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Valuing meteorological services in resource-constrained settings: Application to smallholder farmers in the Peruvian Altiplano

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A B S T R A C T

Changing climate and weather patterns have resulted in reduced agricultural productivity in some parts of the world and put pressure on global food security. Availability and improved quality of meteorological information is seen as a potentially propitious means of adaptation to changing climate conditions. Forecasts of extreme weather events are especially valuable in resource-poor settings where climate-related vulnerability is high, such as for smallholder farmers in low-income countries. In this paper we provide estimates of frost warnings valuation in the context of small-scale quinoa production in the Peruvian Altiplano using a cross-disciplinary approach. We first present a detailed contextual assessment of quinoa production in the study region based on agrometeorological and socio-economic data that was obtained through a representative farm household survey conducted in December 2016. Building on this assessment, we propose a stochastic life-cycle model, replicating the lifetime cycle of a quinoa-producing household, in order to derive a theoretical valuation of frost warnings. Calibrating the model to our data we provide estimates of frost-warning valuation which are in the range of $30–50 per household per year, depending on the forecast accuracy and agents' risk aversion. In a last step, using the observational data from the farm household survey, we show that access to existing meteorological services is empirically associated with avoided losses in agricultural production that amount to $18 per average household and per year. Our findings point to high climate vulnerabilities of smallholders in the Peruvian Altiplano and potentially large welfare gains from incorporating improved meteorological services into their decision-making process. At the same time, we highlight that attention must also be paid to complementary non-meteorological interventions that bear the potential to leverage these welfare gains.

1. Introduction

Weather and climate influence natural and human living conditions and thereby also the basis for sustainable development. A broad range of livelihood decisions is intimately linked to the state of the atmosphere which is particularly true for agrarian communities in developing countries that depend directly on weather- and climate-sensitive natural resources for income and well-being.

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In fact, smallholder farms play an essential role for food security with 70% of food calories for people living in Latin America, sub-Saharan Africa, South and East Asia being provided by farmers using less than five hectares of land (Samberg et al., 2016). The heavy dependence of small-scale agriculture on sunshine, rainfall and temperature is mirrored by a recent climate-induced increase in global food insecurity (Food and Agricultural Organization of the United Nations, 2017). Furthermore, anthropogenic climate change is adding new challenges to agricultural systems through increased frequencies and severity of extreme events such as droughts and intense precipitation, as well as shifts in temporal distribution of rainfalls (IPCC, 2019). Vulnerable populations in developing countries are particularly exposed to such calamities due to insufficient financial and technical capacities to manage climate risks (IPCC, 2014).

Meteorological services are supposed to channel weather and climate information to individuals or organizations in a way that supports decision-making. It has been widely shown that the use of meteorological services in economic activities creates societal value through improved outcomes of weather- and climate-sensitive decisions and serves as a possible adaptation strategy to changing climate conditions (Zillman, 2005). Furthermore, due to its risk-reducing mechanism, improved availability of and access to meteorological information is considered a key component for increasing climate resilience and societal preparedness for agrarian communities in developing countries (Wilby et al., 2009). Several techniques have been used to assess these benefits including decision-making models, contingent valuation analysis, as well as qualitative and participatory studies (Freebairn and Zillman, 2002; Soares et al., 2018). A substantial body of this literature focuses on quantifying the monetary value for different sectors including agriculture, energy, water, and transport. Different literature reviews show that in most valuation studies, in addition to the focus on monetary benefits, there is a strong emphasis on the expected value of meteorological services, i.e. *ex ante* use of the services, rather than on the analysis of observational data that describe the actual service utilization, i.e. *ex post* use of the services, (Meza et al., 2008; Soares et al., 2018). *Ex ante* approaches to quantify the potential value of meteorological services generally rely on simplifying assumptions which bear the risk of underestimating the complexity of the users' weather- and climate-sensitive decision processes and, thus, possibly over- or under-estimate the actual benefit of the service (Waldman et al., 2020). The empirical character of *ex post* valuations can contribute to a more realistic understanding of the actual value of meteorological services and provide insights into how these services can be better tailored to user needs. Building on a review of valuation studies of seasonal climate forecast, Soares et al. (2018) conclude that the literature could considerably benefit from integrated methodological approaches combining *ex ante* and *ex post* valuations as well as paying more attention to participatory studies.

An additional issue that is frequently discussed in the valuation literature is the decision-making context that shapes the value of the meteorological services. Analyzing and quantifying specific values that correctly reflect the broader cultural, socio-economic, and institutional context requires a nuanced understanding of target populations' livelihood decision-making process and climate vulnerabilities. For example, not all potential beneficiaries actually make use of meteorological information as the scope of the services does not fit the end-users' requirements or due to costs related to information analysis and decisions adjustment. Moreover, the proposed services must be complementary with end-users capacities to act upon the information. This is particularly true for smallholder farmers in low- and middle-income countries where the effective use of these services remains a considerable challenge due to prevailing livelihood constraints (Patt and Gwata, 2002; Vogel and O`Brien, 2006; Hansen et al., 2011) and the regulatory environment (Orlove and Tosteson, 1999). Paying adequate attention to the contextual environment where the service utilization is supposed to occur is typically challenging due to limited socio-economic data availability at sub-national level, particularly in resource-constraint settings (Turvey, 2007; Azzarri et al., 2016).

It is well-established that small-scale agriculture on the Peruvian Altiplano is highly vulnerable to climate and weather hazards due to its high exposure related to the mountainous topography and inter-annual climatic variation (Vargas, 2009). Recent vulnerability research in this region has shown that the integration of weather forecasts in agricultural decision-making bear the potential to positively influence socio-economic outcomes at the farm household level (Sietz et al., 2012). In the face of competing development targets, there is a strong need for an accurate understanding of the returns to public investments in meteorological service provision and the appropriate level of funding, which is particularly true for highly resource-constrained settings such as small-scale agricultural production in Peru (WMO/Madrid Action Plan). While monetary quantification through economic analysis is one possible way to assess the value of meteorological services, it has been shown that there are some benefits that cannot be meaningfully quantified, which calls for more methodological diversity in value assessment (Vargas, 2009). To date, despite the potential benefits of such interventions, little systematic evidence is available on the economic value of meteorological services in the Peruvian Altiplano (Lechthaler and Vinogradova, 2017).

The present paper contributes to the literature in three ways: first, we offer an economic valuation of user-tailored meteorological service provision for smallholder quinoa farmers on the Peruvian Altiplano. Second, we build the valuation on a thorough empirical analysis of end-users' decision-making context. Third, we quantify the value exploiting an integrated methodology, which combines an *ex ante* approach based on a decision-making model, and an *ex post* approach that analyzes observational data. The methodology consists of the following elements: In a first step, we assess the agrometeorological and socio-economic context focusing on climate-related vulnerability based on representative primary data collected through a farm household survey in the study region. Results serve to derive a hypothetical meteorological service tailored to the target population and to estimate parameters needed for the economic valuation model. In a second step, the economic benefits of the meteorological service are quantified by calibrating a stochastic life-cycle model (*ex-ante*) and compared to empirical estimates of avoided production losses using multivariate regressions that are based on farm household data (*ex-post approach*). Building on the initial contextual assessment, the potential economic value of the service is then interpreted and discussed against the background of possible implementation constraints.

Results show that smallholder quinoa farmers are particularly exposed to frost events. The valuation model indicates that the benefit of a tailored meteorological service in the form of a frost warning is in the range of $30–50 per household per year, depending on the forecast accuracy and agents' risk aversion. Empirical estimates confirm that access to *currently available* meteorological information in the study region is significantly associated with avoided crop loss which amounts to approximately $18 per household per year. This figure may seem to be relatively low. However, it reflects to a large extent the quality of the current services and the utilization rate. Hence, our findings point to the need of (i) improving the quality of the data that underpin the meteorological service as well as (ii) overcoming prevailing user constraints in the target population, such as understanding of the forecast and trust in the service provider. Apart from interventions that are specific to the meteorological service, this study also highlights the need to pair improvements of meteorological interventions with complementary vulnerability-reducing measures, which include better social and financial protection mechanisms.

The remainder of this paper is organized as follows. Section 2 summarizes the methodology of the farm household survey. Section 3 provides the results of the socio-economic and agrometeorological context assessment. Section 4 presents the *ex-ante* valuation model, while Section 5 presents the *ex-post* empirical assessment. Section 6 discusses the results and provides policy recommendations. Section 7 concludes.

2. The farm household survey

In a first step, we establish an empirical description of quinoa farmers' livelihoods on the Peruvian Altiplano in order to gain an in-depth understanding of climate-related vulnerabilities as well as socio-economic and production characteristics. This contextual assessment will then inform the design of the economic model and provide parameter estimates for the model calibration. To that end, we collected primary data in December 2016 through a cross-sectional household survey based on a representative sample of 726 individuals in the region of Puno in south-eastern Peru. The study population consisted of smallholder farmers defined as those farm households that own or cultivate less than 10 ha of land. The design of the survey and sample size calculation was guided by a focus on collecting the minimal essential data required to obtain a given precision of the key indicators. To ensure representativeness of the data, study participants were selected based on a cluster sampling design in the region of Puno. We randomly selected 15 districts and in each of them 5 villages. Within each village, smallholder farmers were selected using a convenience sampling approach based on their availability on the day of data collection. Within the farming household, the interview was conducted with the member first responsible for agricultural production without specific consideration of demographic selection criteria. In each district, we interviewed at least 50 participants. From the 750 potential interviews, 726 were included for analysis based on data quality and completeness criteria.

A structured questionnaire was designed to elicit socio-economic and production-related characteristics of the target population. Moreover, to properly describe the socio-economic mechanism through which the meteorological service may generate benefits, specific questions have been included to characterize farmers' climate-related vulnerability. It has been widely shown that the measurement of vulnerability to environmental change is conceptually and practically challenging Adger (2006) with no commonly accepted approach available. For the present study we use the definition provided by the Intergovernmental Panel on Climate Change (IPCC) describing climate vulnerability as a function of the system's exposure and sensitivity to adverse climate hazards, and of its adaptive and coping capacity (IPCC, 2014). Exposure and sensitivity was measured by the number of exposures to adverse weather or climate shocks during the last five years (reported by farmers) and the corresponding severity, which was measured on a 5-point Likert scale (ranging from hardly any losses to total loss). Adaptive capacity was described as the reported number of management options available in the face of specific weather or climate hazards. The coping capacity was measured through access to social and financial protection mechanisms in the aftermath of adverse events as well as the presence of specific individual strategies. Finally, to better understand possible implementation constraints, the questionnaire covered specific questions on utilization of and perceptions on available meteorological information.

In preparation of the field survey, we obtained detailed contextual information on quinoa farming in Puno through 15 semi-structured interviews with local agronomists, civil authorities and project officers from non-governmental organizations, which served as a basis for the survey and questionnaire design. The final structured questionnaire was pretested twice and further adapted to the local context and smallholders' understanding.

To group respondents by wealth category, we created a wealth index applying principal component analysis to participants' responses on asset possessions (Filmer and Pritchett, 2001). This data reduction technique produces linear combinations of the variables (components) with the first component typically explaining a high proportion of the variation. Based on the asset index, households have then been assigned to three categories: low-wealth group (below the 40th percentile), middle-wealth group (below the 80th percentile), and the high-wealth group (above the 80th percentile).

In the next section, we present the key insights from the farm household data.

3. Socio-economic and agrometeorological context

The study site

The study site lies in the Peruvian Altiplano at average altitudes between 3800 and 4000 m a.s.l. covering an area of 72000 km^2. The area has a subtropical highland climate characterized by arid conditions in austral winter from May to September and a wet summer from October to April (Peel et al., 2007) with occasional frosts during the nights (SENAMHI-FAO, 2010). Puno has a population of 1.4 million inhabitants (4.5% of the country) and 43% of the economically active population is working in the agricultural sector of which 85% are smallholders with <10 ha of farm land (Minam, 2013). Due to a short growing season (<180d), the extensive agricultural production, the low technological development as well as climate and soil constraints, the agricultural productivity lies

Table 1
Summary statistics of socio-economic characteristics.

Variable	Low wealth Mean (n = 290)	Middle wealth Mean (n = 287)	High wealth Mean (n = 184)	Sample average Mean (n = 726)
Socio-demographic characteristics				
Sex (M/F)	49%/51%	44%/56%	52%/48%	48%/52%
Age	53	45	45	48
Formal education	82%	92%	97%	90%
Illiteracy rate	21%	9%	5%	13%
Income and farm				
Agricultural land [ha]	1.45	2.36	2.90	2.10
Access to irrigation	1.7%	2.1%	3.4%	2.2%
Annual income [USD]	1340	2393	3663	2233
< USD 1.90* per day	38%	13%	8%	22%
Self-consumption rate	65%	67%	55%	64%
Coping strategies after adverse events				
Access to crop insurance	2%	2%	3%	2%
Access to bank credits	1%	4%	14%	5%
Access to external assistance	8%	7%	3%	7%
Engage in casual work	49%	66%	64%	58%
Reduce food consumption	47%	41%	52%	46%
Meteorological information				
Informed about events	79%	80%	90%	82%
Trust in accuracy	60%	53%	58%	58%
Do not fully understand information	44%	46%	26%	42%

Notes: PPP Conversion factor: 1.57; Currency rate: 1 PEN = 0.29 USD (December 2016).

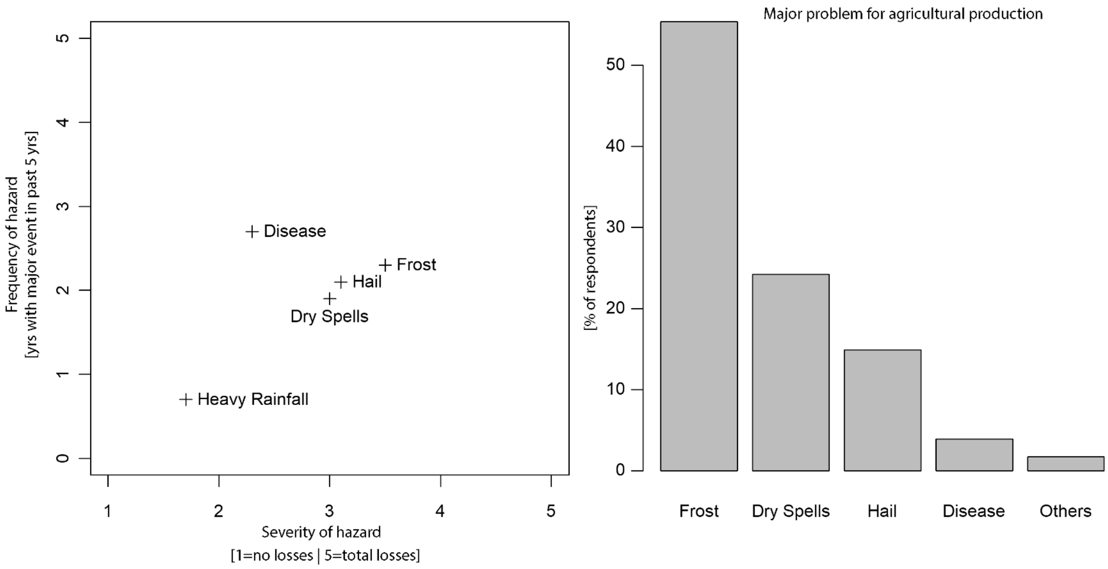


Fig. 1. Hazards and exposure.

below the national average. The largest part of the agricultural production is rain-fed and the main food crops are potatoes, quinoa and broad beans which are cultivated during the austral summer (from October to April).

Socio-economic context

Table 1 shows socio-economic and demographic characteristics of the survey participants. Results generally reveal that low wealth farmers are socially and economically worse-situated as compared to high income farmers. Between 82% and 97% of the farmers attended a formal education with the high wealth group having the highest proportion of educated individuals and the lowest illiteracy

Table 2
Benchmark calibration.

Planning horizon, days	T	365
Duration of safe season*, days	τ	275
Rate of time preference	ρ	$0.1/T$
Elasticity of marginal utility	ε	0.8
Initial stock*, kg	S_0	185
Quinoa price, $/kg	p	1
Expenditure on prevention, $	Δ	$0.1pS_0$
Forecast accuracy	q	0.8

Notes: * indicates that the parameter is calibrated on the basis of the survey data.

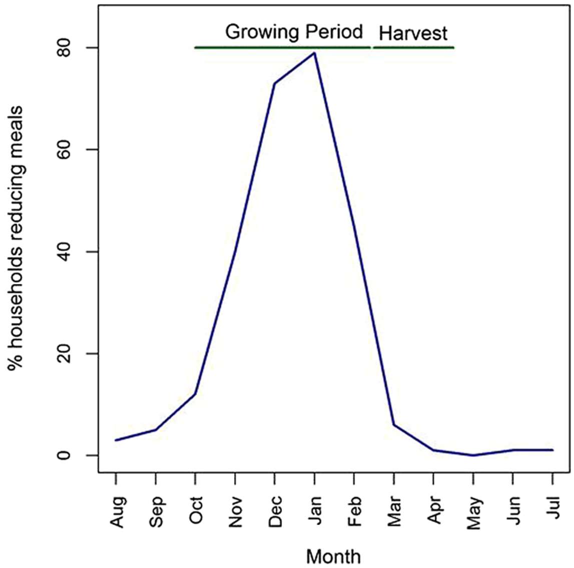


Fig. 2. Share of households reducing meals.

rate (5% in the high wealth group versus 21% in the low wealth group). The agricultural landownership varies between 1.45 ha and 2.9 ha with the high wealth farmers cultivating larger land. Cultivations are mostly rain-fed; only 2% of farmers on average have access to irrigation. Annual income ranges from 1340 USD in the low wealth group to 3663 USD in the high wealth group. Data show that 38% of farmers in the low wealth group and 8% of farmers in the high wealth group live with less then 1.90 USD per day. Furthermore, farmers strongly depend on their own agricultural production which indicates potentially high exposure to production shocks such as adverse weather and climate events. In particular, in the high wealth group, 55% of crop yields were self-consumed. Self-consumption is more prevalent in the low wealth group with the share of self-consumed crops being 65%.

Exposure, sensitivity and adaptive capacity

Climate and weather exposure of quinoa production varies with the type of climate hazard. Fig. 1 shows the likelihood of being affected by an adverse shock (reported number of years with major event during the past 5 years) and the severity of the according hazard in terms of average crop loss per risk type. Severity was measured on a 5-point Likert scale ranging from hardly any losses to total loss. We find that in terms of average loss per event, frost is the most important hazard type for the agricultural production followed by hail and dry spells (also including late start of the rainy season). In fact, on average more than half of the crops have been lost in case of a frost event during the growing season. Although pests and disease occur more frequently, these events have a lower impact on yields and are thus less important for the farmers in the region. These findings are corroborated by participants' answer about the major problem for the agricultural production. Frost was mentioned by more than half of the farmers being the most relevant problem. On the other hand, 93% of farmers claimed they could apply management options to protect their crops from frost shocks (principally anti-frost fire) if timely informed about the upcoming hazard.

Coping strategies

Coping strategies are described in Table 1. It can be seen that vulnerability to adverse production shocks is aggravated by a lack of social and financial protection mechanisms. In fact, on average only 2% of farmers reported to have crop insurance and only 5% have access to bank credits. Especially access to bank credits is skewed towards the high wealth group with 14% of high wealth farmers being able to get credit as compared to 1% in the low-wealth group. 7% of farmers have received external assistance after bad harvests with low wealth farmers being more likely to have access to emergency relief (8% of farmers as compared to 3% in the high wealth

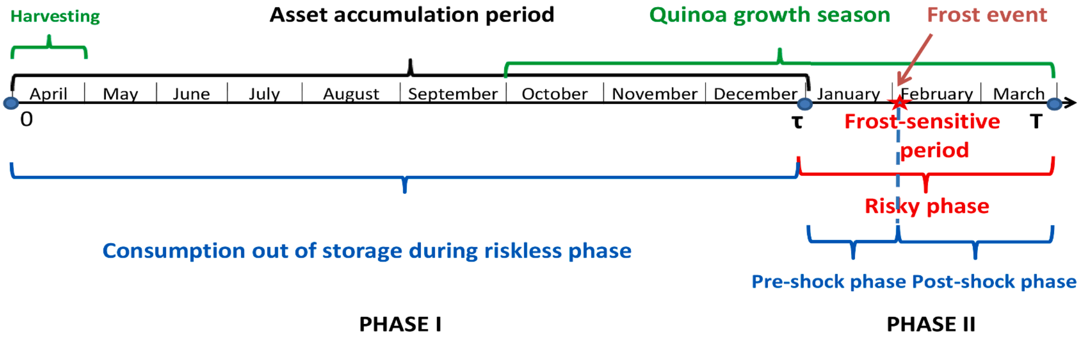


Fig. 3. Farming and phenological cycles.

group). In case of a major crop loss, the majority of farmers (58%) rely on casual external work and almost half of the farmers (46%) had to reduce food consumption. The largest percentage share of households who reduced meals pertains to the months of December-February, i.e. the peak of the growing season .

Utilization of meteorological information

Although 82% of the farmers reported to be regularly informed about upcoming weather events, only 58% think that the provided forecasts are accurate and informative enough about their specific area, while 42% claimed to have difficulties with understanding the information (see Table 1). Farmers from the high wealth group were more likely to access meteorological information as compared to the low wealth farmers (90% versus 79%). Also, high wealth farmers revealed a better understanding of the information with only 26% of participants claiming to have difficulties to interpret the information as compared to 44% in the low wealth group.

Building on these findings, the next section develops an economic model that mimics the quinoa production cycle and exposure to frost events in order to elucidate the economic value of access to meteorological information.

4. Ex ante perspective: Model of quinoa farming

4.1. Farming cycle

A life-cycle of a quinoa-farming household can be described by a sequence of identical farming cycles. Each farming cycle corresponds to one year and a representative household is assumed to be infinitely-lived. Time is continuous and indexed by t. We let the first day of April be the first day of the cycle and denote it by $t = 0$, while the end of the cycle, the last day of March, is denoted by $t = T$. We shall decompose the cycle into two phases, corresponding to a riskless and a risky period during the year. Since farmers are mostly exposed to crop losses through frost events during florescence from January to March, we shall refer to this period as the risky phase, or Phase II, while the riskless phase, Phase I, corresponds to all other months of the year, April - December. If we denote the first day of January by $t = \tau$, the duration of Phase I is $[0, \tau)$ and the duration of Phase II is $[\tau, T]$. The setup is illustrated in Fig. 3.

The objective of the household is to maximize the present value of welfare over the life-cycle, i.e. over a sequence of farming years. We assume that the instantaneous welfare function is given by $u(c_t)$, where c_t denotes current consumption, $u'(.) > 0$ and $u''(.) < 0$. Since each farming year is symmetric, we shall first focus on the optimal program within one such year and then proceed to the program over the whole life-cycle. The objective function of the household within one year can be written as

$$\max_{c,\ \widetilde{c}} \quad \int_0^\tau u\left(c_t\right)e^{-\rho t}dt + \mathbb{E}\left\{\int_\tau^T u\left(\widetilde{c}_t\right)e^{-\rho t}dt\right\},$$

where $\widetilde{c}_t$ stands for consumption rate in the risky phase, ρ is a constant rate of time preference and $\mathbb{E}$ denotes expectation operator with respect to the timing and intensity of the weather shock.Phase I

The farmer starts each yearly cycle with a stock of stored quinoa, denoted by S_0, inherited from the previous harvesting season. His activities during Phase I consist of consumption and saving. Saving is necessary for accumulation of precautionary capital, which will be used for remedial measures during the risky phase. His constraints over the first phase can be written as

$$\dot{S}_t = -R_t, \quad S_0 \quad \text{given}, \tag{1}$$

$$c_t = \alpha R_t, \tag{2}$$

where R_t denotes the usage of stored quinoa at time t (either for consumption or sales) and $\alpha \in [0, 1]$ denotes the share which goes to current consumption, to be specified below. The remaining share, $i_t = (1 - \alpha)R_t$, is used for capital accumulation, so that the stock of assets at the end of the first phase is equal to $k_\tau = \int_0^\tau p_t i_t dt$, where $p_t = p, \forall t$ is the market price of quinoa assumed constant over the cycle. Moreover, since access to banking services in our study region is rather low (5% on average), we assume that no interest can be earned on accumulated assets and no borrowing can take place.

Let us assume that the utility function takes the standard CRRA form, $u\left(c\right) = \frac{c^{1-\varepsilon}}{1-\varepsilon}$, where $\varepsilon > 0$ is the constant relative risk aversion coefficient. Then the solution to the optimization problem is characterized by a declining optimal consumption rate:[1]

$$c_t = c_0 e^{-\frac{\rho}{\varepsilon}t}, \quad c_0 = \frac{\alpha\rho/\varepsilon}{1-e^{-\frac{\rho}{\varepsilon}\tau}}\left(S_0 - S_\tau\right). \tag{3}$$

The stock of assets to be held on date τ is given by

$$k_\tau = \int_0^\tau p\left(1-\alpha\right)R_0 e^{-\frac{\rho}{\varepsilon}t}dt = \left(1-\alpha\right)p\left(S_0 - S_\tau\right). \tag{4}$$

The present value of welfare in Phase I is given by

$$W^I = \int_0^\tau u\left(c_t\right)e^{-\rho t}dt = u\left(c_0\right)\frac{1-e^{-\frac{\rho}{\varepsilon}\tau}}{\rho/\varepsilon}. \tag{5}$$

Phase II

The second phase is stochastic since it involves a random weather event. At the same time, the second phase corresponds to roughly the second half of quinoa growth season, during which the plant is particularly sensitive to low temperatures. The exact timing of a frost event is thus less important relative to the severity of the event. In other words, the most relevant factor for crop survival is how cold a particular night may happen to be. We shall model the intensity of a frost event by a random variable ω with the probability density function f_ω and support Ω. Furthermore, we shall assume that when a frost occurs, only a fraction $x(k_\tau, \omega)$ of the plantation survives until the end of the cycle. Denoting the stock of growing quinoa at time t by Q_t, we have

$$Q_{T_+} = \begin{cases} Q_{T_-}, & \text{if no frost occurs,} \\ x\left(k_\tau, \omega\right)Q_{T_-}, \quad x \in \left[0, 1\right), & \text{if a frost occurs,} \end{cases} \tag{6}$$

with $\partial x/\partial k_\tau \geqslant 0$ and $\partial x/\partial\omega > 0$.

Since neither the timing, nor the severity of the weather shock affect the current consumption of the household (they do affect the future harvest though), the objective of the household in Phase II, from the perspective of date τ, can be written as

$$\max_{\widetilde{c}_t} \int_\tau^T u\left(\widetilde{c}_t\right)e^{-\rho(t-\tau)}dt,$$

subject to the storage depletion constraint $\dot{S}_t = -\widetilde{c}_t, \ \forall t \in [\tau, T]$ and $S_T = 0$, i.e. the subsistence household completely depletes its food supply from the previous harvest by the end of the cycle. We also assume that the household does not accumulate any assets during the risky phase. This implies that the maximization problem above can be reduced to finding the optimal depletion rate of the storage stock. The solution is similar to the one obtained in Phase I, namely consumption declines at a rate $-\rho/\varepsilon$ from an initial starting point, given by:

$$\widetilde{c}_\tau = \frac{S_\tau\rho/\varepsilon}{1-e^{-\frac{\rho}{\varepsilon}\left(T-\tau\right)}}.$$

The time-τ welfare in Phase II can be obtained as:

$$W^{II} = \int_\tau^T u\left(\widetilde{c}_t\right)e^{-\rho(t-\tau)}dt = u\left(\widetilde{c}_\tau\right)\frac{1-e^{-\frac{\rho}{\varepsilon}\left(T-\tau\right)}}{\rho/\varepsilon} \tag{7}$$

and the present value of the overall yearly welfare becomes

$$W = W^I + e^{-\rho\tau}W^{II} = u\left(c_0\right)\frac{1-e^{-\frac{\rho}{\varepsilon}\tau}}{\rho/\varepsilon} + e^{-\rho\tau}u\left(\widetilde{c}_\tau\right)\frac{1-e^{-\frac{\rho}{\varepsilon}\left(T-\tau\right)}}{\rho/\varepsilon} \tag{8}$$

The optimal stock of quinoa to be held on date τ is such that the expected present value of marginal utility of consuming an extra unit of storage before time τ must be equalized with the present value of marginal utility of consuming it after τ. By differentiating (8) and setting the optimality condition to zero we obtain

[1] Such a declining pattern of consumption is clearly visible in our data. For instance Fig. 2 shows that the share of households who reduced their consumption increases starting from March and is the highest during December and January.

$$S_\tau = S_0 \frac{\alpha^{1-\frac{1}{\varepsilon}}\left(1 - e^{-\frac{\rho}{\varepsilon}\left(T-\tau\right)}\right)}{\alpha^{1-\frac{1}{\varepsilon}}\left(1 - e^{-\frac{\rho}{\varepsilon}\left(T-\tau\right)}\right) + e^{\frac{\rho}{\varepsilon}\tau} - 1}.$$

Hence, we may write

$$c_0 = \psi_1(\alpha)S_0, \quad \widetilde{c}_\tau = \psi_2(\alpha)S_0, \quad \text{where} \tag{9}$$

$$\psi_1\left(\alpha\right) = \frac{\alpha\rho/\varepsilon}{\alpha^{1-\frac{1}{\varepsilon}}\left(e^{-\frac{\rho}{\varepsilon}\tau} - e^{-\frac{\rho}{\varepsilon}T}\right) + 1 - e^{-\frac{\rho}{\varepsilon}\tau}}, \tag{10}$$

$$\psi_2\left(\alpha\right) = \frac{\alpha^{1-\frac{1}{\varepsilon}}\rho \Big/ \varepsilon}{\alpha^{1-\frac{1}{\varepsilon}}\left(1 - e^{-\frac{\rho}{\varepsilon}\left(T-\tau\right)}\right) + e^{\frac{\rho}{\varepsilon}\tau} - 1} \tag{11}$$

and the yearly welfare:

$$W = u\left(S_0\right)\Psi\left(\alpha\right), \quad \Psi\left(\alpha\right) = \psi_1^{1-\varepsilon}\frac{1 - e^{-\frac{\rho}{\varepsilon}\tau}}{\rho/\varepsilon} + \psi_2^{1-\varepsilon}\frac{e^{-\frac{\rho}{\varepsilon}\tau} - e^{-\frac{\rho}{\varepsilon}T}}{\rho/\varepsilon}. \tag{12}$$

Note that the yearly welfare depends on (i) the optimal choice of consumption propensity α, to be discussed below, and on (ii) the stock of quinoa at the beginning of the cycle. The latter is equal to the harvest of the previous farming year and is subject to the weather shock, as described in (6). Therefore, the lifetime welfare of the household is a random variable. Availability of a frost warning which predicts severity of the frost thus has a potential for increasing the lifetime welfare by reducing or eliminating harvest losses. The next section describes this mechanism and provides a metric for evaluating welfare-enhancing effect of a frost warning.

4.2. Valuation of frost forecast

Availability of a frost forecast (FF) may serve as a mechanism for enhancing a rural households' welfare if a warning is provided in a timely manner, so that farmers have sufficient time to apply preventive measures and thus avoid crop losses.[2] As an example, the main provider of weather forecasts in Peru (Senamhi), issues a four-level frost warning, which is released two to three days in advance on their webpage and disseminated via radio broadcasts and text messages to reach remote rural areas. Where effectively implemented, local authorities and sectoral experts are supposed to overlay the warning with their agronomic knowledge and advise local communities and individual farmers. Based on the received information, the farmers, in turn, decide on the implementation of protective measures.

The value of the frost forecast can be gauged by the value of avoided crop losses. Hence, it depends not only on the characteristics of the forecast itself (such as accuracy, skill, resolution, transparency, ease of understanding) but also on the characteristics of the user and the user's environment. In particular, the valuation of the forecast will depend on the farmer's prior information about weather shocks and ability to proactively take measures based on this information. We shall therefore distinguish two cases. In the first case, referred to as "static response", the farmer does not take into account any possible variations in weather patterns and thus expects that a predefined amount of prevention will suffice to protect the crop. In the second case, referred to as "proactive response", the farmer decides on the optimal prevention measures given the knowledge about the distribution of the frost intensity. This information is based either on traditional environmental weather predictors, transmitted from generation to generation, and/or on the meteorological service (scientific knowledge), which is assumed to be superior in terms of accuracy. In fact, our survey revealed that one out of two farmers favors traditional indicators over science-based information which was mainly due to a lack of trust in national weather services. In what follows we examine the "static" case and relegate the analysis of the second case to the appendix.

Static Response

In our sample, more than 80% of farmers receive warnings about upcoming weather events using different types of currently available meteorological information. However, over 40% of farmers do not fully understand the provided information. This suggests

[2] A typical prevention measure consists of anti-frost fires, e.g. installing tires along the perimeter of the plantation and burning them on a frosty night.

that a large proportion of households either relies on other means of predicting weather or does not attempt to make any predictions at all. In the latter case a similar amount of prevention will be applied from one farming year to another. In this case of “static response” we assume that a farmer expects that installation of preventive measures in the amount Δ will help prevent crop losses.[3] He ignores (or does not understand) inter-annual variations in weather patterns and thus does not take into account the weather shock ω (or its distribution) when choosing the propensity to consume. The farmer thus accumulates $k_\tau = \Delta$, which implies that the optimal propensity to consume, α^*, is an implicit solution to[4]:

$$\alpha p S_0\left(e^{\frac{\rho}{\varepsilon}\tau}-1\right)+\alpha^{1-\frac{1}{\varepsilon}}\Delta\left(1-e^{-\frac{\rho}{\varepsilon}\left(T-\tau\right)}\right)=\left(pS_0-\Delta\right)\left(e^{\frac{\rho}{\varepsilon}\tau}-1\right) \tag{13}$$

Given α^*, the optimal consumption rates and yearly welfare can be found from Eqs. (9)–(12). The total lifetime welfare, however, is a random variable due to the presence of a random weather shock ω. The *expected* total lifetime welfare can be obtained as a discounted sum of the yearly welfare over an infinite planning horizon:

$$\begin{aligned}\mathbb{E}_\omega[W]= & \ \mathbb{E}_\omega\int_0^\infty W_i\left(S_{0,i}\right)e^{-\rho i}di= \\ = & \ \mathbb{E}_\omega\Psi\left(\alpha^*\right)\int_0^\infty u\left(S_{0,i}\right)e^{-\rho i}di=\Psi\left(\alpha^*\right)\int_\Omega\left\{\int_0^\infty u\left(S_{0,i}\right)e^{-\rho i}di\right\}f_\omega d\omega.\end{aligned} \tag{14}$$

Recall that the stock of quinoa at the beginning of the yearly cycle is equal to the harvest of the previous farming cycle. We can therefore write generically $S_0 = Q_{T_+} = x(k_\tau,\omega)Q_{T_-}$. Inserting this into the equation above we get

$$\mathbb{E}_\omega\left[W\right]=\Psi\left(\alpha^*\right)\int_\Omega\left\{\int_0^\infty\frac{\left(x\left(k_\tau,\omega\right)Q_{T_-}\right)^{1-\varepsilon}}{1-\varepsilon}e^{-\rho i}di\right\}f_\omega d\omega=\frac{\Psi\left(\alpha^*\right)Q_{T_-}^{1-\varepsilon}}{\rho(1-\varepsilon)}\int_\Omega x(\Delta,\omega)^{1-\varepsilon}f_\omega d\omega. \tag{15}$$

We shall assume that FF is in general not perfect. Meteorological information is often subject to errors, which can be classified into Type 1 and Type 2 error. Type 1 error refers to a situation where the forecast predicts no event, while an event actually occurs. Type 2 error refers to a situation where the forecast predicts an event, while no event actually occurs. This is also referred to as “false alarm”. In our analysis below we shall assume that Type 2 error of FF is negligible because such an error will ultimately not lead to welfare losses for a farming household. This is in contrast to Type 1 error, which can lead to substantial crop losses (more than 60% on average in our data). We therefore focus on Type 1 error only and assume that FF is characterized by the “forecast accuracy” or quality, which we denote by $q\in(0,1]$. The value $q=1$ signifies perfect forecast quality, i.e. a forecast which is always correct. A value of less than unity, say 0.8, signifies that FF correctly predicts a frost event only 80% of the time.

Suppose that a frost warning, if correct, guarantees that the entire plantation survives the weather shock, i.e. $x = 1$, provided that the amount of traditional prevention, Δ, has been invested. When such FF is available, the expected lifetime welfare becomes

$$W^{FF}=q\frac{\Psi\left(\alpha^*\right)Q_{T_-}^{1-\varepsilon}}{\rho(1-\varepsilon)}+\left(1-q\right)\mathbb{E}_\omega\left[W\right]. \tag{16}$$

The first term represents the deterministic part of the lifetime welfare which prevails q percent of the time (when the forecast is correct and the entire crop plantation survives). The second term is the expected welfare which accrues in the remaining $1-q$ percent of the time when Type 1 error occurs.

The contribution of FF to the lifetime welfare gain can be found by computing a percentage increase in consumption (when FF is not available) needed to achieve W^{FF}. Let us denote such percentage increase in consumption by z.[5] Then we have

$$\frac{\Psi\left(\alpha^*\right)\left(zQ_{T_-}\right)^{1-\varepsilon}}{\rho(1-\varepsilon)}\int_\Omega x(\Delta,\omega)^{1-\varepsilon}f_\omega d\omega=\frac{\Psi\left(\alpha^*\right)Q_{T_-}^{1-\varepsilon}}{\rho(1-\varepsilon)}\left[q+\left(1-q\right)\int_\Omega x(\Delta,\omega)^{1-\varepsilon}f_\omega d\omega\right], \tag{17}$$

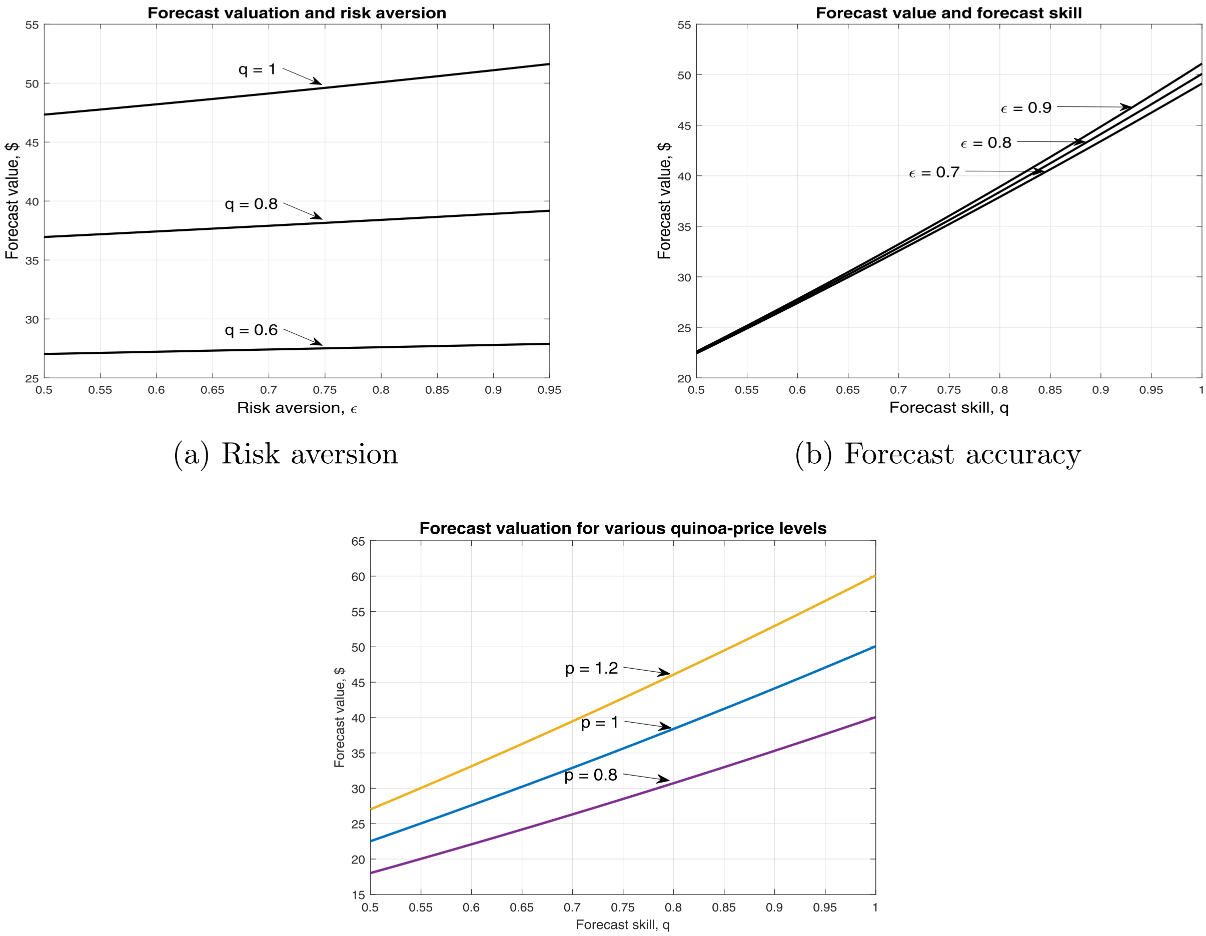
implying that

[3] In reality, farming practices evolve dynamically and change from year to year, depending on the specificities of that particular farming year, even without access to scientific knowledge about weather conditions. We may think about all these dynamic practices leading to the same outcome, namely prevention of crop losses. The time-invariant amount Δ may thus capture all the costs associated with one or another prevention mechanism. We return to this point in the discussion section (Section 6).

[4] Eq. (13) has a unique solution, which satisfies $\alpha\in(0,1)$, if $\varepsilon\geqslant 1$ and two solutions if $\varepsilon\in(0,1)$. In the latter case, the largest of the two is chosen.

[5] An alternative way of deducing the valuation of frost warnings is to compute a percentage increase in welfare which is generated by the availability of the warning, i.e.:

$$FFV=\frac{W^{FF}-\mathbb{E}_\omega[W]}{\mathbb{E}_\omega[W]}=q\left(\frac{1}{\int_\Omega x(\Delta,\omega)^{1-\varepsilon}f_\omega d\omega}-1\right)=z^{1-\varepsilon}-1.$$



(a) Risk aversion (b) Forecast accuracy

(c) Quinoa price

Fig. 4. Forecast valuation for alternative calibrations of risk aversion, forecast accuracy and quinoa price.

$$\frac{\Psi(\alpha^*)\left(zQ_{T_-}\right)^{1-\varepsilon}}{\rho(1-\varepsilon)}\int_\Omega x(\Delta,\omega)^{1-\varepsilon}f_\omega d\omega = \frac{\Psi(\alpha^*)Q_{T_-}^{1-\varepsilon}}{\rho(1-\varepsilon)}\left[q+\left(1-q\right)\int_\Omega x(\Delta,\omega)^{1-\varepsilon}f_\omega d\omega\right], \tag{18}$$

As an illustration, let us posit that $x = g(\Delta)\omega$ and that $\omega \sim Uniform\left(\underline{a},\overline{a}\right)$ with $\underline{a} \in \left[0,1\right)$ and $\underline{a} < \overline{a} \leq 1$. Furthermore, when traditional preventive measures are sufficient for crop preservation, $g(\Delta) = 1$. Then x is simply equal to ω and

$$\int_\Omega x(\Delta,\omega)^{1-\varepsilon}f_\omega d\omega = \int_{\underline{a}}^{\overline{a}} \omega^{1-\varepsilon}d\omega = \frac{\left(\overline{a}^{2-\varepsilon} - \underline{a}^{2-\varepsilon}\right)}{2-\varepsilon}$$

and thus

$$z^{Uniform} = \left[\frac{q(2-\varepsilon)}{\overline{a}^{2-\varepsilon} - \underline{a}^{2-\varepsilon}} + \left(1-q\right)\right]^{\frac{1}{1-\varepsilon}} \tag{19}$$

Alternatively, we may posit $\omega \sim Beta(a,b)$, then $\int_\Omega x(\Delta,\omega)^{1-\varepsilon}f_\omega d\omega = \int_0^1 \frac{\omega^{(1-\varepsilon)(a-1)}(1-\omega)^{b-1}}{B(a,b)}d\omega = \frac{\Gamma(a+1-\varepsilon)\Gamma(a+b)}{\Gamma(a)\Gamma(a+b+1-\varepsilon)}$ and

$$z^{Beta} = \left[\frac{q\Gamma(a+1-\varepsilon)\Gamma(a+b)}{\Gamma(a)\Gamma(a+b+1-\varepsilon)} + \left(1-q\right)\right]^{\frac{1}{1-\varepsilon}}, \tag{20}$$

where $B(a,b)$ is the beta function and $\Gamma(.)$ is the gamma function. Note that if the traditional prevention measures are not sufficient, on average, to preserve the entire crop ($g(\Delta) < 1$), then the percentage increase in consumption is larger, i.e. the frost warning is more valuable for any given quality q.

4.3. Numerical illustration

To illustrate the computation of a frost warning valuation we assume that the survived crop share, ω, is distributed according to the Beta distribution with parameters $a = 2.839$ and $b = 1.6241$. These values are calibrated to our data on Peruvian quinoa farmers, which we collected during the field survey in December 2016.[6] We also need to choose a value for the elasticity of marginal utility, ε, which we initially set equal to 0.8 and subsequently vary to check the sensitivity of the results to changes in this parameter. The calibration of the remaining parameters is summarized in Table 2.

With this calibration we find from Eq. (13) that the optimal consumption propensity, α^*, is equal to 0.6421, which is very close to the share of self-consumption reported by the farmers in our sample (see Table 1). Substituting this value into Eq. (12), we obtain the yearly welfare. We find that availability of FF improves yearly welfare by about 8.5%, which translates into a consumption gain of \$38.4 per year per household, assuming that an average household consumes 76 kg of quinoa per year and the received quinoa price is 1\$/kg. With an average quinoa cultivation area of 0.48 ha per household, we obtain a valuation of \$80 per hectare. This estimate undoubtedly depends on the chosen parameter calibration. Most of our parameter values are region-specific and can therefore be viewed as the best calibration choice. There is, however, one parameters which is individual-specific, namely the risk aversion coefficient ε. The results may also depend on our calibration of the forecast accuracy.

In order to check the sensitivity of our results to changes in ε and q, we plot the frost warning valuation for various calibration specifications. Fig. 4a shows that the frost forecast value (FFV for short) increases in risk aversion and in forecast accuracy. For an 80% forecast accuracy the value of FF ranges between \$37 and \$39.2 per year per household, while a forecast which is only 60% accurate on average is valued between \$27 and \$28. Fig. 4b confirms the positive relationship between FFV and accuracy and also shows that the valuation is relatively insensitive to changes in risk aversion ε. At the 80% forecast accuracy FFV changes from \$37.9 to \$38.9 as ε increases from 0.7 to 0.9. Fig. 4c shows the change in FFV due to a change in quinoa price. Because we assume that the forecast is valued by the dollar amount of quinoa consumption increase, any percentage change in quinoa price translates into the same percentage change in FFV.

5. Ex post perspective: Empirical verification

5.1. Estimation strategy

In a next step, we apply multivariate regression analysis to the farm household data to examine the sensitivity of the actual quinoa harvest to individuals' access to currently available meteorological information. Our results allow us to retrospectively assess the value of this information by quantifying avoided losses that are associated with better informed decision-making. In order to have a suitable metric to measure differences in harvest during the last season based on farmers' recall, the Relative Harvest Index (RHI) developed by Patt et al. (2005) has been adopted. The basic idea is to obtain a comparable indicator of recent adversity in crop losses by comparing last season's harvest with its historical baseline. More specifically, for farmer i, the RHI is defined as

$$RHI_i = \frac{(A_i - B_i)}{(G_i - B_i)}, \tag{21}$$

where A_i is the actual harvest and B_i and G_i are the harvests of a typical bad and good year respectively. To construct the Relative Harvest Index, harvest measures were obtained through a recall-based approach asking farmers to indicate the actual harvest volume as well as a typical bad and good harvest volume during the last 5 years. Thus, the RHI is 0 in case the actual harvest corresponds exactly to the bad year and 1 if it corresponds exactly to a good year. Being a unit-less and normalized measure ranging between 0 and 1, this index allows comparing crop outcomes of farmers operating under different production conditions.

The regression is then defined as follows:

$$RHI_{ijs} = \alpha_s + \gamma Z_{js} + \beta \mathbf{X_{ijs}} + \delta m_{ijs} + \epsilon_{ijs}, \tag{22}$$

with RHI_{ijs} being the Relative Harvest Index for farmer i in district j and province s. α_s denotes a province-specific effect and Z_{js} is a district-specific Gini coefficient accounting for income distribution. $\mathbf{X_{ijs}}$ contains different control variables measured at the level of the individual farmer including socio-economic information (wealth category, size of cultivated land, literacy, disability, and sex), reported number of exposures to different climate events during the last growing seasons (drought, frost, hail, heavy rainfall as well as pest and diseases), and the number of available management options as an indicator of the farmer's adaptive capacity. $\mathbf{X_{ijs}}$ further contains the number of frost days and precipitation quantity. These meteorological variables were obtained from weather stations in the study region. More specifically, each household has been matched with the number of measured frost days in January and February

[6] To calibrate a and b we need only two pieces of information about the distribution of losses, for example the median (or the mean) and the variance. We prefer to use the median in order to reduce the effect of outliers. Our data show that the median share of crop which "survived" frosts is 0.66 while the variance is 0.04237. From the properties of Beta distribution we know that $med\left[\omega\right] \approx \frac{a-1/3}{a+b-2/3}$ and $var\left[\omega\right] = \frac{ab}{(a+b)^2(a+b+1)}$.

Table 3
Regression results for predictors of the Relative Harvest Index (RHI).

Variable	Regression 1 RHI (n = 717)	Regression 2 RHI (n = 717)	Regression 3 RHI (n = 717)	Regression 4 RHI (n = 717)
Socio-economic indicators				
Wealth category 2	2.48	2.45*	2.17	2.37
	(2.25)	(2.26)	(2.26)	(2.26)
Wealth category 3	6.43**	6.44*	6.24**	6.62*
	(2.85)	(2.88)	(2.88)	(2.89)
Size of land	0.77	0.84	0.92	0.89
	(0.60)	(0.61)	(0.61)	(0.61)
Literacy	1.89	1.84	1.99	1.66
	(3.03)	(3.03)	(3.03)	(3.03)
Disability	2.08	2.07	1.96	1.97
	(2.06)	(2.07)	(2.06)	(2.06)
Sex	1.71	1.63	1.44	1.61
	(2.05)	(2.05)	(2.05)	(2.05)
Exposure to weather and climate				
Exposure to drought	−1.24	−1.26	−1.27	−1.24
	(1.11)	(1.11)	(1.11)	(1.11)
Exposure to frost	−2.86**	−2.79**	−2.67**	−5.84$
	(1.17)	(1.18)	(1.17)	(2.08)
Exposure to hail	−1.45	−1.52	−1.46	−1.28
	(1.06)	(1.07)	(1.06)	(1.07)
Exposure to rainfall	−1.36	−1.27	−1.39	−1.32
	(1.17)	(1.18)	(1.18)	(1.18)
Exposure to pests/diseases	1.73$	1.77$	1.80$	1.70$
	(0.58)	(0.59)	(0.59)	(0.59)
Collective factors				
Gini coefficients	−18.57*	−18.00*	−17.58*	−17.25*
	(9.77)	(9.84)	(9.84)	(9.82)
Adaptive capacity				
Informed about event	5.67**	5.78**	6.05**	6.08**
	(2.56)	(2.67)	(2.67)	(2.67)
Management options (MOs)	1.82$	1.82$	2.23$	0.09
	(0.68)	(0.69)	(0.73)	(1.37)
Measured weather/climate				
Frost days		0.47	2.27	2.48*
		(0.75)	(1.40)	(1.4)
Precipitation sum		−0.03	-0.025	−0.01
		(0.07)	(0.07)	(0.07)
Interaction frost days*MOs			-0.58	−0.63*
			(0.38)	(0.38)
Interaction frost exposure*MOs				0.92*
				(0.50)
R^2	0.21	0.21	0.21	0.22

Notes: Robust standard errors are used throughout (in parenthesis). Statistically significant: * $p < 0.1$, ** $p < 0.05$, $\$p < 0.01$

(during flowering of the quinoa plant) and the accumulated seasonal precipitation during the 2015/16 growing season obtained from a gridded data set derived from weather stations satellite images which is provided by the Peruvian National Weather Service (Senamhi Peru). m_{ijs} is a dummy variable having value 1 if the farmer has been informed about adverse climatic events during the last season.

5.2. Results

Table 3 presents estimation results based on ordinary least squares regressions. Variables are classified as socio-economic characteristics, meteorological exposure, collective factors, adaptive capacity and measured weather/climate. Column 1 does not include any measured weather and climate data, while column 2 does include the number of frost days and precipitation sum. Columns 3–4 additionally include the interaction terms between the number of applied management options and the intensity of relevant climate hazards. Results reveal that the socio-economic status, as reflected in the wealth group, is positively and significantly related to the RHI, whereas all other socio-economic variables (literacy, sex and disability to work) do not seem to play a significant role. Being part of the highest wealth category is related to an increase of around 6.4 percentage points in the RHI. Furthermore, in line with the descriptive results, farmers that reported to be more frequently exposed to frost, had a lower RHI. Reported exposure to frost is associated with a decrease of approximately 3 percentage points in the RHI. When the interaction between reported frost exposure and applied management options is taken into account (regression 4), the decrease in RHI reaches approximately 6 percentage points. Exposure to pest and diseases was positively related to the RHI which likely reflects the reverse relation between a high crop density and diseases transmission. The Gini coefficient is negatively and significantly associated with the RHI which indicates that relative crop losses are higher in villages with higher dispersion of income. An increase of inequality represented by 0.1 increase in the Gini coefficient is related to a decrease of 1.8 percentage points in the RHI. Furthermore, the number of reported management options available in case of adverse climatic events is also positively associated with the RHI which indicates that better adaptive capacity contributes to crop protection. A single management option is on average associated with an increase in the RHI by 1.8 percentage points. However, when accounting for the interaction between management options and the reported frost exposure (regression 4), this association loses its significance. The number of frost days and precipitation sum, as obtained from the gridded data, are not significantly associated with the RHI (except for specification 4). Finally, farmers that have been informed about the adverse climatic events exhibit a significantly higher RHI.

The RHI for informed farmers lies around 6 percentage points above the non-informed farmers pointing to the productive potential of better informed agricultural practices. Using data from our representative sample, a 6% increase in the RHI corresponds with an average increase in the current production volume A_i of 18.5 kg per household. Assuming a price of 1 USD per kg gives us an average value of roughly 18.5 USD per household (38.6 USD per hectare). This estimate corresponds to the *ex-ante* value of a frost forecast with a low accuracy (40%) as presented in Section 4 (see Fig. 4a). As the empirical *ex-post* valuation only shows the benefit based on access to the currently available information, which is supposedly imprecise due to low data quality and low density of measurement stations in the study region, it is plausible that the derived economic value is inferior to the potential value predicted by the *ex-ante* model.

6. Discussion and policy implications

Economic research generally shows that access to meteorological information is beneficial for target populations with benefits varying with the type of the service and the sector under consideration. Even though there exists a large body of such valuation studies, there is a strong emphasis on using *ex ante* methodologies that quantify the potential monetary value of meteorological services, as opposed to the actual value. Building on a contextual assessment of target populations climate-related vulnerabilities on the Peruvian Altiplano, the present paper applies and integrates an economic valuation combining an *ex ante* approach with an empirical *ex post* valuation that uses observational data on service utilization allowing for a more accurate description of the societal benefit of the services.

The contextual assessment reveals considerable vulnerabilities to weather and climate hazards of smallholder quinoa farmers. In fact, smallholder communities are characterized by low adaptive capacity and a lack of appropriate coping mechanisms in case of adverse meteorological events. Resilience to recover from weather- or climate-induced income shocks is low, with more than 20% of smallholder farmers living with less then 1.9 USD per day and social protection mechanisms being virtually absent. Smallholders rely to a large extent on their own production for food consumption with crop failure directly affecting food security. The situation is particularly critical for the economically disadvantaged populations with poor farmers being systematically more vulnerable to adverse climatic events.

Frost is the most relevant meteorological hazard for quinoa production in terms of frequency and severity. Results show that farmers can act upon frost forecasts to protect their crops. Ex ante economic benefits of this service applied to quinoa producers in Puno are estimated at 80 USD per hectare per year for a forecast accuracy of 80%. Given the total area of quinoa cultivated in 2015/2016 in Puno (35’694 ha) the linearly extrapolated value for the Puno region amounts to 2.9 million USD per year. At the individual level, the service would generate approximately 2% of the annual income and 0.7% of the agricultural share of GDP in the region of Puno (Minam, 2013). The per hectare value of the frost warning is considerably higher than the estimated hypothetical value of a climate service in the coffee sector (21 USD) and in the maize sector (14 USD) in the region of Cusco in Peru (Lechthaler and Vinogradova, 2017). This difference may reflect the fact that the value of the frost forecast was derived through a careful consideration of farmers’ vulnerabilities and prevailing management options which allowed to target a tailored service with a high potential economic benefit. On the other hand, the estimated value is based on a meteorological service with a single component (frost forecast) and economic benefits are likely to be increased by an integration of different types of information on hazards for which appropriate management options exist (such as dry spells). In this sense, the current estimates can be considered a lower bound with the service bearing the potential of higher benefits through a more comprehensive design. Furthermore, we do not explicitly model the variety of preventive mechanisms or traditional knowledge which could reduce crop losses but assume for simplicity that losses can be prevented provided that a given amount of assets is available. In this sense, we do not provide a detailed mechanism of loss prevention and abstract from all the details of the dynamic farming process. It is well-documented, however, that even in the absence of scientific information farmers make continuous adjustment to their farming practices based on their own experience or experience of others in the community (see, e.g. Ramisch, 2010).

Results further reveal that the economic value critically depends on the quality of the meteorological service with economic benefits being positively related to the forecast accuracy. Looking at the empirical estimation, access to meteorological information is associated with a potential gain of 38.6 USD per hectare through avoided losses which lies considerably below the ex-ante predicted benefits. This divergence is likely to reflect the low quality of meteorological services currently provided in the region of Puno, which is mainly driven by limited availability of meteorological data or low effectiveness of management options. To realize the potential economic benefit of the frost forecast, data quality, station density, and meteorological service provision needs to be improved in the study region. It should be noted, though, that results also indicate that improving the forecast without complementary measures will not be sufficient to realize its full value.

The present findings further suggest that, despite the economic potential tailored meteorological services hold for the target populations, the actual service provision must go beyond the pure technical supply in order to effectively reduce the high vulnerability and enable economic benefits. First, although a great part of smallholders make use of existing information channels (mainly radio), these actual services are critically perceived by farmers in terms of accuracy and comprehension. This is particularly true for the more disadvantaged farmers where comprehension of the information is weak. Participatory approaches must therefore be envisaged to develop user-friendly services that involve the target communities, the sectoral experts, as well as the providers of meteorological services. In order to ensure equitable access to the services, attention must be paid to the inclusion of the poorest households as they tend to be more vulnerable than their wealthy counterparts (Soares et al., 2018). Furthermore, there is also a need to examine the potential for meteorological services to exacerbate existing inequities. Wealthy or otherwise powerful individuals or groups are generally more able to take part in participatory activities unless specific effort is made to ensure that disadvantaged or marginalized groups can equally shape the final forecast products. Second, it should be noted that improved meteorological information is only one element for reducing socio-economic vulnerability to meteorological shocks. Although better informed decision-making bears the potential to protect crops by strengthening ex-ante preparedness, adverse consequences of these hazards cannot be completely avoided. More context-specific research and advisory is required to establish effective management measures that are complementary to meteorological services. Considering the lack of social protection mechanisms and access to financial markets in the Puno region, particular attention should be paid to enhancing coping strategies for overcoming economic insecurity. Next to disaster relief in case of emergencies, improved financial coverage and inclusion should be foreseen that brings vulnerable smallholders into formal financial systems.

7. Conclusions

Weather- and climate vulnerability for smallholder quinoa farmers is high in the Peruvian Altiplano in the region of Puno where communities are characterized by low adaptive capacity and a lack of appropriate coping mechanisms. Exposure to frost events is particularly harmful for quinoa production with crop failure crucially threatening farmers' income stability and food security. A tailored frost forecast bears the potential to considerably improve the end-users' socio-economic status generating a yearly benefit of 80 USD per hectare. To actually realize this benefit, meteorological data quality must be improved to achieve a sufficient forecast accuracy. Furthermore, prevailing trust in and comprehension of meteorological information is low, which requires considerable efforts to make an according service useful and beneficial for the target population. Next to improving farmers' preparedness through better access to meteorological services, appropriate financial mechanisms should be made available in order to strengthen coping mechanisms in the aftermath of an adverse meteorological event.

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.

Appendix A

Proactive Response

In the "proactive response" scenario we consider farmers who do understand climate information and actively incorporate it in their livelihood decisions. They observe changing climate conditions and, in particular, average hazard rates and intensity of weather shocks. Their coping strategy consists of optimally choosing the propensity to consume α, in order to maximize the total lifetime welfare. Let us assume that frost arrivals follow the Poisson process with the hazard rate λ. The objective of the household is, as before, to maximize the total lifetime welfare, i.e. the sum of yearly welfare over an infinite planning horizon. The state variable of this problem is the storage stock Q which obeys the following dynamics over the lifetime. The stock Q is depleted to zero by the end of a year. At the end of each year it gets replenished with the new harvest, Q_{T_-}, determined by the quinoa growth function. Further, depending on whether a weather shock has occurred and how severe it has been, the stock at the end of the year is reduced by $(1 - x(k_\tau, \omega)) \in [0,1]$. The HJB equation for the maximization problem can be written as

$$\rho V\left(Q\right) = \max\left\{W\left(Q\right) + \left(Q_{T_-} - Q\right)V_Q + \mathbb{E}_\omega \lambda\left[V\left(\widetilde{Q}\right) - V\left(Q\right)\right]\right\},$$

where $\widetilde{Q} = x(k_\tau, \omega)Q$. The term $W(Q)$ represents the yearly welfare as a function of Q, as in Eq. (12), the next term is the change in the stock over a year, that is total depreciation plus the new harvest. Finally, the last term is the expected value of the change in the program when a weather shock occurs. The optimality condition with respect to the consumption propensity reads

$$\frac{\partial W}{\partial \alpha} + \lambda \int_\Omega \frac{\partial V\left(\widetilde{Q}\right)}{\partial \widetilde{Q}} \frac{\partial x}{\partial \alpha} Q f_\omega d\omega = 0. \tag{23}$$

Assuming again that $x(k_\tau, \omega) = g(k_\tau)\omega$, we may rewrite the optimality condition as

$$\frac{\partial W}{\partial \alpha} + \lambda \frac{\partial g(\alpha)}{\partial \alpha} Q \int_\Omega \frac{\partial V\left(\widetilde{Q}\right)}{\partial \widetilde{Q}} \omega f_\omega d\omega = 0. \tag{24}$$

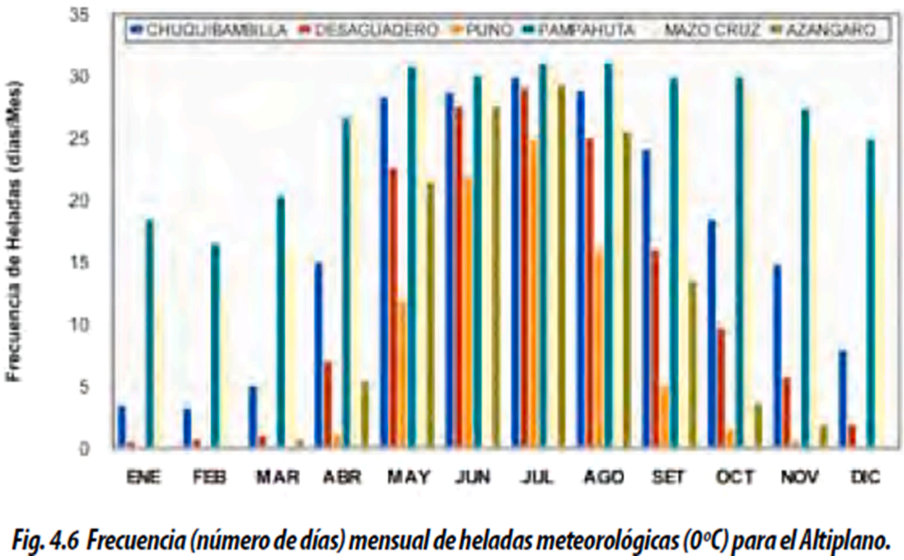


Fig. 5. Meteorological frost frequency in Puno, number of days for each month.

Suppose, for simplicity, that the new harvest grows proportionately to the seeds sown at the beginning of the season, which constitute a fraction of the initial stock. Then we may write $Q_{T_-} = \eta Q$. This simplifying assumption allows us to explicitly find the value function of the program:

$$V\left(Q\right) = \frac{\widetilde{\Psi}(\alpha)Q^{1-\varepsilon}}{1-\varepsilon}, \quad \widetilde{\Psi}\left(\alpha\right) = \frac{\Psi(\alpha)}{\rho - (\eta - 1)(1-\varepsilon) - \lambda\left[\int_{\Omega} x(\alpha)^{1-\varepsilon} f_{\omega} d\omega - 1\right]}. \tag{25}$$

Recalling in addition expression (12), we can simplify condition (24) further:

$$\frac{\partial \Psi}{\partial \alpha} + \lambda\left(1-\varepsilon\right)\widetilde{\Psi} g^{-\varepsilon} g'\left(k_{\tau}\right)\frac{\partial k_{\tau}}{\partial \alpha}\int_{\Omega} \omega^{1-\varepsilon} f_{\omega} d\omega = 0. \tag{26}$$

Expression (26) provides and implicit solution for the optimal consumption propensity, α^{opt}. The maximized expected lifetime welfare, V^{opt}, can be found by substituting α^{opt} into (25).

When the forecast is available, the effects of the weather shocks can be completely mitigated, so that $\omega = 1$ in each farming year. The average lifetime welfare, as a function of α, becomes

$$W^{FF}_{Proac} = \int_0^{\infty} u\left(xQ_{T_-}\right)\Psi\left(\alpha\right)e^{-\rho i} di = \frac{u\left(gQ_{T_-}\right)\Psi(\alpha)}{\rho}. \tag{27}$$

The optimal choice of α is governed by the condition

$$\frac{\partial W^{FF}_{Proac}}{\partial \alpha} = 0 \Leftrightarrow g\left(k_{\tau}\right)\Psi'\left(\alpha\right) + \left(1-\varepsilon\right)g'\left(k_{\tau}\right)\frac{\partial k_{\tau}}{\partial \alpha}\Psi = 0. \tag{28}$$

Eq. (28) provides an implicit solution for α^{FF}, which, upon substitution into (27), gives the maximized lifetime welfare with available forecast.

We may infer the lifetime welfare increase due to the availability of the forecast using a similar approach as in the "traditional response" case. Assuming that the forecast quality is equal to q, we compute the percentage increase in consumption in the scenario without a forecast which would bring about the same level of lifetime welfare as in the deterministic scenario:

$$z_{proac} = \left\{\left(1-q\right) + q\left(\frac{g(\alpha^{FF})}{g(\alpha^{opt})}\right)^{1-\varepsilon}\left(\frac{\Psi(\alpha^{FF})}{\widetilde{\Psi}(\alpha^{opt})}\right)\frac{1}{\int_{\Omega}\omega^{1-\varepsilon} f_{\omega} d\omega}\right\}^{\frac{1}{1-\varepsilon}} \tag{29}$$

We proceed next to the numerical calibration. The main challenge is to decide on the functional form of the crop survival function $x(k_{\tau}, \omega)$, where k_{τ} stands for the preventive measures and ω is a random variable representing the share of plantation which survives following a frost event. So far, we have made an assumption that x can be written as $x = g(k_{\tau})\omega$, where $g(k_{\tau})$ is a function which maps preventive measures into quinoa yield. Hence, we need to make an assumption on the shape of $g(.)$. Let us assume that

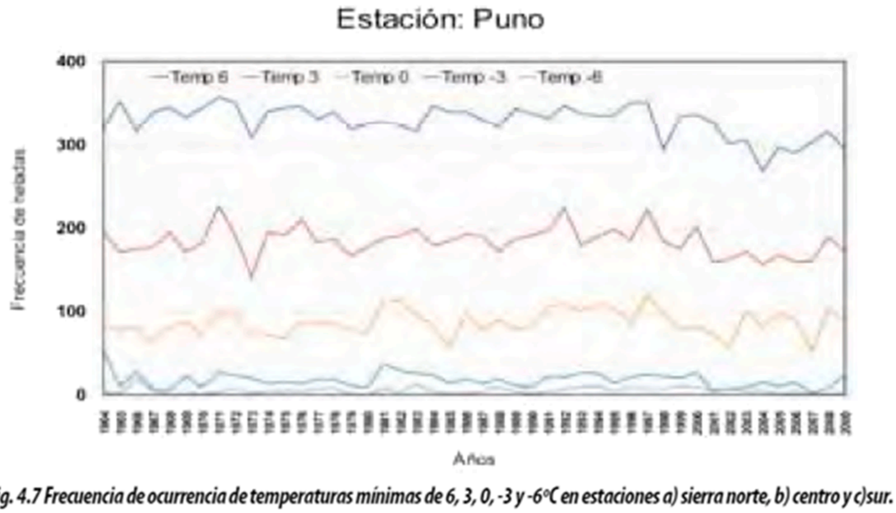


Fig. 6. Historical yearly frequency of minimum temperatures of 6, 3, 0, −3, and −6 °C in Puno from 1964 to 2009.

Table 4
Benchmark calibration of the proactive case. * indicates that the parameter is calibrated on the basis of the survey data.

Planning horizon, days	T	365
Duration of safe season*, days	τ	275
Rate of time preference	ρ	$0.1/T$
Elasticity of marginal utility	ε	0.8
Initial stock*, kg	S_0	185
Quinoa price, $/kg	p	1
Expenditure on prevention, $	Δ	$0.1pS_0$
Forecast accuracy	q	0.8
Frost arrival rate	λ	10
Baseline survival	$\overline{g}$	0.5
Multiplicative parameter	γ	0.5
Concavity parameter	β	0.01
Quinoa productivity	η	1.05

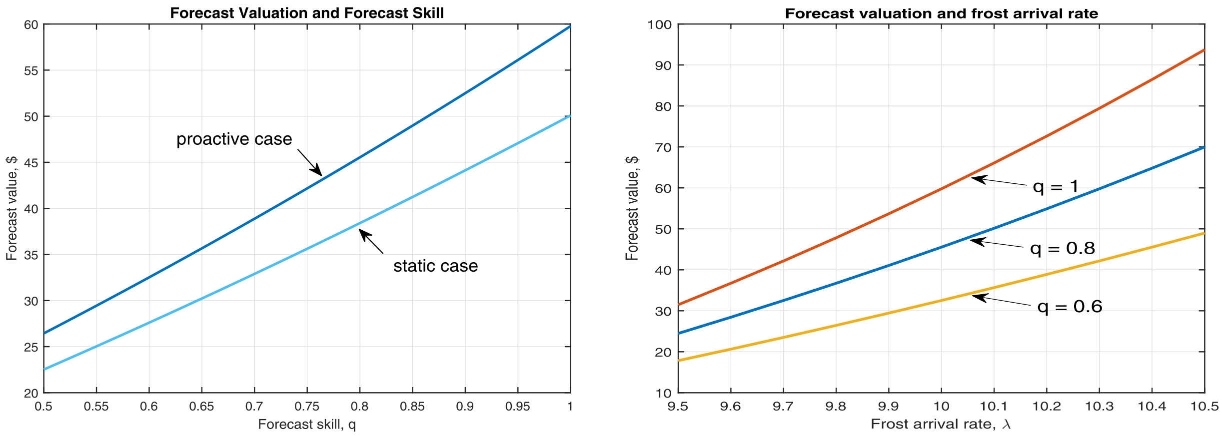
$$g = \overline{g} + \gamma\left(\frac{k_\tau}{\Delta}\right)^\beta,$$

where $\overline{g}$ is some baseline yield in the absence of any prevention, Δ is the amount of prevention applied in the static-response case, and γ and β are parameters governing how preventive capital feeds into the yield, compared to the benchmark static case. For example, if a "proactive" farmer applies the same amount of prevention as a "static" farmer, she would obtain $\overline{g}+\gamma$ in terms of yield per year.

Next, we also need to calibrate the intensity of the Poisson process, which governs frost occurrences. To do so, we rely on the data provided by SENAMHI, the Hydrological and Meteorological Service in Peru. Detailed data on frost occurrences can be found in "Atlas de Heladas del Peru" SENAMHI-FAO, 2010). Below, we reproduce two key figures which serve as the basis for our calibration.[7] Fig. 5 shows the number of frost days for each month and for several regions on the Altiplano. The Puno region is shown in orange. One can clearly see that the majority (over 80%) of frosts in Puno occur during the austral winter, i.e. from May to September. The remaining less than 20% occur during austral summer which is also the quinoa cultivation period. Fig. 6 shows the number of days in a given year with minimum temperatures of 6, 3, 0, −3, and −6 °C.

For our purposes, we would be most interested in the number of days with minimum temperature of less or equal to −3 °C at which quinoa plant suffers substantial damage during anthesis (Jacobsen et al., 2005, Table 3; Jacobsen et al., 2007, Tables 1–2). According to the Atlas, there are on average 53 days per year with minimum temperature of at least −3 °C SENAMHI-FAO, 2010, p. 32). Recalling that we are only concerned with the "risky" time of the year, running from January to March, during which only about 19–20% of frosts take place, we obtain an average arrival rate of approximately 10. We summarize the parameter calibration in Table 4.

[7] Unfortunately, the resolution of images in the Atlas is not very high. This is why we mention key numbers in the text.



(a) Static vs. proactive valuation.

(b) Frost arrivals and forecast skill.

Fig. 7. Forecast valuation for proactive farmers.

We present our results in the two figures below. Fig. 7a shows forecast valuation for the static and the proactive case as a function of forecast skill. We observe that the valuation is always larger for the proactive farmer than for a farmer who relies exclusively on myopic prevention. The difference in the valuation is relatively small, around \$4, for a forecast with a skill of 50%, while for a perfectly skilled forecast it more than doubles to about \$10. This represents 20% of the total forecast value (\$50) in the static case. However, we also find that the forecast valuation in the proactive case is highly responsive to the frost arrival rate, λ. We demonstrate this for 3 levels of forecast skill in Fig. 7b, where the arrival rate is plotted on the horizontal axes. For small variation in λ of $\pm 5\%$ we observe substantial change in FFV for all 3 skill levels. For example, with $q = 0.8$ we find that for $\lambda = 10$, the value is $FFV = 45.54$; for $\lambda = 10.5, FFV = 69.99$, while for $\lambda = 9.5, FFV = 24.48$. For comparison, in the static case $FFV = 38.4$. Such high sensitivity to arrival rate calls for extremely precise calibration if one strives to derive the value of scientific knowledge, as compared to traditional knowledge (reflected here in the “static” case).

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