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Research Article

Predictor of willingness to pay for early warning climate system and agronomy advisories services in Albania: A case study of medicinal plant in "Malesi e Madhe"

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Abstract

Access to useful climate information is critical for adaptation needs of Albanian smallholder farmers, yet empirical studies documenting the socioeconomic, environmental and household predictors of access to and willingness to pay for climate information services have been limited to date. This paper addresses the need by identifying the predictors of access to and willingness to pay for climate information by smallholder farmers in the northern area of Albania, a "dangerous hotspot" where slight changes in rainfall and temperature often result in considerable yield losses. The study uses data collected from 201 household surveys in 5 communities across 29 districts in the "Malesia e Madhe" region of Albania using a simple random sampling method. Sampling was conducted in end 2023 and start of 2024 and participants were interviewed face to face by questionnaires following a contingent valuation method for collecting data for willingness to pay for early warning climate system. The EFA analysis was performed on farmer's awareness to climate changes and their impact on quality and productivity. Our findings suggest that the majority of smallholders are aware of duration of drought (95%), increase of number of hot days (88.1%) and presence of weeds (59.7%). From the findings, farmers perceive that climate changes have affected the quality of medicinal plants in the last 5 years, by increasing the number of hot days (96%), number of rainy days (93.5%) and duration of drought (86.6%), also farmers perceive that climate change has impacted the yield level by duration of drought (87.1%), increase of hot nights (78.1%) and number of rainy days (76.1%). The findings suggest that the majority of smallholder farmers were not willing to pay for the cost of receiving climate information delivered via SMS. The results from the marginal analysis suggest that access to climate information is influenced by farm topology factors. The marginal effects logistic regression shows statistically significant effect in household predictors such as farmer's size and income. Results suggest that the provision of climate information should be defined and adopted to meet the needs of smallholder farmers with different socioeconomic backgrounds to enable farmers manage climate risks and build reasonable adaptive capacity.

Keywords: farmer's awareness, early warning weather system, willingness to pay, risk perceived and managed.

1. Introduction

Agriculture is one of the main pillars of economy in Albania. Agriculture contributes significantly to Albanian GDP and provides employment to thousands of low-income families across the country. This sector has experienced moderate growth over the past decades, especially in the last decade where the use of information technology and communications (ICT) was reaching its peak in the agricultural sector.

If we analyze the level of use of information systems in rural areas and the structural problems faced by actors and economic subjects in the Albanian terrain, the role of ICT in economic activity in these areas remains weak and with invisible effects (Mulliri, Shahu and Baraku, 2021)

During the analysis and implementation of an agricultural information system, the primary step is to identify the demands and preferences of the actors that are part of this system. As a result of the above, the purpose of the study is to evaluate farmers' preferences for agricultural information by type, including weather, production technology, information on inputs, and information on services such as transport, insurance, credit and counseling prices. In the last decade, there have been several attempts to build sustainable information systems in agriculture. We can mention the attempt of German technical cooperation (GTZ) and the Ministry of Agriculture to build an Agriculture market information system, which monitors farm gate, import and export prices on a monthly and annual basis. This system failed because it only covered the information of fruits and vegetables and there was no coherence of the prices published in the system.

According to a well detailed report written by Zhllima (2022) which presents the National AKIS Action Plan Albania a sequence-based description of specific objectives and relevant actions for adopting, legitimizing, and developing an AKIS in Albania. Also in 2016, Swiss-supported RisiAlbania[1] and Creative Business Solutions launched the agricultural information and Intelligence System (AGIS) to provide accurate data to banks seeking to credit agribusinesses, which in now day is not accessible. During the last years several studies have been carried out on the willingness to pay for an AMIS, it is worth mentioning here the study carried out by Zhllima et al (2022), which analyzes WTP for information, but did not take into account the factors that influence WTP or farmers' commitment. Unlike the results for AMIS and the factors that influence it, studies related to the analysis of the willingness to pay for systems that provide climate information and the factors that influence this willingness are not available in Albania.

But the change in climatic conditions has turned out to be the most critical issue at the global, regional and local level to the point that it is considered the most serious challenge for humanity in the current century (Kumar, 2014).

Climate change is a serious threat to agriculture sector, deeply affecting the activity

[1] For more info: https://www.eda.admin.ch/countries/albania/en/home/news/news.html/countries/albania/en/meta/n ews/emba ssy/2016/switzerland-supports-innovative-e-platform-of-agricultural-infor

of farmers. Manifestations of climate change are diverse, including floods, droughts, strong winds and global warming. These climatic changes have direct effects on the agricultural sector and on adaptations to these changes. Adaptations of farmers to changes in climatic conditions can bring consequences in the changes in biodiversity, changes in harvest time, reduced consumption efficiency, and spread of pests and diseases (Brida., 2013; Falco, 2019; Huong, 2019; Loboguerrero, 2019).

To manage such risks, farmers need clearer and more complete information for both types of climate (long-term over months or years) and weather (short-term changes in conditions). This would enable farmers to make important decisions about the management of crops, land and water before and during the growing seasons (Kim and Ikpe and Sawa, 2016).

According to Dinku, et al., (2014) prior knowledge of climate information is important as it helps farmers to make decisions about the distribution of resources and the type of agricultural crops in a season. Climate information coupled with agro-advisory services offers greater potential to increase the capacity of farmers to adapt to climate variability. Effects on climate change and increased climate variability mean that farmers must make critical management decisions based on the availability of climacteric information (Mase and Prokopy, 2014)

The use of EWS is related to climate preparedness and the efficient use of available resources. EWS enables small farmers to build resilient strategies to identify risks and disasters thus avoiding crises in the right time and efficient use of resources. So, the structures: availability, efficiency and accessibility of EWS are a function of the level of appropriation of individual and social capital. Conception, Implementation and Implementation of EWS is accompanied by some obstacles and limitations that we will address below. The implementation of EWS is partially rational and logical, as it consists of a series of social and organizational processes (Thomalla and Larsen, 2010). The effective distribution of EWS at the societal level depends on the stability and adequate measures of the relevant capital: human, financial and physical. Similarly, EWSs should be well designed, especially on the language front (Perera and Agnihotri and Seidou and Djalante, 2020), so it should be clear which type of farmer or user it is aimed at, so inappropriate design may not be useful for rural farmers who are more affected by climate events, market failures, hunger, and poverty. This is because effective communication is a vital component, as it can help farmers make informed decisions and take appropriate action. Thus, the compromise in the structural design of EWS shows a stable result. On the other hand, farmers' ability to engage with EWS is also contingent on their levels of service uptake. This positioning of farmers is vital because availability does not always translate into accessibility or applicability. For example, a farmer with low financial capital may still be somewhat able to exploit EWS if they have strong social networks compared to the farmer lacks economic and social capital. Therefore, the willingness to such systems and small owners is strengthened or weakened through interactions between farmers and their context, where farmers with low capital index will be less likely to take advantage of EWS (Darnhofer, 2014).

2. Methodology

In this research, the Descriptive Statistics Analysis was adopted to analyze the data with Statistical Package for Social Science (SPSS) and STATA 15 software. Descriptive statistics are useful and effective as it can summarize a large amount of data like a group of samples and populations. This involved the use of frequencies, percentage, and means for presenting descriptive finding of the survey. It was also used for the initial analysis of rating score data of the various research variables (Akadiri, 2011).
This study used the single-bounded DC choice model, as shown in Figure 1, where B_i is the offered price to the respondent i, YES(R1=1) denotes that the individual is willing to pay the offered price, and NO(R1=0) denotes that
the individual is not willing to pay the offered price.

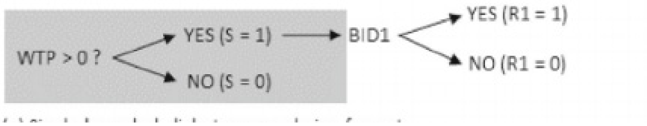

Figure 1. Single-boundary DC model
Source: Aizaki, Hideo & Nakatani, Tomoaki & Sato, Kazuo & Fogarty, James et al., (2022).

The individual WTP (WTPi) is the maximum price that the respondent i is willing to pay for a product or service, such as early warning weather system Assuming that the individual WTP is a linear function of the explanatory variables vector (Hi) and the vector of parameters (α). According to Akhtar et al. (2016) and Kong et al. (2014), the following equation is used to find out the WTP:

$$Wi = \alpha^i H_i + \beta_i (1)$$

where W is the consumer's WTP, i indicates individual i, i = 1, 2, …, n, and εi is a scalar value of residual, which includes factors that affect Wi but are not explicitly expressed as interpretation variables.
If the respondent answers "yes," he/she is willing to pay the offered price Pi for the information derived from Early warning climate system, and if the respondent answers "no," he/she is not willing to pay the offered price. Assuming βi follows a specific distribution (such as the logistic distribution), Equations (2) and (3) describe the probability of respondent i answering "yes" and "no" at the offered price:

$$Prob(Y)_i = Prob(W_i > P_i) = 1 - F(P_i; \alpha), (2)$$
$$Prob(N)_i = P_r(W_i < P_i) = F(P_i; \alpha), (3)$$

where G(·) is the cumulative probability distribution function of P_ii. In practice, WTPi is unobservable, what we observe is the answer of YES or NO for each respondent. Using an econometric dummy variable zi defined by

$$Z_i (4)$$

Relations (2) and (4) bring us:

$$\text{Prob}(Zi=1)=\text{Prob}(\beta_i > Pi-\alpha^i Zi) \quad (5)$$

Relations (3) and (4) bring us:

$$\text{Prob}(Zi=0)=\text{Prob}(\beta_i <= Pi-\alpha^i Zi) \quad (6)$$

The Maximum Likelihood Estimation (MLE) estimate the parameters of a regression model. MLE use values of the regression model parameters that maximize the likelihood function. The MLE function is:

$$L = \prod_{zi=1} \text{Prob}(\beta i > Pi - \alpha i Zi) \prod_{zi=0} \text{Prob}(\beta i <= Pi - \alpha i Zi) \quad (7)$$

The likelihood function defines the probability that the observed values of the dependent variable (Dummy Variable of WTP) can be predicted by the observed values of the independent variables.

If the distribution of βi is the logistic, we have the logit model, where Prob(zi=0) is as below:

$$\text{Prob}(\beta i =<= Pi - \alpha i Zi) = \frac{1}{1+\exp\,(Pi-\alpha i Zi)} \quad (8)$$

If βi follows a normal distribution N (0, σ2) , then we have the probit model, where Prob (zi=0) is as Equation (9):

$$\text{Prob}(\beta i =<= Pi - \alpha i Zi) = \int_{-\infty}^{Pi-\alpha i Zi} \frac{1}{2\pi^{1/2}} \exp\left(-\frac{t^2}{2}\right) dt \quad (9)$$

In this study, the value of each parameter was estimated using probit and logit models using the maximum likelihood estimation, and the expected value of WTP per individual that respondents' WTP for Early warning climate changes system was based on these parameter values.

We are using the quantitative methods Exploratory Factor Analysis to exploit the most influential drivers of farmers' perceptions, hazards, and adaptions of the climatic phenomena that have occurred in their area during the last 5 years (Akhmedova, 2020; Olya and Altinay, 2016). EFA was used to assess the reliability of the surveyed items and to refine the outcome variable. EFA has no minimum sample size required, previous research has shown that for samples with N below 50, it provides reliable results (Velicer and Fava, 1998; de Winter, 2009). The sample size required, is conditioned by high communalities, no cross-loading factors and strong primary factor loading on the intended factor (Costello and Osborne, 2005). By combing those conclusions, together with the Bartlett' test and KMO (Kaiser, 1974;

Weide and Beauducel, 2019), we concluded that the small sample size, was sufficient for the analysis.

3. Results and Interpretation

1.1 *Farmers' perceptions toward climate changes affecting quality and productivity of medicinal plans*

From the results of Ling et al., (2022) it can be analyzed that the direct impact of climate change awareness is significant on perceived usefulness and consequence awareness. Farmers have different attitudes towards risks, which is manifested in the negative impact of low risk avoidance and adaptive strategies (Wens and Mwangi and van Loon and Aerts., 2021), such as in our studies in low level on Willingness to pay for an Early warning climate system. The stronger the farmers' risk awareness, the more inclined they are to manage climate risks (Khan and Lei and Shah and Ali and Khan and Muhammad and Huo and Javed, 2020). From the result, it was noticed that in the last 5 years, farmers have perceived high changes in the occurrence of natural events, such as the increase in the period of drought (95%), the increase of number of hot days (88.1%) and the presence of weeds (59.7%).

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Droughts increase yield losses, the risk of infestations, weeds and diseases. Moreover, droughts also affect soil functions, and play a role in desertification (Mysiak and Jaroslav and De Salvo and Maria and Santato, Silvia and Amadio and Mattia, 2013).

To help people make better decisions regarding drought hazards the integrated and modification of existing technologies, including various satellite-based systems and people's experiences, is one logical and promising option (Orimoloye, 2022). Datasets obtained from sensors for climate forecast, can be delivered at a spatial resolution format that is worth considering to complement or replace in-situ observations. Local measurement failure including inadequate coverage and lack of spatial consistency are frequently compensated for using databases obtained from sensors. The interaction of drought-inducing main climatic elements (rainfall, temperature, soil moisture, evapotranspiration, and vegetation) is reasonably well-understood (Enenkel, 2015; Afuye, 2021). One key issue is that large-scale planning necessitates accurate drought forecasts several months in advance, which are currently insufficient (Yaseen and Shahid, 2021).

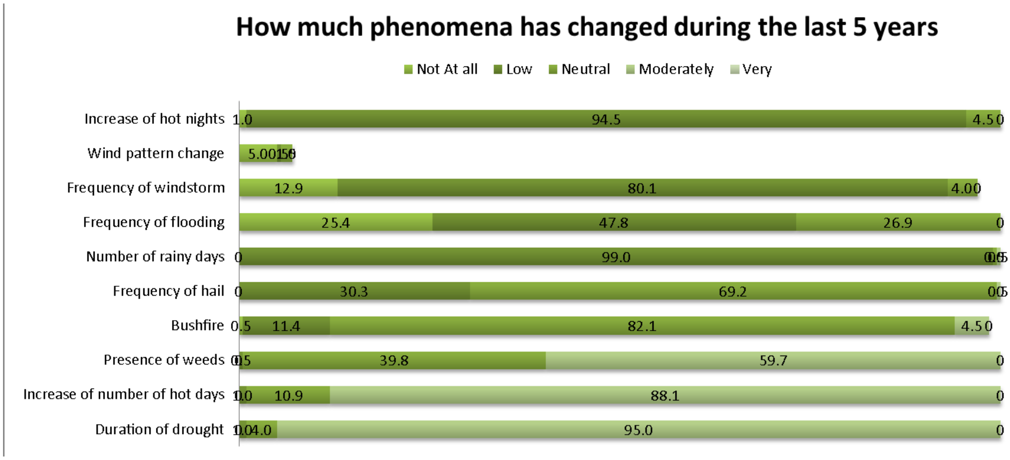

Figure 1. Farmer's perceptions towards climate change in the last 5 years

An EFA was performed using a principal component analysis and varimax rotation. Because no rule of factor extraction appears superior to all the others, none should be used alone (Costello, 2005). The minimum factor loading criteria was set to 0.50. The communality of the scale, which indicates the amount of variance in each dimension, was also assessed to ensure acceptable levels of explanation. The result show that all communities were over the 0.50., Table 4 points out the appropriateness of applying EFA to the survey data matrix, after eliminating the item, "Frequency of flooding," whose MSA coefficient was low (<0.5). Bartlett's test of sphericity on the final dataset of 10 items was statistically significant (= 68.483; p=0.014 < 0.05), and the final overall MSA of Kaiser-Meyer-Olkin (KMO) test was sufficiently high (0.541), highlighting the appropriateness of EFA and its ability to evaluate research data. Finally, the factor solution derived from this analysis yielded three factors for the scale, which accounted for 80.141% of the variation in the data.

Table 4 . KMO and Bartlett's Test (Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalization.)

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		0.541
Bartlett's Test of Sphericity	Approx. Chi-Square	68.463
	df	45
	Sig.	0.014

Source: Author

Table 5. EFA Results

Items	1	2	3
F1.1 - Wind pattern change	*.901*		
F1.2 - Frequency of windstorm	*.884*		
F1.3 - Population dynamics of pest and disease	*.808*		
F1.4 - Presence of weeds	*.606*		
F2.1 - Number of rainy days		*.794*	
F2.2 - Increase of hot nights		*.712*	
F2.3 - Bushfire		*.707*	
F3.1 - Duration of drought			*.878*
F3.2 - Frequency of hail			*.822*
F3.3 - Increase of number of hot days			*.698*

Source: Author

The three factor identified as part of this EFA aligned with the theorical propositions in the research. Factor 1 includes item F1.1 to F1.4. Factor 2 gathers items F2.1 to F2.3 and factor 3 was represented from item F3.1 to F3.3. Factor loading are presented in table 4.

Refering to Ebi and Loladze et al., (2019) it has been revealed that a high concentration of CO2 reduces the quality of fodder like the reduction in protein, iron, zinc, and vitamins B1, B2, B5, and B9. In the future climate scenarios pastures, grasslands, feedstuff quality and quantity, as well as biodiversity would be highly affected (Habib-ur-Rahman and Ahmad and Raza and Hasnain and Alharby and Alzahrani and Bamagoos and Hakeem and Ahmad and Nasim and Ali and Mansour and Sabagh, 2022), for this reasons different kinds of adaptation actions in soil, water, and crop conservation, and well farm management should be adapted in case of long-term increasing climate change and variability (Williams, 2019). From the result of figure 2, it was noticed that in the last 5 years, farmers have perceived moderate impact in quality of medicinal plants as effect of increase in the period of drought (86.6%), the increase of number of hot days (96%) and number of rainy days (93.5%). Climate changes does not affect a given species range, but it may affect its productivity or its quality – in the case of a medicinal plant, primarily its potency or chemical composition – either positively or negatively. It is possible that increased drought stress would increase the potency of some medicinal plants. A decrease in biomass with uncontrolled natural drought would frequently be so great as to outweigh any gains in concentration of active metabolites, even if those benefits were known for consumers and the dosage was decreased to compensate. Sometimes chemical content is higher under water stress but lower at high temperature (Chung and Jong and Jung and Chang and Seung and Sang, 2006). High temperatures, like drought stress, may lead to an increased concentration of secondary metabolites as a consequence of a significantly reduced biomass (Jochum and Mudge and Thomas, 2007). Medicinal plants are easily affected by climate change.

Medicinal plants are compounded by many volatile aromatic elements subjected to the alteration of secondary metabolite components, and in the concentration of secondary metabolites, which the drought and increase of heat negatively influence medicinal plants. Only E- CO2 has a positive effect in medicinal plant growth and other traits (Kumari and Lakshmi and Krishna and Patni and Prakash and Bhattacharyya and Singh and Verma, 2022).

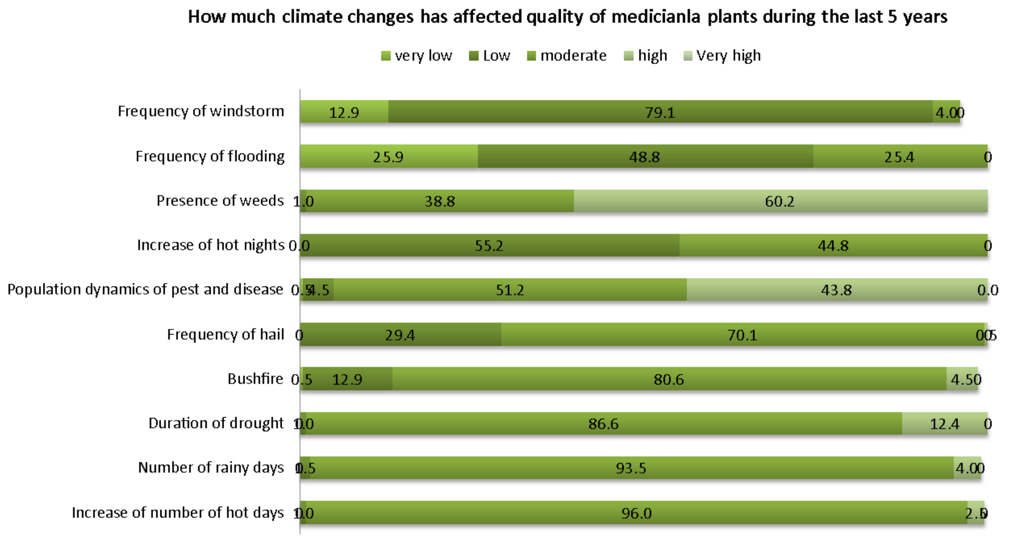

Figure 2. Farmer's perceptions towards impact of climate change in quality of medicinal plants in the last 5 years

Table 5 points to EFA analysis after eliminating the item, "Increase of hot nights", "Wind pattern change" and whose MSA coefficient was low (<0.5). Bartlett's test of sphericity on the final dataset of 9 items was statistically significant (= 147.892; $p < 0.001$), and the final overall MSA of Kaiser-Meyer-Olkin (KMO) test was sufficiently high (0.621), highlighting the appropriateness of EFA and its ability to evaluate research data. Finally, the factor solution derived from this analysis yielded three factors for the scale, which accounted for 61.581% of the variation in the data.

Table 5 . KMO and Bartlett's Test (Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalization.)		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		0.621
Bartlett's Test of Sphericity	Approx. Chi-Square	147.892
	df	36
	Sig.	0.000

Source: Author

Table 5. EFA Results for impact of climate changes in quality of Medicinal Plants

Items	1	2	3	4
F1.1 - Frequency of flooding	*.692*			
F1.2 - Frequency of windstorm	*.658*			
F1.3 - Population dynamics of pest and disease	*.743*			
F1.4 - Presence of weeds	*.516*			
F2.1 - Frequency of hail		*.670*		
F2.2 - Bushfire		*.624*		
F3.1 - Increase of number of hot days			*.832*	
F4.1 - Duration of drought				*.808*
F4.2 - Number of rainy days				*.596*

Source: Author

The four factors identified as part of this EFA aligned with the theorical propositions in the research. Factor 1 includes item F1.1 to F1.4. Factor 2 gather items F2.1 to F2.2, factor 3 was represented from item F3.1 and factor 4 F4.1 and F4.2. Factor loading are presented in table 5.

Extreme weather events impact the availability and supply of medicinal and aromatic plants on the global market, and in the future increases in extreme weather events are likely to affect negatively medicinal and aromatic plant yields even further (Roy, 2016). Impacts from environmental factors such as changes in temperature, elevated CO2, elevated ozone, UV light, and drought were associated with adverse impacts on plant growth and yield, and significant increases or decreases in secondary metabolite content (Pant, 2021). From the result of figure 3, it was noticed that in the last 5 years, farmers have perceived high impact on productivity of medicinal plants as effect of increase in the period of drought (87.1%), the increase of number of hot nights (78.1%) and number of rainy days (76.1%).

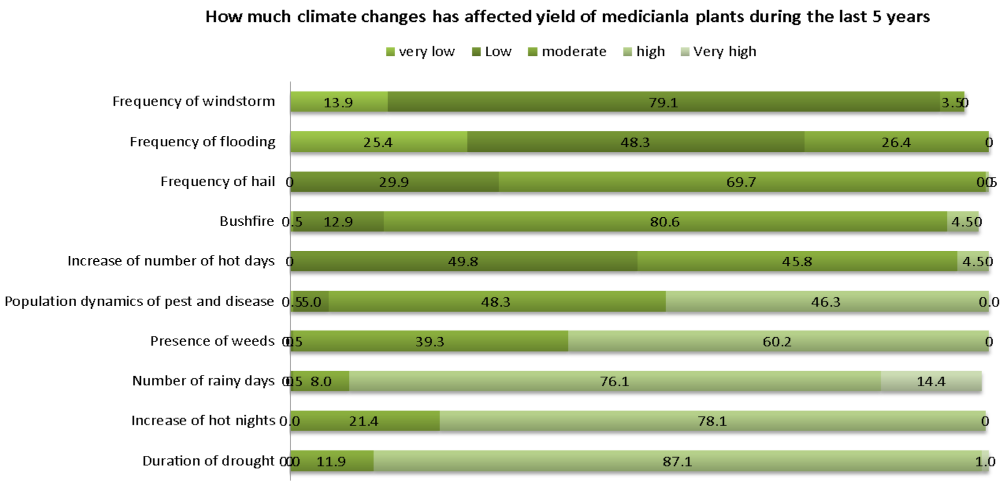

Figure 3. Farmer's perceptions towards impact of climate change in yield of medicinal plants in the last 5 years

Table 6 explain EFA analysis after eliminating the item, "Frequency of hail"," Wind pattern change", "Increase of hot nights", "Bushfire" and whose MSA coefficient was low (<0.5). Bartlett's test of sphericity on the final dataset of 7 items was statistically significant (= 164.967; p < 0.001), and the final overall MSA of Kaiser-Meyer-Olkin (KMO) test was sufficiently high (0.559), highlighting the appropriateness of EFA and its ability to evaluate research data. Finally, the factor solution derived from this analysis yielded three factors for the scale, which accounted for 64.313% of the variation in the data.

Table 6 . KMO and Bartlett's Test (Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalization.)		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		0.559
Bartlett's Test of Sphericity	Approx. Chi-Square	164.967
	df	21
	Sig.	0.000

Source: Author

Items	1	2	3
F1.1 - Frequency of flooding	*.692*		
F1.2 - Population dynamics of pest and disease	*.760*		
F1.3 - Presence of weeds	*.888*		
F2.1 - Duration of drought		*.778*	
F2.2 - Number of rainy days		*.505*	
F2.3 - Increase of number of hot days		*.806*	
F3.1 - Frequency of windstorm			*.783*
Source: Author			

The three factors identified as part of this EFA aligned with the theorical proposiotions in the research. Factor 1 includes item F1.1 to F1.3. Factor 2 gather items F2.1 to F2.3, factor 3 was represented only from item F3.1.Factor loading are presented in table 6.

1.2 *Farm typology predictors of willingness to pay for early warning climate system*

The binary logistic regressions were used to analyze the farm typology determinants of farmers' WTP. The results reveal a difference between the determinants of demand for early warning climate system and WTP (Table 7a and Table 7b). The variables significantly affecting farmers' demand for early warning climate system are farmers' age, access on internet and experience in farming sectors.

Table 7a. Logistic regression on willingness to pay for early warning climate information system, by farm typology in study communities

Table 7a. Logistic regression on willingness to pay for early warning climate information system, by farm typology in study communities

Variables	Odds Ratio	Std. Err.	z	P>z	[95% Conf. Interval]	
Cultivated Area	*1.03**	*0.02*	*1.88*	*0.06*	*1.00*	*1.06*
Rented Area	*1.00*	*0.01*	*0.05*	*0.96*	*0.98*	*1.02*
Cost of production						
Increased	*0.50*	*0.81*	*(0.43)*	*0.67*	*0.02*	*11.90*
Increased much	*3.90*	*7.99*	*0.66*	*0.51*	*0.07*	*216.12*
Total farmer's income	*1.00**	*0.00*	*(1.73)*	*0.08*	*1.00*	*1.00*
Income from medicinal plants	*1.00*	*0.04*	*(0.11)*	*0.92*	*0.93*	*1.07*
Constant	*0.03*	*0.09*	*(1.23)*	*0.22*	*0.00*	*8*
Observations	*200.00*					
-2 Log likelihood	*(16.71)*					
P-value > Chi Square	*0.0001*					
Pseudo R-square	*0.45*					

*, **,*** *denotes parameter estimates are significant at 10%, 5% and 1% respectively.*
Source: Author's survey (November 2023 – January 2024).

Table 7b. Marginal effects on willingness to pay for early warning climate information system, by farm typology in study communities

Variables	dy/dx	Std. Err.	z	P>z	[95% Conf. Interval]	
Cultivated Area	*0.001**	*0.000*	*1.650*	*0.098*	*0.000*	*0.001*
Rented Area	*0.000*	*0.000*	*0.050*	*0.959*	*0.000*	*0.000*
Cost of production						
Increased	*-0.015*	*0.042*	*-0.350*	*0.724*	*-0.097*	*0.067*
Increased much	*0.063*	*0.116*	*0.550*	*0.585*	*-0.164*	*0.290*
Total farmer's income	*0.000*	*0.000*	*-1.550*	*0.121*	*0.000*	*0.000*
Income from medicinal plants	*0.000*	*0.001*	*-0.110*	*0.915*	*-0.001*	*0.001*

*,**,*** *denotes parameter estimates are significant at 10%, 5% and 1% respectively.*
Source: Author's survey (November 2023 – January 2024).

The analysis shows, that the farm size positively affects the WTP for early warning climate system at a threshold of 6%. The farm size in most cases is linked to land access. Farm size in many studies tends to have a positive influence on access to Climate information services. In order to reduce the magnitude of loses (Onyeneke, 2023), larger-scale farms had enlarged access to CIS (Muema, 2018; Oyekale, 2015) Furthermore, and larger-scale farms are more elastically on capacity to adjust farm activities according to the climate information. Larger farms are more likely to adopt climate change adaptions practices to maintain their profitability (Ogisi and Begho, 2023). According to the marginal effect estimates, a unit (Dynym) increase in farmers' land size is detected to lead to an increase of 0.1% reduction in the probability to pay for climate information.

Total farms income has a significant (*p=0.08<10%)* effect on farmers' WTP decision, but as it can be seen from Table 10b, the total income of the farm has no marginal effect on WTP. According to Muema et al. 2018 the existence of another off-farm source of income raises the probability to use CIS by 7 %. Less resourced smallholder farmers are not likely to access CIS (Antwi-Agyei, 2021). Also farmers with an alternative source of income and farmers with larger land sizes had increased access to online platforms (Fay Buckland and Campbell., 2021).

The results indicate that rented land, production cost, income derived from medicinal plants, does not have a statistically significant impact on farmers' WTP for early warning climate system. (Tables 7a and 7b).

4. **Conclusions and Recommendations**

This study emphasizes that the access of early warning climate system and use of climate information can help smallholder farmers in making decisions, but there is a black side how this type of information affects farm income and adaptation strategies to these climatic changes.

This study identified the socioeconomic factors influencing access to and willingness to pay for climate information by smallholder farmers in north Albania, region of "Malesi e madhe". Findings show that access to and the willingness to pay for climate information by smallholder farmers have been detected to be influenced by both individual and environmental specific factors. The marginal effects logistic regression shows statistically significant differences in the predictors of climate information access as well as willingness to pay by smallholder farmers. It can be concluded that climate information accessibility and the willingness to pay for climate information among farmers are predicted by factors such as farming experience, farm age, and access to internet.

It showed that a large majority (85.6%) of farmers expresses awareness about climate changes in the last 5 years. Findings highlight that the majority of smallholders are aware of duration of drought (95%), increase of number of hot days (88.1%) and presence of weeds (59.7%) which impact the productivity of medicinal plants. From the findings farmers perceive that climate changes have affected the quality of medicinal plants

in the last 5 years, by increasing the number of hot days (96%), number of rainy days (93.5%) and duration of drought (86.6%), also farmers perceive that climate change has impacted the yield level by duration of drought (87.1%), increase of hot nights (78.1%) and number of rainy days (76.1%).
Results suggest that the provision of climate information should be defined and adopted to meet the needs of smallholder farmers with different socioeconomic backgrounds to enable farmers manage climate risks and build reasonable adaptive capacity.

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