurity severity in a household using a series of nine questions asked with a recall period of four weeks. Each successive question represents an increasing level of food insecurity condition ranging from anxiety or uncertainty (*worrying about running out of food for the family*), to severe food insecurity where a household has to go without food for a whole day and night. Each respondent was asked nine occurrence questions (*Yes/No*) if the household experienced the condition described in the question. This was followed by frequency of occurrence question with responses ranging from 0=never (*if "No" to occurrence question*), 1=rarely (1-2times), 2=sometimes (3-10 times) and 3=often (>10times). The questions were asked to the person mostly responsible for preparing meals in the household. HFIAS score for each household was then computed as the sum of all the frequency-of-occurrence during the past four weeks for the 9 food insecurity-related conditions. A score of zero or one would indicate a food secure household, while the maximum score of 27 would indicate a severely food insecure household.

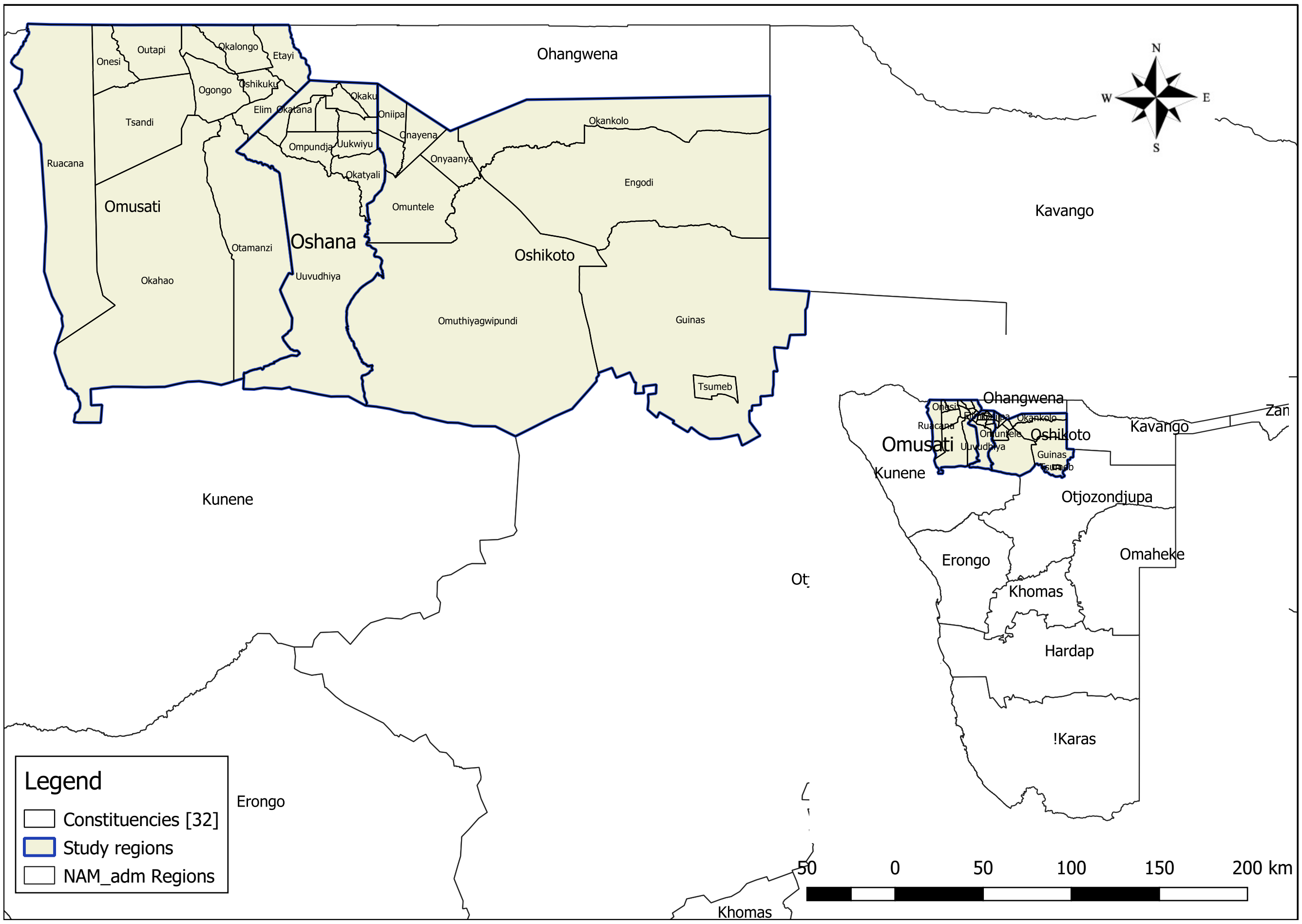

Fig. 2. Map of the study regions (Source: Authors)

4.2.2. Months of adequate household food provisioning (MAHFP)

This indicator captures changes in household food access over time and was constructed following the Food and Nutrition Technical Assistance III Project (FANTA) guidelines (Bilinsky and Swindale, 2010, 2005). The respondents were asked, starting with the current month, to think back 12 months and indicate whether there were months their households did not have access to sufficient food to meet their needs. If yes, the respondents were asked to identify those months they did not have enough food to meet their family needs. The indicator was computed by adding up the months a household was unable to meet their food needs and subtracting that number from 12. MAHFP has the advantage of capturing over time, in the context of Namibia, the joint effect of different strategies on households' food security such as own food production, farm storage (mainly millet (*mahangu*)), and interventions that increase households' access to food (old-age grants, food relief and other social programs).

4.2.3. Household dietary diversity score (HDDS)

Household dietary diversity score is also a measure of food access in terms of dietary quality and diversity and was constructed following the Food and Nutrition Technical Assistance III Project (FANTA) guidelines (Swindale and Bilinsky, 2006). The indicator measures the quality of the household food diet using food groups rather than different types of foods consumed by a household. The guideline categorizes different food types into 12 food groups namely (1) cereals, (2) roots & tubers, (3)vegetables, (4) fruits, (5) meat, poultry & offal, (6) Eggs, (7) Fish and sea food, (8) pulses, legumes & nuts, (9) milk & dairy products, (10) oils & fats (11) sugar & honey and (12) Miscellaneous (*condiments, coffee, tea*). Respondents were asked systematically if they had consumed any of the food types in each of the food groups, any time in the last four weeks. Given the importance of own farm production and market transactions in household food diversity (Sibhatu and Qaim, 2018; Sibhatu et al., 2015), respondents were specifically asked to include food groups consumed from own production or purchased from local markets, retail stores and cooker shops (*local name for spaza shops*) as well as food donations and government relief. The questions were again asked to the person in the household most responsible for preparing meals. The HDDS was computed by adding the number of food groups consumed by a household, with possible score ranging from 0-12.

4.2.4. Household adaptive capacity

Adaptive capacity in the context of climate risks is the ability of an individual, community or government to make adjustments or take actions that protect them from suffering losses or harm from the adverse effects of climate change (Grothmann and Patt, 2005; Thathsarani and Gunaratne, 2018). Following this definition, adaptive strategies at the household level were grouped into five categories namely: those related to 1.crops, 2.livestock, 3.land management, 4.water management and 5. other non-farm strategies. An index was constructed for each household by adding up all the strategies it had adopted from those five categories. Another indicator of weighted household adaptive capacity was constructed for each of the five categories using weighted principal component analysis. Let X_i be a normalized value of the i^{th} adaptive strategy for $i = 1, 2, ..., k$. The j^{th} principal component P_j can be computed as:

$$P_j = \alpha_{ji} \sum_{i=1}^{k} X_{ji} \quad for \qquad i = 1, 2, ..., k \qquad and \qquad \sum_{i=1}^{k} \alpha_{ji}^2 = 1. \tag{8}$$

α_{ji} coefficient is the eigenvector.
Each of the components explains a proportion ϕ_j of the variance in K responses. Since principal components are independent, this paper will use all the weighted principal components to ensure that the total explained variance is fully accounted for in computing the weighted household adaptive capacity index ($HACI\_wgt$). We use variance of each principal component ϕ_j as its own weight. We compute the index by summation of the weighted components because the principal components are orthogonal to each other.

$$HACI\_wgt = \sum_{j=1}^{c} \phi_j P_j \quad for \qquad j = 1, 2, ..., c \tag{9}$$

Thathsarani and Gunaratne (2018) used the approach to construct an index for measuring the adaptive capacity to climate change in Sri Lanka. The following is a brief description of the strategies comprising each of the five categories discussed above.

The crop-related strategies include adoption of dry tolerant and early maturing (drought escaping) crops, staggered planting (*planting different portions of land at different times in the season*), introducing new crops not grown before, using conservation agriculture (min. tillage, mulching, etc), cultivating plots in different geographical areas and storing food to smooth consumption during lean periods. Strategies considered under livestock management included use of supplementary feeding (*stored hay, crop residues and buying feeds*), changing the composition of livestock herds, purchasing new livestock types (e.g. shifting from cattle to goats/sheep and camels), seeking grazing rights from other traditional authorities, de-stocking, moving livestock to other geographical areas, purchasing new types of the same animals (*e.g. more productive or stress-tolerant cattle*) and collective action (grazing associations). Under land management category, respondents were asked if their households had looked for planting land in a better place, increased area cultivated to grow more crops, introduced irrigation, adjusted planting times (early planting), changed harvesting times, changed use of fertilizers and/or pesticides/herbicides, used seasonal forecasts and drought early warning systems, used local extension services for advice on farming and used soil and water conservation methods/technologies. Water management strategies considered such things as sinking and rehabilitating boreholes, rainwater harvesting, use of earth dams, rehabilitation of water points and deliberately conserving and protecting water for use in dry season. The last category included all other non-farm-based strategies like starting a business, migration, and off-farm employment.

4.3. Summary statistics by access to climate forecast information

This subsection presents a summary of descriptive statistics for the key variables, with mean comparisons between the treatment and control groups. A t-test was used to check for balance on the observable characteristics between the two groups (Table1). A significant difference could indicate the presence of selection bias between the two groups. The mean differences in outcomes were significant between the two groups. Households in the treatment group had a higher dietary diversity score, higher spending on food, and more adaptive strategies than the control group. The weighted household adaptive capacity for all five categories of adaptive strategies showed consistent results with those obtained by summing adaptation strategies. Based on observable characteristics, the results also indicate that the households in the two groups were significantly different.

Household heads in the treatment group were on average three years younger and had a year more of schooling than those in the control group, ceteris paribus. Most of the households were female-headed in both the treatment (54%) and control groups (57%). The average household size was six persons. The two groups had the same average landholding (6.5ha) and cultivated almost the same area of land. Participation in social groups was higher among the households in the treatment group than in the control group. However, there was strong community support for ceremonies like weddings or funerals. Over three-quarters of the households in both the treatment and control groups relied heavily on government food and drought relief. The households in the treatment group had significantly higher off-farm income and slightly more pension income than those in the control group.

Livestock ownership of all types was higher among the households with access to climate information than the households without access. On average, 43% of households had cattle (cows, bulls and oxen), 67% small ruminants, 56% pigs, 31% donkeys, and almost every household had poultry. Almost all households (95%) owned mobile phones, three-quarters owned at least a radio and 16% owned a television. Ownership of radios and televisions was higher among households that had access to climate forecast information.

4.4. Source, Trust and Sufficiency of Information

Some of the major barriers to effective utilization of useful climate information by decision-makers are credibility, legitimacy, scale and user's perception of information fit in their decision-making (Patt and Gwata, 2002; Lemos et al., 2012; Cash et al., 2003). This section examines the channels through which households receive information for decision making on the farm. It presents the level of trust and farmers' perception about the sufficiency of information received from various sources for decision-making. Radio was the main channel of communication, through which 70% of farming families received seasonal climate information (Table 2). Only 18% had complete trust in information from this source, and 38% rated it as insufficient for decision-making. About a quarter of farmers received information from friends and family; a fifth of them trusted this source but only 36% rated such information as sufficient for decision-making. Six per cent of farm families received information via television with 40% rating the information as sufficient for farm decisions. Only 5.5% received information via their mobile phones, despite 95% of households owning them. Digital technology could potentially be used successfully for information dissemination but this would require increasing reliability of network connectivity and the rural electrification infrastructure.

Less than 1% of households interviewed indicated that they had received climate information through extension services. This finding corroborates other studies that have found gaps in extension services as boundary institutions for information dissemination in southern Africa (O'Brien et al., 2000; Vogel and O'Brien, 2006). Access to extension services increases significantly both the likelihood of accessing climate information, and also of integrating it in farm decision making (Amegnaglo et al., 2017; Patt and Gwata, 2002). However, past research in Namibia show that communal subsistence farmers have limited access to improved technology, extension and other agricultural support services compared to commercial farmers (Jona and Terblanche, 2015; O'Brien et al., 2000). O'Brien et al. (2000) found farmers in Ohangwena and Okavango, two regions bordering our study area, to have not received any preseason forecast information from an agricultural extension agency.

Table 1: Mean comparison test between treatment and control groups

Variable	Treated	Control	Mean comparison test			Overall		
	Mean	Mean	Mean diff	Std. Err.	Mean	SD	min	max
Outcome variables								
Dietary diversity (hdds)	7.32	6.39	0.93***	0.15	6.93	1.98	2	11
HFIAS	5.79	6.44	-0.65	0.49	6.04	6.03	0	27
MAHFP	10.43	10.75	- 0.32	0.20	10.55	2.44	0	12
Total food spending (N$)	566.92	374.12	39.31***	192.80	485.13	505.17	0	7800
Adaptive strategies	12.23	9.07	3.16***	0.41	10.89	5.38	1	30
Wgt_HAC_overall	2.17	1.72	0.46***	0.08	2.00	1.00	0	5.37
Wgt_HAC_crop	0.533	0.48	0.05*	0.02	0.51	0.28	0	1.09
Wgt_HAC_livestock	0.23	0.18	0.07***	0.02	0.23	.27	0	1.21
Wgt_HAC_landmgt	0.50	0.37	0.14***	0.02	0.45	0.21	0	0.90
Wgt_HAC_watermgt	0.52	0.40	0.12***	0.03	0.47	.32	0	1.26
Wgt_HAC_nonfarm	0.36	0.29	0.07***	0.02	0.34	0.37	0	1.11
Head characteristics								
Head age (years)	60.56	63.06	2.51*	1.34	61.62	16.92	5	103
Male head (%)	45.58	40.22	5.36	3.92	43.38		0	100
Head education (grade)	6.00	5.16	0.84**	0.32	5.64	4.03	0	12
Household characteristics								
Number of migrants	2.0	1.5	0.50**	0.154	1.8	1.95	0	14
Household size	5.9	5.3	0.61*	0.20	5.6	3.07	1	22
Farm size (ha)	6.52	6.57	0.05	0.36	6.54	4.52	0	38
Cultivated area (ha)	3.69	3.44	0.25	0.17	3.58	2.16	0	15
Social networks	19.41	11.19	8.22***	2.78	16.06		0	100
Government relief	78.99	74.37	4.62	3.36	77.03		0	100
Off-farm income (N$)	31520.06	7428.91	24091.15***	8031.32	21300.69	43746.57	0	480000
Pension income (N$)	10266.22	7316.61	2949.62	2418.73	9015.01	30558.09	0	500000
Mobile money service	27.73	18.05	9.68***	3.27	23.62		0	100
Livestock assets								
Cattle (%)	48.14	35.38	12.76	3.86	42.66		0	100
Small ruminants (%)	69.41	64.62	4.79	3.73	67.28		0	100
Poultry (%)	95.74	90.25	5.49**	2.06	93.42		0	100
Pigs (%)	60.90	49.46	11.45***	3.92	56.05		0	100
Donkeys (%)	33.78	27.44	6.34*	3.62	31.09		0	100
Communication assets								
Television ownership (%)	16.22	6.50	9.73***	2.41	12.23		0	100
Radio Ownership (%)	84.31	62.09	22.21***	3.43	74.92		0	100
Mobile phone ownership (%)	95.48	93.14	2.34	1.81	94.5		0	100

***p<0.01, ** p<0.05, * p<0.1

Note: Wgt_HAC_X_i indicated weighted household adaptive capacity for a given category of adaptive strategies X_i. These include those that are crop-based, livestock-based, land management-based, water management-based and off-farm-based strategies

Table 2: Channels for seasonal climate information and early warning

Information Channel	% responses	Not at all	Trust in channels Somewhat	Moderate	A lot	Sufficiency (%)
Radio (n=456)	69.7	7	39	36	18	38
Family and friends (n=154)	24.0	5	33	42	20	36
Television (n=40)	6.1	2	40	43	15	40
Mobile phone (n=36)	5.5	3	72	25	0	25
Community meetings (n=18)	2.8	0	45	44	11	33
Newspapers (n=15)	2.3	0	27	53	20	40
Village leaders (n=9)	1.4	0	22	33	44	45
Teachers (n=3)	0.5	33	67	0	0	33
Extension workers (n=2)	0.3	50	0	50	0	50
Internet (n=1)	0.2	0	0	100	0	0

Although the question was a multiple responses type, most respondents either received information from only radio (60.4%), only family (11%) or a combination of radio and family (11%). Those who checked multiple answers mainly gave a combination of radio and another channels. Questions on trust and sufficiency were asked for each channel separately.

4.5. Access to and use of climate information

The following section discusses in more detail how farmers perceive the role of climate information in their livestock and crop production decisions respectively. Table 3 shows that 44% of the respondents perceived climate information to be important in their decision-making in livestock production. This was about the same proportion of farmers who owned cattle (cows, bulls and oxen), the animals most affected during droughts due their high feed and water requirements. A partial correlation shows a significant relationship between cattle ownership and perceived importance of climate information (Table 4).

The proportion of households that reported having received relevant information for decision-making in livestock management was 45%. When asked how they used the information received in the past, almost half of them had stocked livestock feed in preparation for a dry season or drought, and 36% reported having taken advantage of the information to sell the animals while they were still healthy. Only 6% of households ever took advantage of the information provided to increase their herds in anticipation of good weather, probably because of the financial capital outlay that would be required. Results show that farmers value climate information when making decisions about sale of livestock, stocking of livestock feeds and buying new livestock (Table 4.).

To capture the potential use of climate information, households that had not received climate information that was relevant to livestock management, were asked how they would use it if it became available. About a quarter said they would store livestock feed and 23% said they would sell their livestock while still healthy to avoid loss of value or even death due to drought. Only 3% would increase the size of their herd if they received climate information predicting future favourable weather.

Although 62% of households perceived climate forecast information as having a role in their crop-management decisions, only half actually received it. Limited access to climate information by rural communities has also been reported in West Africa (Tarhule and Lamb, 2003), and Southern Africa (O'Brien et al., 2000). When asked how they used the information, 81% of households reported changing planting dates and 45% stored grain (Table 3). During past periods of inadequate rainfall, 46% planted short-cycle crops while one-third opted for drought-tolerant crops. The correlation of importance of climate information with its integration in farm decisions show that farmers value such information in making decisions about food storage and crop choices.

The majority (82%) of those that had not received climate information said they would adjust their planting time and 46.5% would store grains in anticipation of poor rains in the coming season. However, only a few would have adopted adaptive crops, indicating low awareness of these crops and other alternative adaptive strategies in the study area. Only 16% and 18% of farmers in our survey would have planted short-cycle crops and drought tolerant crops respectively. Most households grew millet (mahangu) and sorghum using saved seed from previous harvests. The results show there is great potential for the role of climate information and awareness of climate change adaptation.

Table 3: Access and use of climate information for decision making in livestock and crop production

Does receiving future climate information have any role in your livestock management? 44.10%
Does receiving future climate information have any role in your crop management? 62.63%

	Climate information for livestock production	
	44.9% received (n=293)	55.1% did not receive (n=360)
Is the information received timely?	50.17%	
	How do you use it	How would you use it
Do nothing (do not/would not use it)	31.40	51.94
Stock livestock feed	49	24
Sell animals while still healthy	36	23
Store water for animals	2	4
Migrate to look to better areas	10	4
Increase herd when good rains expected	6	3
Shift to small ruminants	1	1
	Climate information for crop production	
	51% Received (n=339)	49% did not receive (n=314)
Is the information received timely?	64.90%	
	How do you use it	How would you use it
Change planting time	81	82
Store grain	45	46
Short cycle crops	46	16
Drought tolerant crops	32	18
Plant maize(Planted when expecting good rains)	8	0
Other	0.59	2.23

Table 4: Partial correlations of perceived importance of climate information with livestock types owned and use in farm decisions

	Livestock types	
Livestock types	Partial Corr.	Significance Value
Cattle (cows, bulls, oxen)	0.192	0.000
Poultry	0.031	0.437
Sheep	-0.029	0.464
Goats	0.055	0.163
Donkeys	0.016	0.688
Pigs	0.05	0.2
	use in livestock production decisions	
Livestock decisions	Partial Corr.	Significance Value
Sell animals while still healthy to preserve value	0.28	0.000
Stocking livestock feed for prolonged dry periods	0.34	0.000
Migrate to other areas to look for pasture and water	0.09	0.135
Store water for the animals (boreholes, wells and water points)	0.00	0.958
Buy livestock (restocking or increasing herd size)	0.18	0.002
Switching to small animals (goats and sheep)	0.01	0.809
	Use in crop production decisions	
Crop decisions	Partial	Significance Value
Change planting time (early or delayed rainfall)	-0.05	0.362
Store grain in anticipation of drought or sell if bumper harvest expected	0.26	0.000
Plant drought tolerant crops	0.14	0.013
Plant short cycle crops	0.04	0.526

5. Estimation results

5.1. Determinants of access to climate forecasting information

Results indicate that on average, residing in Oshana and Oshikoto regions decreased household's likelihood of accessing information by 22% and 15%, respectively, compared to those in Omusati region (Table 5). The likelihood of receiving climate information declined with age. This is particularly important given that most household heads are elderly, and a majority are female. Families whose main occupation is farming were on average more likely to access climate information than those who were self-employed, in salaried employment, or not working. This indicates the subsistence nature of agriculture with limited commercial farming opportunities that could attract those in formal or self-employment.

Interestingly, migrant-sending households were on average more likely to receive climate information. Households reported that migrants mostly sent remittances during the time when land was being prepared and crops planted, signalling their interest in supporting farm activities. Migrants are likely to receive climate information because, unlike rural areas, there is electricity in urban areas where they have access to television and reliable communication networks. The extent of a household's social networks and a higher level of perceived trust among people within the village increased the likelihood of receiving climate information. Households whose heads are involved in community decision-making are also more likely to receive information than those that do not participate at all in such decisions.

As expected, owning a television increased the likelihood of receiving climate information by 20%. Similarly, owning a radio increased that likelihood by 29%. Muema et al. (2018) found similar results in Kenya. The results clearly show that, based on observable factors, the treatment group (households that received information) are significantly different from those in the control group before matching. Appendix A, Table A.9 presents the results of a covariate-balancing test which shows that the two groups are well balanced on observable characteristics after matching.

5.2. Test of common support and quality of the matches

Given that the average treatment effect on the treated group (ATT) is defined only in the region of common support, the overlap of the distributions of the propensity scores of the treatment and control groups was examined before and after matching. Figure 3 shows a good overlap of the two distributions after matching, reducing the median bias from 13.3% to only 3.5% (*neighbour matching*), 3.2% (*Kernel matching*) and 4.2% (*radius matching*) (Table 6). The small p-values before matching indicate that the covariates jointly explain the differences in conditional probability of receiving climate information but this significance disappears after matching. Based on the observable covariates, the two groups are statistically similar in their likelihood of receiving climate information. As expected, the pseudo-R-square and the likelihood ratio are low after matching. The null hypothesis is therefore maintained that, conditional on propensity scores, the two groups are similar on observable covariates. These differences in outcomes observed between the two groups can therefore be attributed to climate information.

Table 5: The probit estimation of the determinants of access to climate information

VARIABLES	Probit		Marginal effect	
	Coef.	se	dF/dx.	se
Region (Omusati =base outcome)				
Oshana	-0.538***	0.155	-0.211***	0.061
Oshikoto	-0.378***	0.146	-0.149***	0.057
Head characteristics				
Head gender	0.197*	0.117	0.076*	0.045
Head age	-0.012**	0.005	-0.004**	0.002
Head education	-0.006	0.018	-0.002	0.007
Head training	0.028	0.038	0.011	0.015
Primary occupation (farming=base outcome)				
Pensioner	-0.179	0.169	-0.070	0.066
Salaried employment	-0.604**	0.242	-0.237**	0.095
Not working	-0.444***	0.157	-0.174***	0.061
Self employed	-0.580**	0.242	-0.228**	0.096
Other occupations	-0.427	0.396	-0.169	0.121
Household characteristics				
Household size	0.035*	0.020	0.014*	0.008
Number of migrants	0.095***	0.032	0.037***	0.012
Access to mobile money service	0.155	0.139	0.060	0.053
Number of relatives in the village	-0.034**	0.016	-0.013**	0.006
Households that can give financial assistance	0.026	0.031	0.010	0.012
Households that can give assistance in kind	-0.026*	0.014	-0.010*	0.005
Number of social networks	0.210**	0.106	0.082**	0.041
Trust in the village	0.157**	0.067	0.061**	0.026
Participation in community decision making				
Very little	0.453***	0.162	0.169***	0.060
Somewhat	0.443***	0.173	0.164***	0.063
Moderately	0.689***	0.187	0.244***	0.065
A lot	0.445***	0.169	0.165***	0.062
Government aid support	0.433***	0.142	0.171***	0.056
Wealth (Land, income and assets ownership)				
Area under crops (ha)	0.017	0.034	0.007	0.013
Farm size (ha)	-0.020	0.017	-0.008	0.007
Off farm income	0.005	0.004	0.002	0.002
Pension income	-0.012*	0.006	-0.005*	0.003
Television	0.553***	0.195	0.199***	0.070
Radio	0.742***	0.131	0.289***	0.051
Bicycles	0.001	0.182	0.000	0.071
Vehicles	0.091	0.398	0.035	0.153
Constant	-0.494	0.416		
Model				
Observations	648	648		
LR chi2(32)	141.73	141.73		
Pseudo R-squared	0.160	0.160		

*** p<0.01, ** p<0.05, * p<0.1

Table 6: Summary of covariate balancing

Algorithm	Sample	Ps R2	LR chi2	p>chi2	MeanBias	MedBias	B	R	%Var
Neighbor	Unmatched	0.168	143.54	0.000	14.6	13.4	90.6*	0.88	60
	Matched	0.019	21.77	0.933	4.3	3.5	31.3*	3.18*	47
Kernel	Unmatched	0.168	143.54	0.000	14.6	13.4	90.6*	0.88	60
	Matched	0.012	13.14	0.999	3.5	3.2	26.0*	1.16	47
	Unmatched	0.168	143.54	0.000	14.6	13.4	90.6*	0.88	60
Radius	Matched	0.021	24.13	0.87	4.6	4.2	33.2*	2.90*	47

* if B>25%, R outside [0.5; 2]

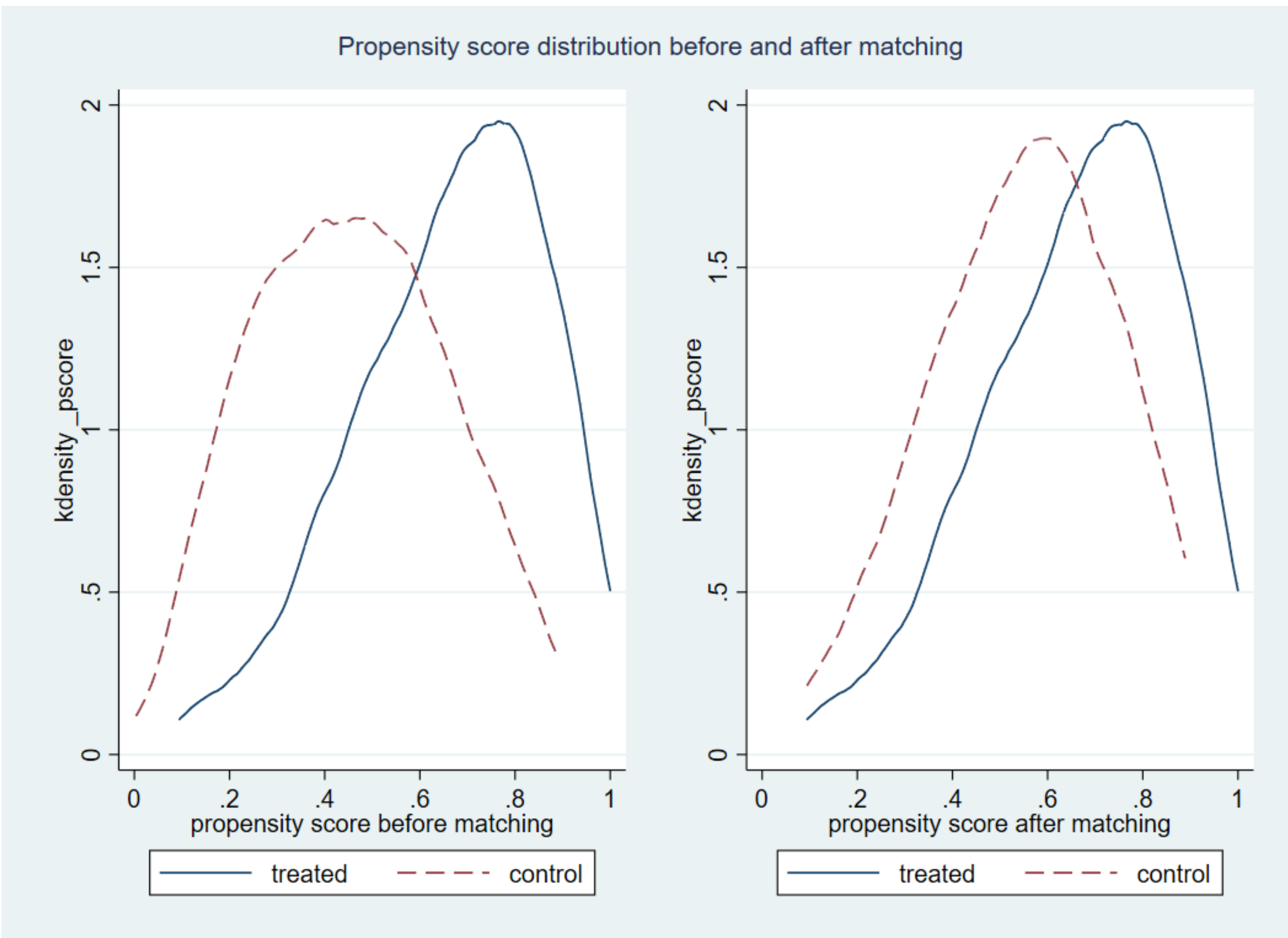

Fig. 3. Propensity scores distribution before and after matching using nearest neighbor matching algorithm (source: authors)

5.3. Impact of climate information

This section presents results of the three matching algorithms which show significant impact of climate information on key outcomes. Households that reported receiving climate information adopted more adaptive strategies on average than those that did not receive information (Table 7). The weighted household adaptive capacity index shows that recipients of climate information had higher score than households with no access to climate information. Decomposing the weighted household adaptive capacity index into its five components shows that, except for the crop-based category, recipients of climate information had a higher index for livestock, land management, water-management and non-farm-based strategies.

Table 7: Impact of climate information on adaptive capacity, dietary diversity and food spending

Variable	Treatment status	Neighbour matching ATT	Neighbour matching S.E.	Kernel matching ATT	Kernel matching S.E.	Radius matching ATT	Radius matching S.E.
Adaptive strategies	treated	11.77		11.70		11.78	
	control	10.12		9.91		9.91	
	difference	1.99***	0.45	2.10***	0.42	2.14***	0.39
Wgt_HACI_overall	treated	2.18		2.16		2.18	
	control	1.84		1.81		1.81	
	difference	0.33***	0.094	0.35***	0.09	0.37***	0.08
Wgt_HAC_crop	treated	0.53		0.53		0.53	
	control	0.52		0.52		0.51	
	difference	0.01	0.03	0.01	0.03	0.03	0.03
Wgt_HAC_livestock	treated	0.26		0.25		0.26	
	control	0.2		0.19		0.20	
	difference	0.05**	0.03	0.06**	0.09	0.06***	0.02
Wgt_HAC_landmgt	treated	0.51		0.51		0.51	
	control	0.40		0.39		0.39	
	difference	0.11***	0.03	0.11***	0.03	0.11***	0.03
Wgt_HAC_water	treated	0.52		0.51		0.52	
	control	0.42		0.41		0.41	
	difference	0.10***	0.04	0.10***	0.09	0.10***	0.04
Wgt_HAC_nonfarm	treated	0.36		0.36		0.36	
	control	0.30		0.29		0.29	
	difference	0.06***	0.02	0.07***	0.02	0.07***	0.02
Dietary diversity	treated	7.33		7.27		7.33	
	control	6.45		6.44		6.44	
	difference	0.88***	0.09	0.83***	0.19	0.89***	0.19
Total food spending	treated	555.64		530.60		555.64	
	control	403.56		397.67		395.09	
	difference	152.08***	43.66	132.93***	37.54	160.55***	40.96
HFIAS	treated	5.81		5.92		5.81	
	control	5.918		5.915		5.868	
	difference	-0.098	0.76	0.002	0.70	-0.056	0.69
MAHFP	treated	10.426		10.41		10.42	
	control	10.50		10.56		10.57	
	difference	-0.82	0.29	-0.15	0.25	-0.15	0.25

*** p<0.01, ** p<0.05, * p<0.1

Note: Wgt_HAC_X_i indicates weighted household adaptive capacity for a given category of adaptive strategies X_i. These include those that are crop-based, livestock-based, land management-based, water management-based and off-farm-based strategies

The matched sample shows that the recipients of climate information on average had more diversified diets, with a consumption of at least seven food groups on average compared to households in the control group who on average consumed six food groups. Recipients of climate information on average spent between N$130 and N$160 more on food than did the non-recipients. This explains the significantly higher score on dietary diversity among households that had access to climate information. The differences in measures of access to food security, i.e. months of adequate household food provisioning (MAHFP) and household food insecurity access scale (HFIAS), between the two groups of households were not significant. These results could be explained by regular distribution of government food relief in the villages as a social protection to households against severe food shortages. Anecdotal evidence from our visits to constituency offices during the listing of villages and households indicated a well coordinated system of identifying needy cases through a network of village elders. Every constituency had lists of all households in every village, and these lists were updated regularly.

5.4. Test for hidden bias for average treatment effects with Rosenbaum rbounds

Rosenbaum's rbounds test was conducted to ascertain whether unobserved variables have a significant influence on the impact results in a way that might affect the inference. The test statistics suggest that there is no evidence of over-estimation or under-estimation of the impact results (Table 8). Results are insensitive to hidden bias caused by unobserved factors or omitted covariates. This implies that the results are robust to any hidden bias and are unlikely to change because of unobserved factors. Critical values of gamma show that unobserved confounders would have to increase the odds of receiving climate information by 80% to change the inference on the adaptive strategies. Similarly, unobserved factors would have to increase the odds of receiving climate information by 85% to change the conclusions made on household dietary diversity. The critical value of gamma for impact on household food spending is 1.15.

Table 8: rbounds Sensitivity analysis for average treatment effects

	Total food spending		Household dietary diversity score		Adaptive strategies	
Gamma	sig+	sig-	sig+	sig-	sig+	sig-
1	0.01	0.006996	1E-10	1.2E-10	7.00E-10	7.00E-10
1.05	0.02	0.002111	2E-09	8.1E-12	7.80E-09	5.20E-11
1.1	0.05	0.000582	1E-08	5.1E-13	6.60E-08	3.70E-12
1.15	0.10	0.000148	1E-07	3.1E-14	4.40E-07	2.50E-13
1.2	0.17	0.000035	6E-07	1.8E-15	2.40E-06	1.60E-14
1.25	0.27	7.80E-06	3E-06	1.1E-16	1.10E-05	1.00E-15
1.3	0.38	1.70E-06	1E-05	0.0E+00	4.20E-05	1.10E-16
1.35	0.50	3.30E-07	5E-05	0.0E+00	1.38E-04	0
1.4	0.62	6.30E-08	1E-04	0.0E+00	4.04E-04	0
1.45	0.72	1.20E-08	4E-04	0.0E+00	1.05E-03	0
1.5	0.81	2.10E-09	0.001	0.0E+00	2.48E-03	0
1.55	0.87	3.60E-10	0.002	0.0E+00	0.01	0
1.6	0.92	5.90E-11	0.005	0.0E+00	0.01	0
1.65	0.95	9.60E-12	0.009	0.0E+00	0.02	0
1.7	0.97	1.50E-12	0.017	0.0E+00	0.03	0
1.75	0.98	2.30E-13	0.029	0.0E+00	0.05	0
1.8	0.99	3.50E-14	0.046	0.0E+00	0.08	0
1.85	1.00	5.20E-15	0.070	0.0E+00	0.12	0
1.9	1.00	7.80E-16	0.102	0.0E+00	0.16	0
1.95	1.00	1.10E-16	0.142	0.0E+00	0.22	0
2	1.00	0.00E+00	0.190	0.0E+00	0.28	0

6. Discussion and Conclusion

There is consensus among scholars that climate variability could make subsistence and rain-fed agriculture in dry lands increasingly untenable. Improved climate forecasts and early warning systems have been suggested as tools to help mitigate and manage climate risks that are inherent in rain-dependent agriculture. However, Africa has not experienced the benefits of improved seasonal climate forecasting, and there is little evidence in the continent of its impact on livelihoods and adaptive capacity. This paper used a representative sample of 653 households from across three regions in Northern Namibia to assess the degree of access to and use of climate information in production decisions. Propensity score matching with sensitivity analysis for hidden bias was used to evaluate the impact of climate information on households' adaptive capacity, food security and dietary diversity. Rosenbaum's rbounds test routine was applied to test for hidden bias. The two groups balanced well on all covariates after matching and results were less sensitive to hidden bias.

We find that most households, when asked about the role of climate information and early warning systems in climate risk mitigation, value its use for decision-making in crop and livestock management. However, only half of those interviewed had received such information. Cattle are severely affected by droughts, and all farmers that owned cattle indicated they would benefit from early warning of droughts. This paper finds livestock farmers to attach significant value to climate information when making decisions about sale of livestock while still healthy and stocking livestock feed if prediction shows an expectation of a bad season. Farmers also value such information when making decisions about buying animals or restocking in anticipation of a good season. Crop farmers attach significant value to climate information when making decisions about food storage for consumption smoothing during the lean period and making crop choices for the coming season. Our results demonstrate that farmers can make rational and optimal decisions if provided with the right information at the right time. Most information was obtained by listening to the radio or talking to friends. Interactive radio programs in local dialects could widen the coverage. Although 95% of households owned mobile phones, only 5.5% had received climate information through them. The network connectivity was very poor in some rural villages. This indicates an opportunity that stakeholders have previously missed, which could be used to provide many rural families with relevant information. There was little contact between the farmers and extension staff, even though Patt and Gwata (2002) find that facilitated groups and functional extension services are the most effective way of communicating seasonal forecast information to farmers.

The responses to climate information by those households that received it were small in scale, with lack of resources and information on alternative adaptive strategies being the key barriers. For instance, crop residues (millet and sorghum stalks) for livestock feed was mainly stored in small bundles on top of tree branches and in quantities that could only last the animals for a short time in the event of drought. Other farmers burnt the millet and sorghum residues during land preparation, suggesting a need for practical field training on how to preserve crop residues for animals using existing technologies like chaff cutting. The limited choice of alternative stress-tolerant crops, the lack of well-functioning markets, and poor rural infrastructure hampered crop diversification. Access to markets can incentivize farmers to invest in improved crop varieties and seek necessary information, including seasonal climate forecasting, from the relevant sources. Current efforts to disseminate seasonal climate forecasts to communal populations are supply-driven and are unlikely to succeed if there is no attention to the demand component. Many households remain vulnerable to socioeconomic and climate shocks, and from our survey, 77% relied on government relief. Households that had not received climate information indicated they would use it were they to receive it. However, they had little awareness of alternative adaptive strategies such as stress-tolerant and early-maturing crops.

Households that reported receiving climate information, on average, had adopted more adaptive strategies than those that did not. The most common adaptive strategies were grain storage, migrating, staggering cropping, using early maturing crops, changing planting and harvesting times, using earth dams, and using stress-tolerant crops. Livestock farmers also invested in supplementary feeding, rehabilitation of water points and water harvesting (infield pits). Communities mainly rely on millet (Mahangu) and sorghum for food. There is a need to explore other potential short-cycle and stress-tolerant crops that farmers can take advantage of to diversify their crops and livelihoods. Most of the crops available to farmers like water melons and legumes are susceptible to environmental stress and diseases (Spear and Chappel, 2018). Increasing their adaptive choices would increase the use and value of climate information.

Dietary diversity and food spending were significantly higher among households that had access to climate information. However, there were no significant differences between the two groups on the other measures of food security, namely months of adequate household food provisioning (MAHFP) and household food insecurity access score (HFIAS). One plausible explanation is the regular provision of government food relief in the villages. The lack of effective dissemination of targeted climate information and of an enhanced capacity for effective response could imply sustained dependence on emergency drought relief from the government rather than sustainable long-term adaptive measures.

In conclusion, the provision of climate information has the potential to enhance the adaptive capacity of communities as well as their nutritional security. However, access to climate information does not alone guarantee its effective use or its integration in decision-making by farmers. Other forms of institutional support, such as extension services, improved reliability of network connectivity and communication infrastructure in the rural areas, input, produce and financial markets, and the relaxation of resource constraints should be complementary. Improving transport and electricity infrastructure can improve access to markets. To increase the level of trust in scientific seasonal climate information, we recommend working with community leaders and finding ways of integrating this information with existing knowledge systems. Our results show that, although half of the farmers received seasonal forecasts, most of them relied on traditional knowledge to make farm decisions. Councilors in charge of constituencies have their slots for announcements in the Namibia broadcasting corporation (NBC) radio. Working with them can ensure that many farmers get information in good time. This is how they announced our survey to local communities and many in the villages said they heard about it over the radio. There is a need for improved collaboration between state and non-state actors to ensure timely dissemination of relevant information to farmers and other stakeholders who need it.

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Appendix A. Covariate balancing test

Table A.9: Covariate balancing test after matching

	Mean			t-test	
Variable	Treated	Control	%bias	t	p>t
Regions (Base category=Omusati)					
Oshana	0.29	0.29	0.1	0.02	0.985
Oshikoto	0.26	0.29	-7.6	-1.01	0.312
Head characteristics					
Head gender	0.45	0.42	6.4	0.86	0.388
Head age	60.45	61.54	-6.4	-0.88	0.377
Head education	5.95	5.79	3.9	0.53	0.596
Head training	1.42	1.34	5.3	0.77	0.441
Primary occupation (farming=base outcome)					
Pensioner	0.27	0.29	-2.9	-0.39	0.698
Salaried employment	0.09	0.07	6.2	0.88	0.38
Not working	0.24	0.24	1.3	0.18	0.858
Self employed	0.07	0.09	-7.7	-0.98	0.327
Other occupations	0.04	0.04	-0.5	-0.06	0.949
Household characteristics					
Household size	5.81	5.72	3.1	0.42	0.672
Number of migrants	1.98	1.85	6.5	0.86	0.392
Access to mobile money service	1.07	0.94	7.7	1	0.318
Number of relatives in the village	0.27	0.31	-9.9	-1.23	0.220
Households that can give financial assistance	2.22	2.41	-4.7	-0.81	0.421
Households that can give assistance in kind	1.60	1.64	-2.4	-0.31	0.755
Number of social networks	2.18	2.54	-9.1	-1.57	0.117
Trust in the village	0.27	0.25	3.5	0.41	0.680
Trust in the village	2.06	2.04	2.8	0.37	0.712
Participation in community decision making					
Very little	0.22	0.24	-5.6	-0.74	0.461
Somewhat	0.19	0.18	3.7	0.5	0.618
Moderately	0.19	0.16	9.1	1.17	0.244
A lot	0.21	0.21	-0.5	-0.07	0.944
Government aid support	0.79	0.84	-11.3	-1.66	0.097
Wealth (Land and income)					
Area under crops (ha)	3.67	3.74	-3.5	-0.45	0.654
Farm size (ha)	6.50	6.44	1.3	0.18	0.854
Off farm income	10058.00	9404.10	1.7	0.39	0.700
Pension income	8527.00	7862.70	2.3	0.39	0.697
Wealth: Assets ownership					
Television	0.15	0.18	-10.4	-1.18	0.239
Radio	0.84	0.86	-3.6	-0.59	0.556
Bicycles	0.12	0.09	10.4	1.4	0.163
Vehicles	0.03	0.04	-5.8	-0.63	0.530

Appendix B. Declaration of state of emergency due to drought

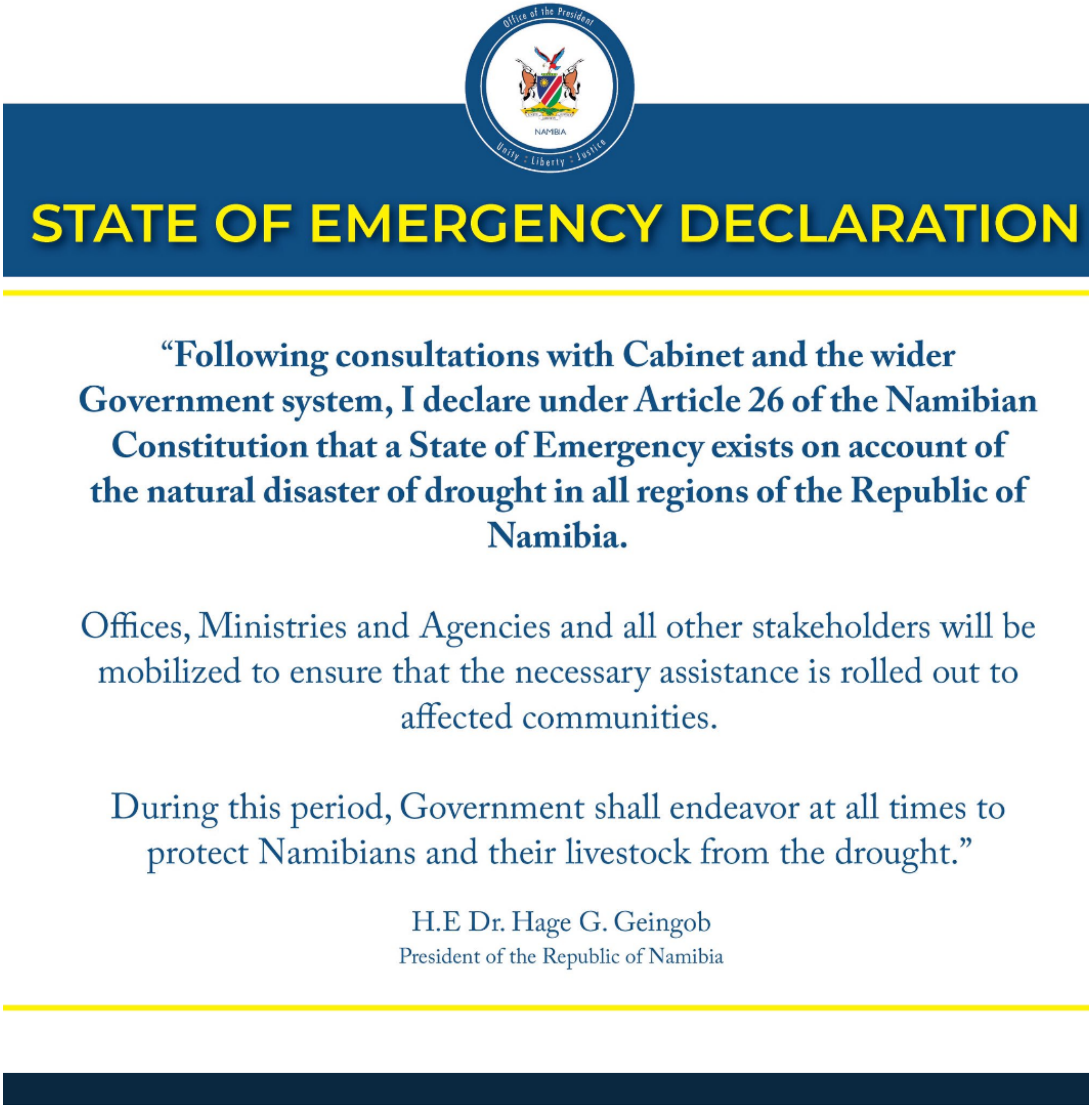

Fig. B.4. Namibia President declaring state of emergency due to drought on 6 May 2019 (source: https://www.africanews.com/2019/05/06/namibia-declares-national-state-of-emergency-over-drought/)