PHILIPP AGRIC SCIENTIST
Vol. 103 Special Issue, 53-66
December 2020

ISSN 0031-7454

Determinants of the Use of Weather and Seasonal Climate Information Among Smallholder Maize Farmers in Bulalacao, Oriental Mindoro, Philippines

Jeffrey Andrew L. Losloso[1,*], Canesio D. Predo[2], Asa Jose U. Sajise[4], Juan M. Pulhin[1,3], and Ma. Victoria O. Espaldon[5]

[1]Interdisciplinary Studies Center for Integrated Natural Resources and Environment Management, University of the Philippines Los Baños
[2]Institute of Renewable Natural Resources, College of Forestry and Natural Resources, University of the Philippines Los Baños
[3]Department of Social Forestry and Forest Governance, College of Forestry and Natural Resources, University of the Philippines Los Baños
[4]Depatent of Economics, College of Economics and Management, University of the Philippines Los Baños
[5]School of Environmental Science and Management, University of the Philippines Los Baños

[*]Author for correspondence; e-mail: jdlosloso@up.edu.ph

This research is part of a Master's thesis.

Access and use of scientific weather and seasonal climate information are considered valuable decision-making tools in climate change adaptation. Using survey data from a sample of 200 farming households in Bulalacao, Oriental Mindoro, this study applied a Fractional Response Model to analyze the factors influencing the use of weather and climate information. Usefulness and reliability of forecast information explained most of the variations of its use, suggesting an increased likelihood in forecast use by 14% and 19%, respectively. Farmers' sex, farm parcel size, and risk attitude are also positively associated with forecast information use, whereas age and reliability of traditional forecasts negatively influenced its use. Effective policies for sustainable agricultural production should consider the need to improve the access and use of weather and seasonal climate information by delivering timely and accurate information that is tailor-fitted to the needs of the farmers. Expansion of information sources and facilitation of access to farm resources should also be prioritized to provide farmers with more opportunities in managing climate risks.

Keywords: decision-making, forecast use, fractional response model, maize farming, weather, seasonal climate

Abbreviations: ENSO – *El Niño* southern oscillation, FRM - fractional response model, IPCC - Intergovernmental Panel on Climate Change, NLS – nonlinear least squares, OECD - Organization for Economic Co-operation and Development, PAGASA - Philippine Atmospheric and Geophysical and Astronomical Services, PAO - Provincial Agriculture Office, QMLE - quasi-maximum likelihood estimation, SCF - seasonal climate forecast, TC - tropical cyclone, TV – television, WNP - western north pacific

INTRODUCTION

As the global temperature continues to rise, more complex shifts become apparent in weather and climate systems. These shifts have made the weather and climate more unstable. It is in this instability that forecasts have become more valuable. This is the important backdrop by which the need to understand the use of scientific weather and seasonal climate information by smallholder maize farmers in the Philippines begins. Scientific forecast information refers to processed data and empirically-validated knowledge about the atmospheric ocean conditions. One type of forecast information is weather information, which refers to meteorological conditions over a short period (hours to days). In contrast, seasonal climate information provides the average atmospheric ocean system's state over longer periods (months to seasons) (Ziervogel and Calder 2003). The Philippines, being geographically situated in the western North Pacific (WNP) Ocean, has become a common path of tropical cyclones and storms. About 70% of WNP tropical cyclones (TCs) formed in or entered the Philippine region from 1945–2011 (Corporal-Lodangco and Leslie 2017). As such, weather and seasonal climate information are vital in improving farm adaptation responses to climate shocks.

Maize or corn (*Zea mays*, Linn.) is the second-largest cereal crop after rice in the Philippines (Haefele et al. 2013). Despite an increasing trend over time, corn production in the country has shown some degree of volatility. Temperature, radiation, rainfall, winds, soil moisture, relative humidity, and carbon dioxide concentration are considered important variables in maize productivity. Erratic changes in these variables are perceived to continue as the average global surface temperatures are predicted to increase by 2.8°C during this century, with a projection range of 1.8 and 4.0°C (IPCC 2007a). The macro-economic impacts of climate change by 2080 are projected to be more significant in Thailand, Vietnam, and the Philippines, ranging from 1.7% to 2.4% of gross domestic product. (Zhai and Zhuang 2009).

A large body of research in the country has focused on climate change adaptation (CCA) and disaster risk reduction (DRR). These studies have focused on socio-economic and household characteristics as influential factors influencing the adoption of climate change adaptation practices. Climate change adaptation options on agriculture have been found to vary according to cultural, demographic, economic, environmental, and institutional factors (Muema et al. 2018). Institutional elements may include access to agricultural training, organization membership, credit facilities availability, and climate change awareness.

Climate information services (CIS), on the other hand, reduce climate vulnerability by improving information access, facilitating knowledge exchanges, increasing networks (Smit and Wandel 2006), and as a decision-making tool (Sarewitz et al. 2000; Anderson 2010). Locally, researches have been made to identify the role and value of weather and climate information in decision-making and adaptation strategies. However, there has been limited literature that has assessed the influence of the quality of forecast information and the risk perception of farmers in the use of forecast information. At the time of writing, no studies have been found analyzing the factors affecting access and use of weather and climate information. Therefore, this study aimed to fill the gap in the existing literature, primarily on understanding the factors that influence climate change adaptation and farm decision-making as influenced by scientific weather and seasonal climate forecast information. From a multidisciplinary perspective, this study's findings will be valuable in assisting policy formulation to enhance farmers' adaptation to climate change in Bulalacao by improving access and use of weather and climate information.

Uses of Weather and Climate Information

Small-scale maize farm systems, mostly those in rural areas, are highly susceptible to weather and climatic aberrations. Generally, maize farm decision-makers rely on daily, weekly, and monthly reports of weather information such as rainfall and temperature to determine farming decisions in a short time frame. Precipitation is considered the most significant component in maize productivity and quality as it provides the needed moisture to the soil (Rosenzweig et al. 2001). Drought and extreme heat cause stress to the crops and are often aggravated by high solar irradiance and high winds. Under stress conditions, the crop's stomata fold up, lowering the transpiration rate and increasing plant temperatures.

In contrast, excessive rainfall can lead to a decline in productivity due to waterlogging and pest infestations. Both direct and indirect effects of moisture stress on crops allow many pests species to damage crops as they become vulnerable, especially during the early stages of plant development. High soil moisture can also delay field activities and lead to soil erosion. Intense downpour is particularly highly damaging to younger plants, affecting their growth and maize kernel development.

Seasonal climate information on *El Niño*, *La Niña*, and neutral or normal conditions are used in conjunction with farming decisions such as the timing of cropping, irrigation, crop variety choice, among others. In previous studies, seasonal climate information is used primarily for production decisions such as level of capital, maize varietal selection, planting schedule, input costs, level of inputs, and output pricing (Reyes et al. 2009; Zendera et al. 2010; Serra and Mckune 2016).

Determinants of and Adoption Barriers in the Use of Forecast Information

Socio-economic, demographic, and psychological factors have played important roles in improving the access and use of forecasting technology for decision-making (Zendera et al. 2010). In the state of Georgia in the United States, an empirical study on the effect of seasonal climate forecast in risk management among farmers concluded that farmers control risks within a broad spectrum of cultural contexts of social factors and values (Crane et al. 2010).

A study on the uses of seasonal climate forecasts as strategies for managing pastoralists' assets in Baringo County, Kenya, also identified lack of access, culture, lack of information, and insecurity or conflicts as barriers in the uptake of scientific climate information (Ochieng et al. 2017). These implications are also similar to Lybbert (2007), where a Pearson correlation analysis confirmed the significant relationships between average income, access to forecasts, education, and access to extension services. The findings indicated that access to dissemination channels and extension services is a critical component for improving the utility of agro-meteorological information.

Previous studies have also highlighted the importance of perception of climate change and understanding its impacts in the use of forecast information. An individual's perception is commonly associated with socio-demographic profiles, social capital, and agroecological parameters (Deressa et al. 2011; Huda 2013).

Moreover, the quality attributes of forecast information influence its application in decision-making. Previous experimental research has concluded that forecasting is either unreliable or partially reliable (Zendera et al. 2010; Cabrera et al. 2006). Other studies have highlighted the need for improved forecast quality to increase adoption and use in farm decision-making. The study by Lemos et al. (2002) on Ceara, Northeast Brazil stressed the importance of skill, objectivity, and appropriateness of forecast information to increase its adoption rate and effectiveness. Ziervogel et al. (2005) established that a 60–70% accuracy is desirable for climate information to be valuable. The study of Amegnaglo et al. (2017) supported this finding by revealing that farmers could allow no more than two inaccurate reports out of 10 seasonal climate forecasts to continue trusting the information provider. In a local context, Reyes et al. (2009) found that the majority of the maize farmers had a positive reception towards the use of SCF in Isabela, Philippines but still expressed discontent with the adequacy of information (44%), accuracy (28%), and satisfaction level (39%). About 30 percent of the farmers considered seasonal rainfall prediction as "unreliable." Another hindrance to the use of forecast information by farmers is the farms' "rigidity" and the absence of resources to implement adaptation practices (Cabrera et al. 2006).

METHODOLOGY

Description of the study area

Bulalacao, formerly known as San Pedro, is the selected study site. It is located in the southernmost section of the Oriental Mindoro. The 3rd class municipality occupies a total of 321.86 square kilometers and comprises 15 barangays. Based on the 2015 census, the town has a population of 39,107 people (PSA 2016). The high maize productivity, climate condition, and relatively large population of farmers are the main reasons for choosing Bulalacao as the study site. In 2018, the Provincial Agricultural Office (PAO) of Oriental Mindoro recorded a maize production of 7,455.18 metric tons (mt) from 1,870 hectares (ha) of land (PAO 2018). Bulalacao was the top maize-producing municipality among the municipalities in the province, with an average yield of 5.31 mt per ha. It has maintained its rank as the leading producer based on yield per hectare in recent years.

The municipality has a Type I climate, indicating two pronounced seasons: a dry season from November to April and a wet season throughout the rest of the year. Its climate type is different from the rest of the province, which experiences a Type III climate. Thus, it makes it a good experimental site for understanding the factors that influence the use of forecast information given these geographical variations.

Survey Design and Data Collection

Data were collected through a pre-tested structured questionnaire. Information on socio-economic profile, perceptions about climate change, risk behavior, land use and agricultural production, household sources of climate and weather information, forecast attributes, and traditional and indigenous forecasting reliability were collected to identify the forecast information use determinants. The survey was conducted from December 2018 to March 2019.

Sampling and Selection of Respondents

Cochran (1977) modified formula for calculating sample size when the population is finite was used to determine representative sample size. Given the relatively small population of maize-farming households in the study site, the following corrected formula from the standard formula was employed to estimate the sample size. The standard Cochran formula is given as:

$$n_0 = (z^2\,pq)/e^2 \qquad (1)$$

where e is the desired level of precision (margin of error), p is the estimated proportion of an attribute present in the population, and q is 1-p. In calculating the sample size, the desired confidence level is defined by the z value. The z-score is a point along the abscissa of the standard normal distribution and typically falls within the ±1.96σ limits. The calculated value of n_0 is 384, which is the standard Cochran sample size recommendation. The corrected formula is as follows:

$$n = n_0/((1+(n_0-1))/N) \quad (2)$$

In the modified formula, n_0 is the standard sample size, N is the population size, and n is the adjusted sample size for a finite population.

Estimating the sample size for the study's population using a population size of N= 412, the final sample size was derived.

Here, N= 412, n_0 = 384

$$n= 384/((1+(384-1))/412) =198.96 \sim 200$$

Using stratified random sampling, the estimated sample size was proportionally distributed according to maize farmers' total population in Bulalacao. The top nine barangays in the municipality with the highest number of farmers were selected as the pool for the sample size. These barangays are Milagrosa, San Francisco, Maujao, San Isidro, San Roque, Campaasan, Nasucob, Cambunang, and Cabugao (Figure 1).

The sample size distribution per barangay was determined by calculating the percentage share of farmers' population in each barangay against the total farmer population in the municipality. The percentage share of each barangay was then multiplied by the earlier estimated total sample size to get the respondent distribution per barangay.

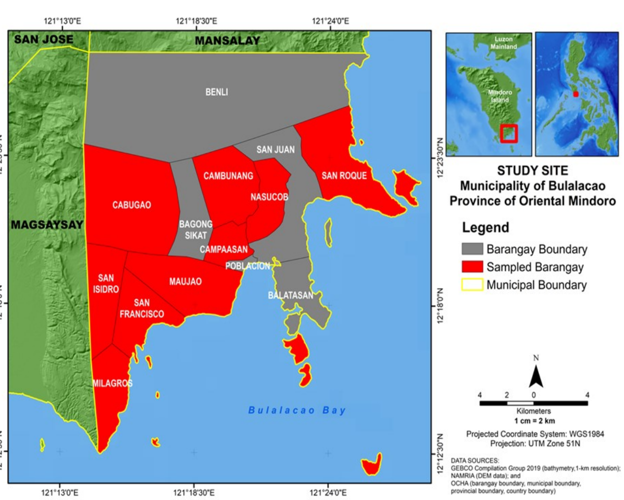


Fig. 1. Location of study and sampling sites.

Empirical Model

Papke and Woolridge (1996) defined the Fractional Response Model (FRM) as a non-linear model using a quasi-maximum likelihood estimation (QMLE) method to deal with situations where the measured variable is a fraction and allows zero or one values. The use of censored regression (Tobit) or the Ordinary Least Squares (OLS) in this situation is regarded as inefficient due to heteroskedasticity. Fractional response variables are bounded, and thus, using a linear model estimated by ordinary least squares might not be appropriate as predictions might lie outside of the [0,1] interval. In FRM, it is assumed that there is a nonlinear relationship between the dependent and independent variables, which is against OLS linearity assumption. Also, estimation of the marginal effects might not be accurate if the model's bounded nature is not accounted for. As such, FRM is asymptotically consistent and efficient compared to other QMLEs and Nonlinear Least Squares (NLS) estimators. The implication is that the dependent variable can either be a discrete, continuous variable, or a mix of both. In FRM, a functional form for G, the logistic function, is created to ensure that the dependent variable's predicted values lie within the bounded interval [0,1]. To overcome problems associated with OLS, Papke and Wooldridge (1996) have used the following model for the fractional response variable's conditional expectation.

$$E(Y_i \mid X_i) = G(X_i \beta), \; i=1,2,\ldots N \quad (3)$$

where $0 \leq Y \leq 1$ corresponds to the dependent variable; N is the sample size, X_i represents the explanatory variables for each observation i, $G(.)$ is a distribution function similar to the logistic function that satisfies $0 < G(z) < 1$ for all $z \in R$.

The QMLE of the parameters is therefore obtained by maximizing the following Bernoulli Log-likelihood function:

$$l_i(b) = Y_i \log[G(X_i b)] + (1 - Y_i) \log[1-G(X_i b)] \quad (4)$$

The empirical FRM specification of the use of forecast information in this study is

$$E(Y_i \mid X_i) = G(X_i\beta) = b_0 + \sum bX_i + \varepsilon_i \quad (5)$$

where $0 \leq Y \leq 1$ corresponds to the percentage of weather and seasonal climate information used; X_i represents the explanatory variables for each observation i and ε represent the error term.

In fractional outcome regression, the original coefficients cannot be easily interpreted as the measure of proportions is usually asymmetric; hence, inference based on the normality assumption can be misleading.

Therefore, the marginal coefficients were used to interpret the results after analyzing the data with a beta regression. The marginal effect is given by,

$$u_0 = \int[\bar{m}\,(\tilde{x},\alpha)\text{-}m\,(\bar{x},\alpha)]\; Q^*\, d\alpha))/D \qquad (6)$$

where $\tilde{x}$ and $\bar{x}$ are two possible values for the X_{it} vector, Q^* refers to the marginal distribution of α, and D is the distance or number of units corresponding to the difference between $\tilde{x}$ and $\bar{x}$. This equation gives the average, over the marginal distribution, of the per-unit effect of changing x from $\bar{x}$ to $\tilde{x}$ (Chernozhukov et al. 2009).

Empirical Model

Specifically, the response variable is the percentage of use of the following weather and seasonal climate forecast information: rainfall, temperature, tropical cyclone, relative humidity, winds, and *El Niño*—Southern Oscillation (ENSO) phase - *El Nino/La Nina*. In this study, seasonal climate information only pertains to ENSO advisories (*El Nino/La Nina*). The explanatory variables used to fit the model are based on similar studies on factors influencing access and climate information utilization (Yong 2014; Ochieng et al. 2017). Hence, *farmer characteristics* (age, sex, education, annual farm income); *farm characteristics* (farm parcel size, monocropping practices); and *institutional factors* (credit access and organization membership) were regressed with the use of forecast information. Additionally, weather and climate forecast attributes (*usefulness, reliability, adequacy*) were also used as independent variables because the quality of information is vital in effective decision outcomes. *Awareness of climate change* and its impacts and *risk appetite* was also considered determinants of the appropriate use of weather and seasonal climate information. Further, the *use or reliability of traditional and indigenous beliefs* may also affect the decision to use modern information. It either serves as an alternative or integrated system with scientific knowledge. With these identified independent variables, the empirical model is specified as:

$$FCUSE = \beta_0 + \beta_1\ AGE + \beta_1\ SEX + \beta_3\ EDUC + \beta_4\ AFINC + \beta_5\ PSIZE + \beta_6\ CRP + \beta_7\ ORG + \beta_8\ CRED + \beta_9\ USF + \beta_{10}\ REL + \beta_{11}\ ADQ + \beta_{12} CCK + \beta_{13}\ TREL + \beta_{14}\ RISK + \varepsilon_i$$

where FCUSE is the percentage of use of weather and climate advisories, particularly daily forecast (rainfall, temperature, relative humidity, winds); 3-5 day forecast (typhoon); and 3-month or seasonal forecast (*El Nino/La Nina*); AGE is the age of maize farmer at the time of the survey (years); SEX is a dummy variable for sex; 1 = male; 0 = female; EDUC is the education in terms of number of years (years); AFINC is the annual farm income (PhP); PSIZE is the size of the nearest parcel to the farmer's residence (ha); CRP is a dummy variable for cropping practices: 1 = monocropping, 0 = otherwise; ORG is a dummy variable for org membership: 1 = with membership, 0 = otherwise; CRED is a dummy variable for loan access: 1 = with access, 0 = otherwise; USF is the percentage of the usefulness of all weather and seasonal climate information per farmer-respondent (actual rating divided by total); REL is the percentage of reliability of all weather and seasonal climate information per farmer-respondent (actual rating divided by total); ADQ is the percentage of the adequacy of all weather and seasonal climate information per farmer respondent (actual rating divided by total); CCK is a dummy variable for climate change knowledge: 1= knowledgeable, 0 = otherwise; TREL is a dummy variable assessing the reliability of indigenous/traditional beliefs: 1 = reliable/somewhat reliable, 0 = otherwise; RISK is a dummy variable for risk attitude under different climate probabilities: 1 - risk - averse, 0 = otherwise ε random error term.

RESULTS AND DISCUSSION

Descriptive Statistics of the Sample

Table 1 shows the descriptive statistics of the surveyed maize farmers with respect to their socio-economic and farm characteristics and institutional access. The other relevant variables used in the model are also presented in the table.

Male respondents represented 86% of the sample size. Respondent age ranged from 24 years old to 77 years old, with a mean of 48 years old. The age structure is skewed

Table 1. Summary statistics of sample households.

Variables	N=225			
	Mean[3]	Min	Max	Expected Sign
Age of farmers (years)	47.82 (11.92)	24	77	+/-
Sex of farmers (% male)	0.86 (0.35)	0	1	+/-
Education (number of school years)	6.55 (3.73)	0	15	+
Farm annual income (pesos)[1]	6.47 (12.79)	0.15	99	+
Parcel size (ha)	1.80 (1.31)	0.12	8	+
Organization membership (% yes)	0.50 (0.50)	0	1	+
Credit access (% yes)	0.67 (0.47)	0	1	+
Useful forecast information (% average)[2]	0.71 (0.12)	0.11	0.96	+
Reliable forecast information (% average)[2]	0.70 (0.12)	0.11	0.96	+
Adequate forecast information (% average)[2]	0.69 (0.13)	0.11	0.93	+
Knowledge of climate change (% aware)	0.55 (0.50)	0	1	+
Traditional or indigenous beliefs (% reliable)	0.37 (0.48)	0	1	+/-
Risk preference (% risk-averse)	0.68 (0.47)	0	1	+/-

Notes: [1]Annual total income is in 10,000 pesos; [2]Average percentage, with respect to all weather and climate information per respondent; [3]Standard errors in parentheses.
Source: Household survey 2018.

towards the prime working age (25-54) and is below the average age, 53, for corn farmers in the country (PSA 2015; PSA 2014). Five percent of the total farmer-respondents are also classified as indigenous peoples (IPs), belonging to the Mangyan tribe. Most of the IPs are upland farmers and residents of barangay San Roque. Older farmers are considered experienced and wise. Thus, they may consider the use of forecast information as necessary in decision-making. An alternative interpretation is that older farmers would prefer using traditional and indigenous methods of forecasting. On the other hand, younger farmers may be more adaptive to newer technologies and forecasting products and services. High dependence on rain-fed agriculture in both municipalities also increases the farmers' vulnerability to climate change.

Ninety-four percent (94%) of farmer-respondents have attended schooling or completed primary education. Almost half of the respondents (48.5%) obtained only elementary education, while only 6.5% received a college education and 2.5%, a college degree. On average, the surveyed population has 6.55 years in school, with the majority completing at least ten years of schooling. Adoption of technologies is influenced by the farmers' knowledge, which is based on education, training, advice, and gathered relevant information (OECD 2001). An educated farmer can be expected to be more receptive and knowledgeable about the adverse effects of climate change, thus, value the importance of forecast information. Technical and technological challenges also accompany access and use of this information in farming. Farmers who have a higher degree of education have a greater chance of dealing with the complexities. On the contrary, farmers may also treat this situation as an opportunity to look for off-farm activities that are less susceptive to climate shocks, reducing the need to rely entirely on forecast information.

Approximately 83% of the maize-farming households had annual farm income less than PhP 100,000, with a minimum income of PhP 1,500. Forty of the 200 respondents had less than PhP 10,000 as annual income from maize production. Six reported having no income due to losses brought by unfavorable climate, pest infestation, and market factors. The average yearly household farm income is about PhP 64,700 or PhP 5,392 per month. This finding suggested that the majority of the smallholder farmers were only producing for subsistence purposes. It is expected that higher income leads to increased use of weather and climate information due to the availability of capital in implementing climate risk management strategies. The studies of Deressa et al. (2011) and Gbetibouo (2009) also found the influence of socioeconomic factors such as age, farm income, and education on climate change adaptation practices.

The respondents' farm sizes ranged from 0.12 to 8 has, with an average size of 1.80 ha. Most of the farms are located within the barangay, close to the farmers' residence, and with ownership title. While most farmer-respondents own their farm lots, a significant percentage of the respondents are also tenants or renters. It is assumed that large farms are more vulnerable to climate variability impacts, thus, requiring better management of associated risks such as the use of forecast information products and services in critical agronomic decisions. Thus, the reliance on forecast information reduces potential crop loss and improves farm management strategies.

Fifty-percent of the total respondents has an organizational affiliation, including farmer's association, religious groups, cooperative, and socio-civic. The result shows that a large number of the farmers were not yet part of an organization. Rural and farmers' organization provides strong social networks for sharing knowledge and information among farmers (Yegbemey et al. 2017). Valuable knowledge may include farming problems, sustainable agriculture practices, risk management, and forecast information interpretation. Thus, organization membership is expected to have a positive correlation with the use of weather and seasonal climate information services.

The results also indicated that 67% of the sample households have access to loans or credit facilities. Access to credit may ease liquidity or capital constraints faced by farmers in availing production resources or services to manage climate risks. Information on daily weather and seasonal climate variability may not be fully utilized if the necessary resources are limited or scarce.

Farmer-respondents were also asked to assess weather and seasonal climate information based on its usefulness, reliability, and adequacy using the following scale: 1- low; 2- average; 3- high. Farmers with no access, unaware or did not receive any of the advisories did not provide any rating. The mean percentage of the responses (71%) indicates that most farmers find the information useful for non-farming and farming activities. Perceived usefulness and ease of use are the fundamental basis of technology acceptance and use (Davis et al. 1989). It is defined by the degree of an individual's perception of a particular technology or system's impact on its intended purpose (Davis 1989). While forecast information appeared to be generally useful, many farmers still find the information "not useful." McOmber et al. (2013) highlighted the importance of a skillful forecast in decreasing uncertainty in climatic outcomes and introducing more appropriate and efficient management decisions in response to the anticipated weather conditions.

Forecast information was found to be both reliable and adequate by 70% of the interviewed farmers. These two attributes are also considered crucial in the effectiveness and applicability of forecast information. Weather and climate forecasts must be accurate, reliable, timely, and have meaning to be beneficial to farmers (Mpandeli 2014). Information also needs to be adequate for farmers to provide management solutions to all potential climate risks. Overall, there is a small difference between the mean average rating of the attributes.

The majority of the households interviewed were aware and knowledgeable of climate change, but only superficially. The farmers were given a probing question by asking them directly about the definition of climate change. Most of the farmers were aware of the climate variables. However, only 55% were confident of claiming to know its concept and definition. This finding showed that a significant number of farmers still have low familiarity with climate change. It is expected that climate change knowledge leads to an increase and improved use of forecast information in managing climate-related risks.

The reliance of maize farmers on local or indigenous beliefs has significantly declined. Of the total respondents, only 37% disclosed that traditional or indigenous practices of foretelling a weather or climate event are still reliable. This indicates that a significant percentage of the respondents have a low level of trust in its prediction accuracy due to increasing weather and climate unpredictability. It is assumed that the low reliability of traditional forecast increases modern or scientific forecast information use.

Risk preference is an important determinant of understanding farmers' behavior in coping with weather variability and the primary driver of farm management decisions (Jin et al. 2015; Jianjun et al. 2015; Gong et al. 2016). The risk attitude of the farmers was derived from their hypothetical-payoff choice decisions. Specifically, two scenarios were presented to farmers: 1) a low yield forecast but with 100 percent certainty for risk-averse farmers; or 2) a high yield forecast but only a 50 percent likelihood for those willing to take risks. The results indicated that 68% of the sampled farmer-respondents are risk-averse. Risk-averse farmers are believed to be more cautious with their decisions and view forecast information as a tool to avoid potential losses. This is supported by Tong et al. 2019 study, which found that greater risk aversion significantly influenced technical efficiency and the adoption of climate-smart agriculture.

Sources of Weather and Seasonal Climate Information

Table 2 shows that most households accessed weather and seasonal climate information through television (TV) and radio. It is common for most households to have cable televisions as a source of both news and entertainment. According to the farmer-respondents, they prefer television because it is more informative and convenient. Visual aids, maps, and dynamic reporting make it easier for them to process and understand the forecast. Advisories on the expected landfall and impact of a weather or climate event were deemed critical. However, the information reported on regular TV and radio news lacks agronomic advice on farming decisions.

Radio is considered a secondary source, mainly by households who do not have television or cable access. It is also commonly used by farmers as a source of weather updates while at farm sites. The use of multiple sources was also predominant in the area, of which the majority were television and radio. These findings are supported by the study of Borines et al. (2009), which found that maize farmers in Bukidnon, Philippines acquire climate forecasts data mostly from TV, radio, and PAGASA stations. Other similar studies also concluded radio and television as the most common mediums through which farmers receive forecast information (Reyes et al. 2009; Zendera et al. 2010; Zongo et al. 2014; Godara et al. 2016; Amegnaglo et al. 2017).

Fellow farmers also appeared to be a key source of forecast information in the community. Michlik and Espaldon (2008) highlighted the importance of social networks such as relatives and neighbors in adapting to

Table 2. Sources of weather and seasonal climate information.

Sources[1]	Rainfall	Thunder-storm	Tropical Cyclone	Winds	Temp.	Rel. Humidity	La Niña/ El Niño
Radio	54	47	49	48	48	34	49
Television	163	163	165	157	157	98	159
Mobile	2	3	14	3	3	1	1
Ext. workers	1	0	1	0	0	0	0
PAGASA station	0	0	0	0	0	0	1
Local beliefs	3	1	0	0	0	0	0
Co-farmers	14	9	15	2	0	0	7
MDRRMC	1	1	6	0	0	0	0

Notes: [1]Multiple responses: Respondents were asked to provide all sources of information.

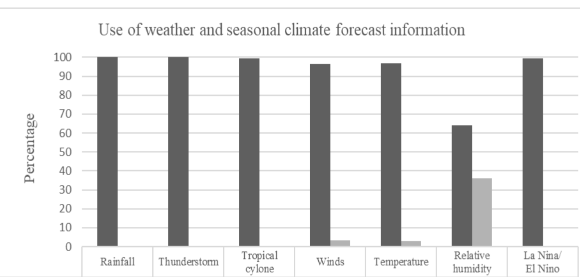
environmental changes. The information exchange among farmers is considered an effective way of obtaining weather and climate updates as they could immediately incorporate it in their farming activities.

Some farmers still depended on local traditional beliefs or indigenous forecasting practices in deciphering weather and climate conditions. The people acquire local knowledge over time by accumulating experiences across generations, society-nature relationships, and community practices and institutions (Kniveton et al. 2014).

Also, the lack of a stable mobile and internet signal limits mobile phones and computers' usefulness as alternative sources. Among the relevant information, relative humidity had the least available media platforms reporting on advisories. Overall, all farmers have the standard equipment, technology, and networks to access some, if not all, relevant basic weather and seasonal climate information on maize production.

Use of Weather and Seasonal Climate Information

Descriptive statistics on the use of weather and climate information are summarized in Figure 2. Almost all the respondents used rainfall, thunderstorm, tropical cyclone, and ENSO information. Fertilizer application, pest management, harvesting, and storage decisions are the most common applications of weather information. The use of weather advisories for irrigation was low as most farmers are rainfall-dependent due to little or no access to irrigation channels. Among the barangays of Bulalacao, only barangays Nasucob and Cabunang are nearby irrigation networks. None of this information, except those directly obtained from PAGASA, have integrated agronomic advisories. Farmers processed this information based on their personal and shared experiences with other farmers. Subsequently, ENSO advisories (*El Nino/La Nina* warnings) are mainly used for tactical decisions, such as crop choice, planting schedule, farmland use, and financial resources allocation. Relative humidity received the lowest use rating due to lack of access to this information on common media sources and channels. The mean use percentage of forecast information is 94%, with values ranging between 29% and 100%. The estimated standard deviation value is 0.09.



	Rainfall	Thunderstorm	Tropical cylone	Winds	Temperature	Relative humidity	La Nina/ El Nino
■ Used information	100	100	99.5	96.5	97	64	99.5
■ No access	0	0	0.5	3.5	3	36	0.5

Fig. 2. Access and use of weather and seasonal climate information.

Determinants of Use of Weather and Seasonal Climate Information

To justify using the Fractional Response Model (FRM), the model's predicted values were compared with those estimated from OLS using the STATA software. The primary motivation for using the FRM is that it logically restricts the predicted percentage values between 0 and 1. In OLS, the predicted values of 24 of the 200 (12%) observations exceeded one which lie outside the defined bounded interval for the response variable. This confirms that FRM is more appropriate than OLS due to the dependent variable's bounded nature – use of forecast information.

Further, Tobit and Multivariate probit models were also considered as alternative regression models. However, the nature of the data does not satisfy these two models' assumptions to generate robust results. All of the respondents disclosed access and use of two or more weather and seasonal climate information, which resulted in the lack of censored variables for Tobit regression. Likewise, the lack of variation in the use of key weather and climate information (rainfall, tropical cyclone, and *El Nino/La Nina*) among the sampled respondents resulted in these dependent variables being dropped.

Table 3 shows that the signs of the coefficients are consistent across different models. The set of significant explanatory variables and degree of significance vary between the OLS and FRM. Age has a 10% significance level in the FRM but is insignificant in the OLS. While the two models have a slightly different set of significant variables, most of the essential variables are the same.

The results and coefficients' consistency and robustness were also tested using the Wald test (Wald Chi-squared test) to compare the selected model's fit to an alternative but nested specification (Table 4). Parcel location and number of farm parcels were fitted in models 1 and 2, respectively. Both these additional variables did not have a significant association with the response variable. The signs and set of significant variables are the same with the final selected model, model 2. However, the confidence level is different for forecast attributes and the usefulness of the information. The constant is also significant in the nested model but insignificant in the final model. Further, the Wald tests

Table 3. Comparison of the estimated OLS and FRM coefficients and marginal effects on the use of forecast information.

Explanatory Variables	Model 1 (OLS) $R^2 = 0.3266$ $F_{13,185} = 6.41$	Model 2 (FRM) Pseudo $R^2 = 0.0933$ Wald chi2$_{14}$ = 166.63	Marginal Coeff. (FRM)
Age	-8.37E-04 (5.52E-04)	-0.02** (8.81E-03)	-9.93E-04 (4.69E-04)
Sex	0.04** (0.02)	0.48** (0.23)	0.03 (0.01)
Education years	-7.62E-04 (1.75E-03)	-0.01 (0.03)	-4.41E-04 1.43E-03
Farm income	9.65E-05 (5.31E-04)	5.98E-03 (9.78E-03)	3.25E-04 5.31E-04
Parcel size	0.01** (5.12E-03)	0.25** (0.11)	0.01 (6.24E-03)
Cropping pattern	-0.02 (0.01)	-0.29 (0.22)	-0.02 0.01
Organization membership	-0.02* (0.01)	-0.31 (0.20)	-0.02 (0.01)
Credit access	-9.66E-03 (0.01)	-0.15 (0.24)	-7.90E-03 (0.01)
Usefulness of W&C information	0.21*** (0.08)	2.50** (1.00)	0.14 (0.06)
Reliability of W&C information	0.21** (0.10)	3.54** (1.50)	0.19 (0.08)
Adequacy of W&C information	-0.04 (0.08)	-0.11 (0.20)	-0.05 (0.07)
Climate change knowledge	2.17E-03 (0.01)	0.11 (0.20)	5.89E-03 (0.01)
Reliability of traditional forecasts	-0.03** (0.01)	-0.42** (0.20)	-0.02 (0.01)
Risk preference	0.03** (0.01)	0.64*** (0.21)	0.03 (0.01)
Constant	0.67*** (0.05)	-0.48 (0.75)	-

Notes: ***, ** and * represent 1%, 5% and 10% significance levels respectively; standard errors in parentheses.
Source: Household survey 2019.

for both the nested models showed that including parcel location and the number of parcels did not result in a statistical improvement in the selected model's fit. The Chi-squared and p-values generated by Model 1 (Chi-square = 1.31, p= 0.24) and Model 2 (Chi-square = 0.92, p-value = 0.34) suggest that we can accept the null hypothesis, indicating that the regression coefficients for parcel location and the number of parcels are not statistically different from zero in estimating the use of forecast information given other explanatory variables in the models. Thus, these parameters can be excluded from the model. The log-likelihood of the selected model (Model 2) was also significant at 1 percent (p-value = 0.00), indicating the model's high explanatory power. According to Wooldridge (2011), a Wald test is a sufficient basis for the fractional response model's overall quality.

The models also tested negative for multicollinearity, with a variance inflation factor range of 1.67-1.69. Heteroskedascity tests (Breusch-Pagan and Cameron and Trivedi) of the OLS model showed that residuals' variance is not homogenous. This finding supports Papke and Woolridge (1996) contention that the use of OLS is inefficient due to heteroskedasticity when used on a model with fractional dependent variables.

The utilization of weather and climate (W&C) information services in maize farming in Bulalacao was relatively high, with a mean usage rate of 94 percent. The regression results showed that the farmer's age and reliable traditional or indigenous beliefs were correlated with a reduced likelihood of using forecast information. In contrast, household size, television ownership, income, farming and group membership sex, parcel size, the usefulness and reliability of forecast, and risk attitude correlated with an increased likelihood of using the information.

Among the explanatory variables, usefulness and reliability obtained the highest marginal effects. A percentage point increase in the usefulness rating of forecast information increased the proportion of information or forecast type used by 14 percentage points. Among the forecast information, rainfall, tropical cyclone, and ENSO advisories received the highest usefulness ratings. Similarly, reliable forecast information increased the likelihood of utilizing it by 19 percentage points. Rainfall information and climate advisories obtained the highest percentage scores for reliability. This finding is corroborated by the study of Borines et al. (2009), which found that farmers ignore SCFs that are perceived as "untruthful." In Garbrecht and Schneider (2007) study, the authors emphasized the influence of the quality of seasonal climate forecast (SCF) on the farmers' perception and adoption of the forecast.

The results also showed that male farmers had a higher likelihood of using weather and seasonal forecast information than female farmers. This gender difference can be attributed to the high percentage of male workers employed in agriculture. Female agriculture workers only accounted for 14% of the Philippines' total female employment (PSA 2019). While maize-farming households were headed by men, women have a contributory role in climate change adaptation through their involvement in relevant agriculture trainings, loan credit applications, and farm management activities. The wives usually attend the agricultural trainings because their husbands are busy attending to farm work.

Table 4. Estimated coefficients and Wald tests of the nested models.

Explanatory Variables	Nested Model 1 Pseudo R^2 = 0.0941 Wald chi2$_{14}$ = 165.65	Nested Model 2 Pseudo R^2 = 0.0941 Wald chi2$_{14}$ = 169.62
Age	-0.02* (8.90E-03)	-0.02** (8.70E-03)
Sex	0.49** (0.23)	0.51** (0.23)
Education years	-4.92E-03 (0.03)	-9.60E-03 0.03
Farm income	6.45E-03 (9.61E-03)	4.75E-03 9.88E-03
Parcel size	0.27** 0.11	0.24** 0.11
Cropping pattern	-0.28 (0.21)	-0.29 0.21
Organization membership	-0.32 (0.20)	-0.32* (0.19)
Credit access	-0.15 (0.24)	-0.18 (0.24)
Usefulness of W&C information	2.63*** (1.01)	2.57** 1.03
Reliability of W&C information	3.49** (1.51)	3.52** (1.52)
Adequacy of W&C information	-1.02 (1.37)	-1.06 (1.37)
Climate change knowledge	0.10 (0.20)	0.10 (0.20)
Reliability of traditional forecasts	-0.44** (0.20)	-0.45** (0.20)
Risk attitude	0.65*** (0.21)	0.64*** (0.21)
Parcel location	0.33 (0.28)	-
No. of parcels	-	0.21 (0.22)
Constant	-0.86 0.83	-0.61 (0.74)
Wald tests Chi2	1.38	0.92
Prob > chi2	0.24	0.34

Notes: ***, ** and * represent 1%, 5% and 10% significance levels respectively; and standard errors in parentheses.
Source: Household survey 2019.

A unit increase in parcel size increased the likelihood of utilizing forecast information by one percentage point. The increase in farm size imposes higher risk and vulnerability to unfavorable weather and climate events. Higher demand for agricultural and climate information is attributed to larger farm size due to higher potential loss brought by climate change (Rehman et al. 2013; Oyekale 2015). Further, climate risk varies according to the farmer's perception of the impact of climate change (Ochenge et al. 2016). As the risk rises with greater farm size, improved climate information is needed to address it.

Risk-averse farmers had a higher probability of utilizing forecast information services by three percentage points than risk-takers. Menapace et al. (2013) stated that more risk-averse farmers perceived a lesser likelihood of potential losses. Jin et al. (2020) also found that risk aversion is positively correlated with climate change adaptation practices, including crop diversification, credit access, crop rotation, and planting of new crop varieties. Based on these studies, farmers would want to access and integrate seasonal climate information into their decision-making to reduce crop losses.

An increase in the farmer's age by one year resulted in a 0.10 percent decreased likelihood of using forecast information. Age is correlated with farming skills and experience. Therefore, older farmers have better climate monitoring and risk spreading skills to cope with climate change risks hence lower demand for seasonal climate information (Yong 2014; Uddin et al. 2014). Similarly, farmers with access to a reliable traditional-based or indigenous forecasting technique reduced the likelihood of utilizing forecast information by two percentage points relative to those with unreliable indigenous sources. The use of indigenous practices in predicting the weather has become less reliable because of climate variability in recent decades (Roncoli et al. 2009).

CONCLUSION

The utilization of scientific weather and climate information among smallholder farmers in Bulalacao was seen to be high. However, the high usage rates only accounted for information that the farmers have access to, knowledgeable, and able to process and integrate into their decision-making. The majority of the households accessed information services through television and radio. The Fractional Response Model was used to analyze the various factors influencing weather and climate information use. The results showed that farmers' age and the reliability of indigenous forecasting practices correlated with a reduced likelihood of using weather and climate information. In contrast, sex, farm size, the usefulness of forecast information, reliability of forecast information, and risk preference increased the likelihood of use.

RECOMMENDATIONS

Based on this study's results, younger farmers had a higher likelihood of using weather and climate information. Therefore, information providers and agricultural institutions should target to educate more younger farmers in climate change adaptation. Knowledge managers should design training and education materials that would be appealing to these younger cohorts. Moreover, youth in farming should be involved in the formulation of relevant policies on climate risk management. While traditional forecasts have significantly and steadily declined in the study site, this study suggests that information service providers still seek opportunities to harmonize both knowledge systems to improve weather and seasonal climate information communication.

The quality of forecast information, particularly usefulness and reliability, was found to increase the likelihood of using the information significantly. Therefore, there is a need for policies or programs to improve the forecast quality of local information provided by PAGASA and other providers to make information more meaningful to the farmers. Information should also not be limited to daily weather, winds, and typhoons but should extend to how it can be utilized in a complex setting, such as enhancing crop productivity, environmental management, risk reduction, among others. Improvement in weather and climate information quality may also be achieved by establishing localized forecasts in the municipality.

Most of the farmers accessed forecast information through their televisions and radios. This study suggests that weather and climate-related agronomic advice available on other media platforms such as the PAGASA website should be broadcasted as well as these are the primary sources of information in the area.

Moreover, while there is high utilization of scientific forecast information among the surveyed households, its effective farm management application was not evaluated. The descriptive analysis of the respondents' socio-economic characteristics showed low educational attainment, climate change awareness, and organization membership. Necessary interventions are needed from both the local and national government and academic institutions to provide opportunities to increase understanding of climate change and its impacts through tailor-fitted climate change education campaigns and programs for farmers.

ACKNOWLEDGEMENT

The authors would like to acknowledge the Australian Center for International Agricultural Research (ACIAR) funding support. We would also like to extend our gratitude to Professor Kevin Parton of Charles Stuart University (CSU) for sharing his valuable knowledge and skills in improving the quality of this paper.

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