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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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ABSTRACT

Climate forecasting is a crucial tool for managing risks in climate-sensitive economic sectors like agriculture. Although rainfed subsistence farming dominates livelihoods in Africa, information on access, integration in farm decisions and impact of improved seasonal climate forecasting remains scanty. This paper addresses this gap using representative data of 653 households across three regions in North-Central 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. The main channels were the radio and farmer's peers, but trust was low. Farmers were found to attach high importance to climate information in relation to decisions about sale of livestock and 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, but on a small scale. 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.

1. Introduction

1.1. Background

The role of climate-information forecasting in an environment where the main economic activity is rain-dependent agriculture cannot be overstated. Rain-fed farming is the dominant source of livelihood for millions of rural families in Sub-Saharan Africa (SSA) (Cooper et al., 2008). High climate variability is characteristic of arid and semi-arid agroecosystems, which are mainly located in SSA, where countries have limited financial and technical capacities to adapt (Thomas & Twyman, 2005). Climate change has in the past contributed to poor agricultural performance in SSA compared to the rest of the world (Barrios, Ouattara, & Strobl, 2008). This trend will worsen given the projected decline in production of the region's most important staple crops (maize, millet, sorghum and cassava), due to climate change (Schlenker & Lobell, 2010). African economies are more sensitive to climate variability (Acevedo, Mrkaic, Novta, Pugacheva, & Topalova, 2018; Dell, Jones, & Olken, 2012; Dell, Jones, & Olken, 2014; Jury, 2002), largely because of the agricultural sector's relatively high share of the total GDP compared to the rest of the developing world (Barrios, Bertinelli, & Strobl, 2006; Diao, Hazell, Resnick, & Thurlow, 2007; Jury, 2002; Szirmai, 2012). Over-reliance on rain-fed agriculture and hydroelectric power is one of the key factors that has curtailed economic growth in Africa following the trend towards declining rainfall since the 1960s (Barrios, Bertinelli, & Strobl, 2010). Taken together, these factors make Africa the most vulnerable region worldwide to the negative effects of climate change (Challinor, Wheeler, Garforth, Craufurd, & Kassam, 2007).

Seasonal climate forecasting and early warning systems are vital to planning and risk mitigation in key economic sectors like agriculture, water, health and transport (Hellmuth, Moorhead, Thomas, & Williams, 2007). Droughts and rainfall variability occur regularly in Southern Africa, with frequency of up to four droughts per decade (Mogotsi, Nyangito, & Nyariki, 2012). Providing farming households in these agro-climatic conditions with timely seasonal climate forecasts can be a good risk-mitigation strategy (Luseno, McPeak, Barrett, Little, & Gebru, 2003; Vogel & O'Brien, 2006). This is of significance to Namibia where most of its rural population dependent on agriculture despite the country being the driest in Sub-Saharan Africa. To underscore the

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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, Mabhaudhi, & Modi, 2019).

Past studies have documented a remarkable improvement in predicting rainfall patterns and climatic events since the devastating 1991/1992 drought in the Southern African region. However, there is little empirical research about its impact on adaptive capacity 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 bridges this gap in literature by looking at the perceived role of climate forecast information, level of access and integration into farm production decisions, and its impact on adaptive capacity and food security in the semi-arid regions of Northern Namibia.

2. Literature review

2.1. The role of climate information forecasting and early warnings

Timely provision of reliable seasonal and long-range climate forecasts can improve farm earnings by allowing farmers to adjust their management decisions and make savings through loss avoidance (Jury, 2002). Policy makers can 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; Hellmuth et al., 2007; Patt, Ogallo, & Hellmuth, 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, Sygna, Nss, Kingamkono, & Hochobeb, 2000). Ziervogel, Johnston, Matthew, and Mukheibir, 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, Katzung, & Nacu-Schmidt, 2019; Devi, 2019; Scully, 2019; Tumwine, 2019).

At the farm level, Amegnaglo, Anaman, Mensah-Bonsu, Onumah, and Amoussouga Gero (2017) and Roudier et al. (2014) demonstrate how West African farmers use seasonal climate forecasting to adjust planting dates, planting area, crop choices, and level of fertilizer application. Farmers in the Southern Africa region can use it as a risk-management tool to enhance food security (O'Brien et al., 2000; Ziervogel, Bithell, Washington, & Downing, 2005; Zinyengere et al., 2011). Farmers in Senegal have used the information to increase yields and reduce crop losses (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 seasonal climate forecasting to be meaningful, institutional and infrastructural support is needed. Increased accuracy of weather forecasts does not necessarily translate to increased farmer welfare (Babcock, 1990). 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. Effective use of improved climate information forecasting can cushion African agriculture against shocks related to climate variability (Roudier et al., 2014; Weaver et al., 2013). However, climate forecast information remains underutilized as a tool for climate risk management and enhancing food security in southern Africa (Vogel & O'Brien, 2006).

2.2. Climate information forecasting and food security

The 1996 World Food Summit defined food security as a situation in which all people always 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 climate variability but climate predictions can play an important role in mitigating these impacts (Archer, Mukhala, Walker, Dilley, & Masamvu, 2007), through forecasting yields of major food crops thereby enabling planners to better respond to production shocks and spikes in food prices (Iizumi, Shin, Kim, Kim, & Choi, 2018). Timely provision of seasonal climate forecasts can enable farmers to make climate-smart farm decisions to avoid losses by choosing adaptive crops and the optimal livestock numbers and composition to have in anticipation of dry-spell or reduced precipitation. This would guarantee some harvest and food security for households and enhance their food storage for consumption smoothing. Households can use early drought warnings to diversify their income sources to cushion themselves against production shocks. If seasonal forecasts predicts a good season, farmers can diversify their production and therefore their diets and 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. 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 early warning systems, both in accuracy and lead-time (Hansen, 2002; Kusunose & Mahmood, 2016; O'Brien et al., 2000; Vogel & O'Brien, 2006; Ziervogel & 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 which include legitimacy and credibility, scale, technical complexity, and timing of the forecast, could limit its integration into farm decisions if not understood by farmers (Patt & Gwata, 2002; Mjelde, Sonka, Dixon, & Lamb, 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, Marx, & Weber, 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 & 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 & 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 families in Sub-Saharan Africa have no access to seasonal climate forecasts. A study conducted 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 & 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 such as the credibility, scale, timing and legitimacy of the forecast information and farmers' capacity to interpret it are discussed in papers by Patt and Gwata (2002), Millner and Washington (2011) and Amegnaglo et al. (2017). Several studies have found significant yield benefits for farmers who integrate climate forecast information in their production decisions (Patt, Suarez, & Gwata, 2005; Roudier et al., 2014). However, even with a good season prediction following a drought, farmers with low resource endowment might lack access to productive inputs and cultivate less land due to loss of livestock and therefore draft power (O'Brien et al., 2000).

2.4. Sources and dissemination of seasonal climate forecast and early warning systems in Africa

Interest in the role of seasonal climate forecasts and early warning in managing climate risks increased globally and in Africa following the devastating drought of 1983/84, 1991/1992 and 1994/1995 as a result of El Niño events. As a result, 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 different regions in Africa was conceived (Ogallo, Bessemoulin, Ceron, Mason, & Connor, 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 (Ogallo et al., 2008; Patt et al., 2007). The three most active RCOFs include the PRÉvisions Saisonniéres 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. Climate experts from Africa and beyond have been meeting annually since 1997 to form consensus forecasts for the upcoming season. PRESSAO and SARCOF meet once a year and GHACOF meets twice, reflecting the unimodal and bimodal 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 most small-holder farmers did not receive it and only a few of those that received it 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).

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 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. Social-cultural, demographic, economic and institutional factors determine the likelihood of accessing climate information, as illustrated in Fig. 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 impede the use of seasonal climate forecasts and climate-smart agricultural practices like planting early maturing and drought-tolerant crops, and selection of hardy livestock breeds (Davies et al., 2019). Integrating scientific climate information with traditional knowledge and involving local and religious leaders in dissemination can enhance access and use. Social networks are likely to increase the access to and use of climate information through peer influence while education would increase the understanding and appreciation of its importance in farm decisions. Other likely determinants are age and gender given that many households are female-headed and by elderly persons. The access, need for and use of climate information can differ significantly between men and women (Diouf et al., 2019; Gumucio, Hansen, Huyer, & van Huysen, 2020). Household size signals availability of family labour and demographic diversity in the household, which increases the likelihood of receiving climate information. Larger households are likely to cultivate more land, invest more capital and labour inputs and therefore be more sensitive to any potential losses. Migrants can share information with their rural families and send resources needed for timely and effective response to seasonal forecasts.

Wealth endowment and ownership of communication assets are important in access and effective utilization of seasonal climate forecasts. Institutional support through agricultural extension services can increase dissemination and integration of climate and agricultural information into farm production decisions, which would also require working markets. Regular government relief assistance and cash transfers, like non-contributory old age pensions (Levine, van der Berg, & Yu, 2011), provide households with social insurance and might influence their incentive to seek information that would mitigate the risks of crop failure or loss of livestock. Wide access to and integration of climate forecast information in production decision-making has the potential to increase the adaptive capacity and reduce vulnerability of livelihoods to climate variability through strategic farm investments and lead to a resilient agricultural sector, improved food security, and reduced reliance on government emergency relief.

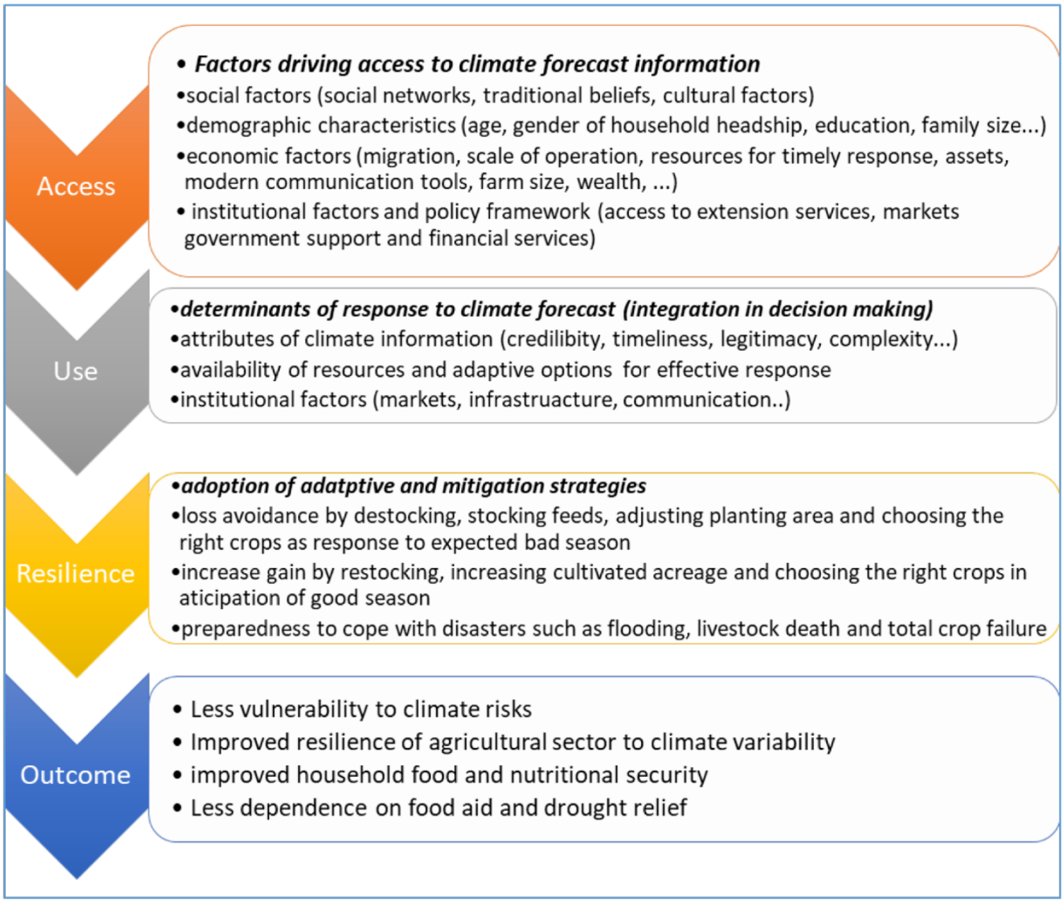

Fig. 1. Drivers of access to and use of climate forecast information and impact pathway (Source: Authors).

3.2. Empirical model

The treatment group comprises households that received climate information 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 information and early warning is not due to self-selection bias. As in other observational studies that do not have the benefit of randomizing the treatment assignment, the main challenge is creating a counterfactual that would 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 adaptive capacity 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

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

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 & Rubin, 1983). This is the conditional probability of receiving climate forecast information given a set of observable characteristics (Rosenbaum & 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 & Sadek, 2002; Imai & Van Dyk, 2004; Rosenbaum & 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 (Eq. (4)).

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

where $\phi = (2\pi)^{(1/2)} exp\left(\frac{X\beta^2}{2}\right)$, $0 < Pr(\tau_i = 1|X_i) < 1$, 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 & Imbens, 2001). The logit model $Pr\left(\tau_i = 1\middle|X_i\right) = \frac{exp(X\beta+\epsilon)}{1-\exp(X\beta+\epsilon)}$ is also commonly used to estimate the propensity scores (Dehejia & Sadek, 2002; Rosenbaum & 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 & 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

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

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 & 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 $\frac{\pi_j(x_j, u_j)}{(1-\pi_j(x_j, u_j))}$

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

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 (Fig. 2).

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.

4.2. Definition and measurement of outcome variables

This section provides a brief definition and description of how the outcome variables were measured or constructed.

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, Swindale, & Bilinsky, 2007). The indicator assesses prevalence of food insecurity severity in a household using a series of nine occurrence questions asked with a recall period of four weeks. Each successive question represents an increasing level of food insecurity condition ranging from anxiety about running out of food, to severe food insecurity . The person mostly responsible for preparing meals in the household was asked nine occurrence questions (Yes/No), each followed by a frequency of occurrence question with responses ranging from 0 = never, 1 = rarely (1–2times), 2 = sometimes (3–10 times) and 3 = often (> 10times). The HFIAS score for each household was computed by summing all the frequency-of-occurrence responses. 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.

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 FANTA guidelines (Bilinsky & Swindale, 2010; Bilinsky & Swindale, 2005). The respondents were asked, starting with the current month, to identify those months in the past year they did not have enough food to meet their family needs. These months were added up and subtracted from 12 to construct MAHFP. 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 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)

HDDS is a measure of food access in terms of dietary quality and diversity and was constructed following the FANTA guidelines (Swindale & Bilinsky, 2006). HDDS measures the quality of diet using 12 food groups rather than different types of foods consumed by a household. These are cereals, roots & tubers, vegetables, fruits, meat, poultry & offal, eggs, fish and sea food, pulses, legumes & nuts, milk & dairy products, oils & fats, sugar & honey and 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 & Qaim, 2018; Sibhatu, Krishna, & Qaim, 2015), respondents were specifically asked to include foods consumed from own production, purchased, donations and government relief. The HDDS was computed by adding the number of food groups consumed, 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 & Patt, 2005; Thathsarani & Gunaratne, 2018). Following this definition, adaptive strategies at the household level were grouped into five categories based on crops, livestock, land management, water management and other non-farm

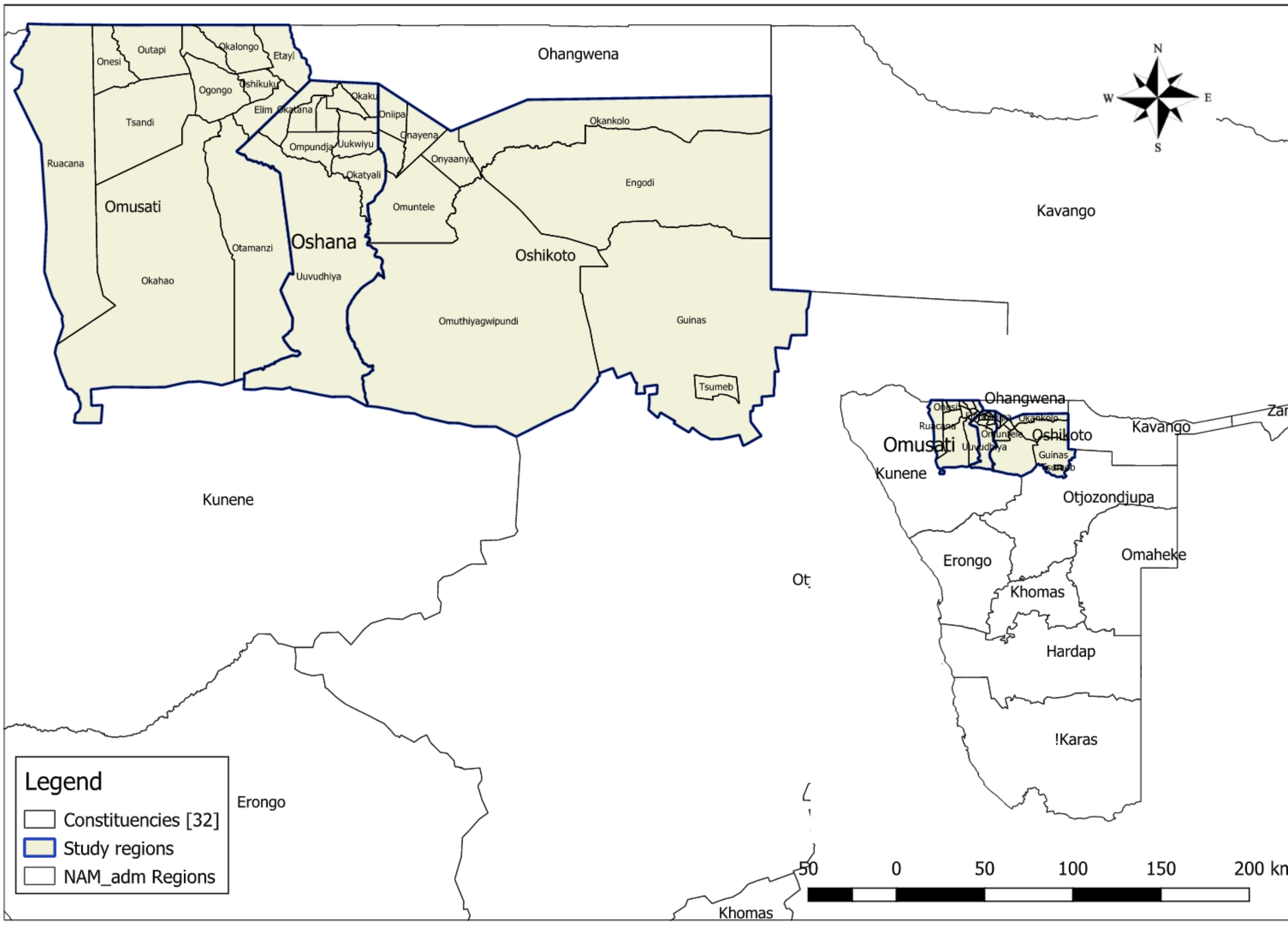

Fig. 2. Map of the study regions (Source: Authors).

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:

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

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.

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

Thathsarani and Gunaratne (2018) used the approach to construct an index for measuring the adaptive capacity to climate change in Sri Lanka.

The crop-based strategies are stress tolerant crops, staggered planting, introducing new crops, conservation agriculture, cultivating plots in different geographical areas and food storage to smooth consumption during lean periods. Livestock-based strategies include supplementary feeding, changing the composition of livestock herds, purchasing new livestock types, seeking grazing rights from other traditional authorities, de-stocking, moving livestock to other geographical areas, purchasing new types of the same animals and forming grazing associations. The land management-based category includes looking for planting land in a better place, increased area cultivated, introduced irrigation, adjusted planting and harvesting times, use of agrochemicals, used seasonal forecasts and drought early warning systems, used local extension services and used soil and water conservation methods/technologies. Water management strategies included sinking and rehabilitating boreholes, rainwater harvesting, use of earth dams, rehabilitation of water points, and conserving and protecting water for use in the 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

A *t*-test was used to check for balance on the observable characteristics between the treatment and control groups (Table 1). A significant difference between the two groups could indicate the presence of selection bias. 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. Female-headed households were 54% in the treatment and 57% in the control groups. The average household size was six persons. The two groups had the same average landholding (6.5ha) and cultivated almost

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 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.

Table 2
Channels for seasonal climate information and early warning.

Information Channel	% responses	Trust in channels				Sufficiency
		Not at all	Somewhat	Moderate	A lot	(%)
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.

the same area of land. The treatment group had more social networks than the control group. Over three-quarters of the households in both the treatment and control groups received government food and drought relief. The recipients of climate information had significantly higher off-farm income, slightly more pension income and owned more livestock of all types than non-recipients. On average, 43% of households had cattle, 67% small ruminants, 56% pigs, 31% donkeys, and almost every household had poultry. 95% of households owned mobile phones, three-quarters owned at least a radio and 16% owned a television. Ownership of radios and televisions was higher among the treated group.

4.4. Source, trust and sufficiency of information

Some of the major barriers to effective utilization of climate information by decision-makers are credibility, legitimacy, scale and user's perception of its relevance for decision-making (Patt & Gwata, 2002; Lemos, Kirchhoff, & Ramprasad, 2012; Cash et al., 2003). Although 70% of farming families received seasonal climate information through the radio, only 18% had complete trust in the information and 38% perceived it as insufficient for decision-making (Table 2). About a quarter of the farmers received information from friends and family; a fifth of them trusted this source and 36% perceived it as sufficient for decision-making. Six percent of farm families received information via television with 40% rating the information as sufficient for farm decisions. Only 5.5% received information via mobile phones.

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 & O'Brien, 2006). Access to extension services increases significantly both the likelihood of accessing climate information, and its integration into farm decisions (Amegnaglo et al., 2017; Patt & 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 & 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 pre-season forecast information from an agricultural extension agency.

4.5. Access to and use of climate information

Results show that 44% of the respondents perceived climate information to be important for decision-making in livestock production (Table 3). This was about the same proportion of farmers who owned cattle, the animals most affected during droughts due to their high feed and water requirements. A partial correlation shows a significant relationship between cattle ownership and perceived importance of climate information (Table 4). 45% of households received relevant information for decision-making in livestock management. When asked how they used the information received in the past, 49% had stocked livestock feed for a dry period, 36% sold the animals while they were still healthy and only 6% increased their herds in anticipation of good weather, probably because of the financial capital 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, 23% would sell their livestock to avoid losses during drought and 3% would increase the size of their herd for a good season prediction. Climate information was perceived as important for crop-management decisions by 62% of households and 51% received it. Limited access to climate information by rural communities has also been reported in West Africa (Tarhule & 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 shows 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 to 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 to avoid losses	36	23
Store water for animals	2	4
Migrate to look for 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)	0.19	0.000
Poultry	0.03	0.437
Sheep	−0.03	0.464
Goats	0.06	0.163
Donkeys	0.02	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

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	

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

5. Estimation results

5.1. Determinants of access to climate forecasting information

Households residing in Omusati have 22% and 15% higher chance of receiving climate information than those resident in Oshana and Oshikoto regions respectively (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 and in salaried employment. This indicates the subsistence nature of agriculture with limited commercial opportunities that could attract those in formal or self-employment. The likelihood of receiving climate information increased with having a migrant member, social networks, participation in community decision-making and owning communication assets like radio and television. 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. 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. Owning a television increased the likelihood of receiving climate information by 20% and owning a radio by 29%. Muema, Mburu, Coulibaly, and Mutune (2018) found similar results in Kenya. The results show that, based on observable factors, households in the treatment group 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 (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. Fig. 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 two groups differ in their conditional probability of receiving climate information, but this difference disappears after matching as indicated by larger p-values, and low pseudo-R-square and likelihood ratio. 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.

5.3. Impact of climate information

Results show that households that received climate information adopted more adaptive strategies on average and had higher scores on the weighted household adaptive capacity index (HACI) than those in the control group (Table 7). Decomposing HACI into its five components shows that, except for the crop-based category, recipients of climate information had a higher score index for livestock, land management, water-management and non-farm-based strategies.

Recipients of climate information on average had more diversified diets and spent between N130 and N160 more on food than did the non-recipients, which partly explains the significantly higher score on dietary diversity. There were no significant differences in indicators of access to food security (HFIAS and MAHFP) between the two groups perhaps because of the regular distribution of government food relief in the villages as a social protection to households against severe food shortages. There is 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.

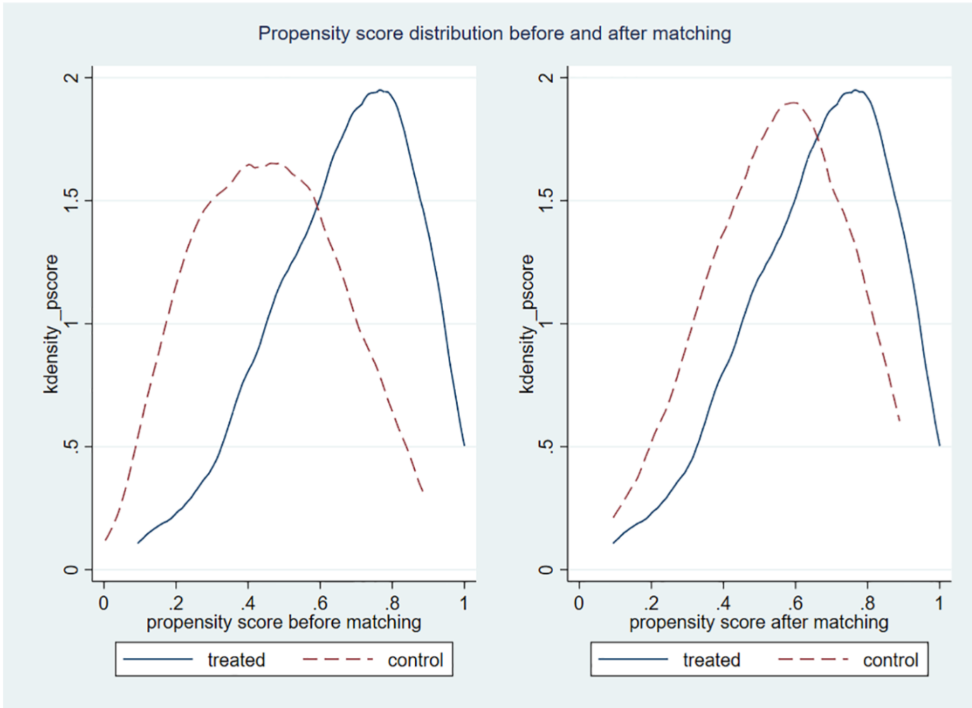

Fig. 3. Propensity scores distribution before and after matching using nearest neighbor matching algorithm (Source: Authors).

6. Discussion and conclusion

There is consensus among scholars that climate variability could make subsistence rain-fed agriculture in dry lands increasingly untenable. Improved climate forecasts and early warning systems are important tools for climate risk mitigation and management. However, access and use remain low in Africa with little empirical evidence of its impact. This paper used a representative sample of 653 households from across three regions in Northern Namibia to assess the access to and use of climate information in production decisions. Propensity score matching with sensitivity analysis for hidden bias was used to evaluate its impact on households' adaptive capacity and food security. 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 value the role of climate information and early warning systems in farm decisions as climate risk mitigation and management tools. However, only half of those interviewed had received such information. Farmers who owned cattle, usually the animals most affected by droughts, indicated that they would benefit from climate information and early warning. Livestock farmers attach significant value to climate information when making decisions about sale of livestock while still healthy and stocking livestock feed in anticipation of a bad season or buying animals or restocking in anticipation of a good season. Crop farmers attach significant value to climate information when making decision 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. Information was obtained through the radio or peer interactions and a few cases through mobile phones. The network connectivity was very poor in some rural villages. Interactive radio programs in local dialects and use of mobile phones are opportunities 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 & Gwata, 2002) find that facilitated groups and functional extension services are the most effective ways of communicating seasonal forecast information to farmers.

Lack of resources, well-functioning markets and awareness of available adaptive options and poor infrastructure are key barriers to effective utilization of climate information. For instance, farmers stored crop residues for livestock feed on top of tree branches in small bundles that could only last the animals for a short time in the event of drought. Other farmers burnt the 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. Access to markets can incentivize farmers to invest in improved crop varieties and seek necessary agricultural and seasonal climate information from the relevant sources. Current efforts to disseminate seasonal climate forecast 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

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].

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.

Table 8
rbounds Sensitivity analysis for average treatment effects.

Gamma	Total food spending sig+	Total food spending sig−	Household dietary diversity score sig+	Household dietary diversity score sig−	Adaptive strategies sig+	Adaptive strategies 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

survey, 77% received government relief.

Households that received climate information, on average, had higher adaptive capacity than those that did not. The most common adaptive strategies were grain storage, migrating, staggering cropping, using stress tolerant and early maturing crops, changing planting and harvesting times and earth dams. Livestock farmers also invested in supplementary feeding, rehabilitation of water points and water harvesting (infield pits). Communities mainly rely on millet 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 watermelons and legumes are susceptible to environmental stress and diseases (Spear & 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, the differences in indicators of food access between the two groups were insignificant perhaps because of 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 and nutritional security of rural communities. However, provision of climate information does not alone guarantee its integration in farm production decisions. Other forms of institutional support such as extension services, reliability of network connectivity and communication infrastructure, and developing market value chains, should be complementary. Improving transport and electricity infrastructure can improve access to markets. Many farmers relied on their traditional knowledge in weather prediction to make decisions. Working with leaders and finding ways of integrating climate information with existing knowledge systems can increase its relevance and integration in 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. 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.

CRediT authorship contribution statement

Zachary M. Gitonga: Conceptualization, Methodology, Data curation, Formal analysis, Writing - original draft. **Martine Visser:** Funding acquisition, Writing - review & editing. **Chalmers Mulwa:** Data curation, Writing - review & editing.

Declaration of Competing Interest

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

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Appendix A. Covariate balancing test

See Table A.9.

Table A.9
Covariate balancing test after matching.

Variable	Mean		%bias	t-test	
	Treated	Control		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

See Fig. B.4.

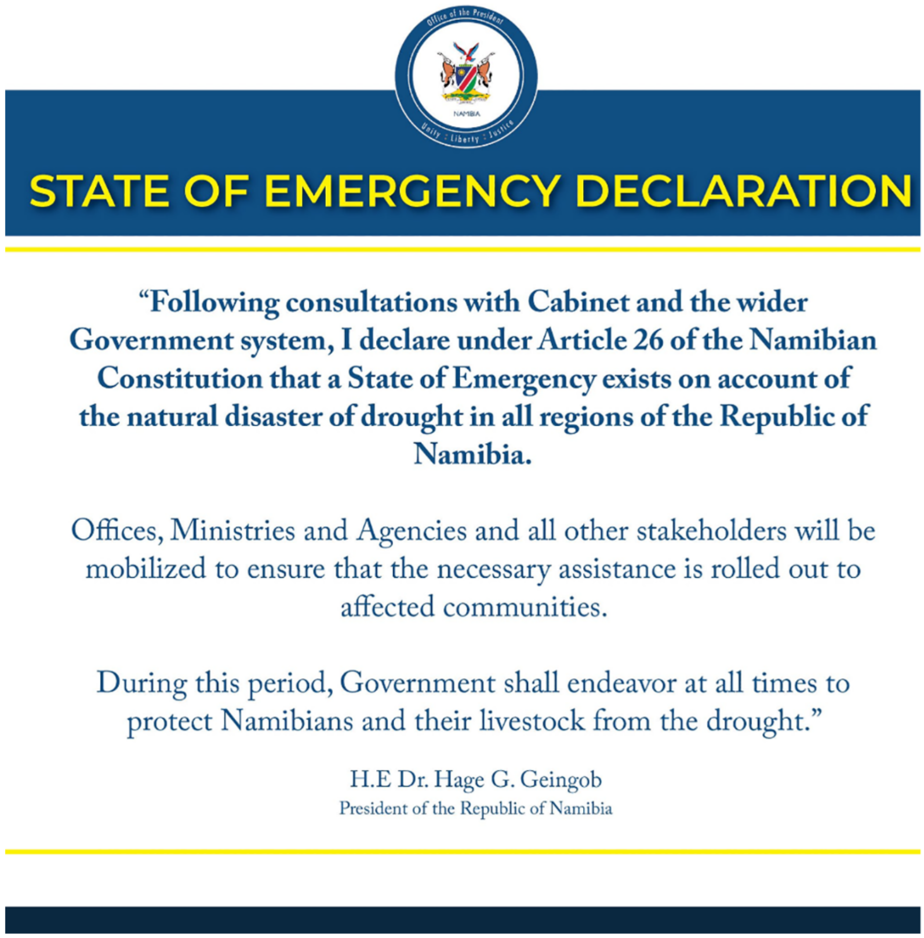

Fig. B.4. Namibia President declaring state of emergency due to drought on 6 May 2019 (Source:https://www.africanews.com/2019/05/06/namibia-declares-national-state-of-emergency-over-drought/).

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