Valuing Climate Services in the Agricultural Sector: Optimal Land Allocation using Seasonal Climate Forecasts

Master's Thesis

at the

Oeschger Centre for Climate Change Research

University of Bern

presented by

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December 8, 2016

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Abstract

The high vulnerability of agriculture to climatic variability poses severe economic risks. Climate services, such as seasonal climate forecasts, could potentially reduce this vulnerability by enabling farmers to make decisions based on early information regarding expected climatic conditions for the coming season(s). This thesis aims to estimate the potential value of seasonal climate forecasts when allocating land for agriculture. Therefore, a theoretical model was developed, and then applied to the region of Puno in Peru. The application relies on using statistical climate data and simulated yields for two crops (quinoa and potatoes). By examining two competing scenarios, where key decisions are made either with or without seasonal climate forecasts, the difference in expected revenue between the two scenarios gives an application-based estimate of the benefit of seasonal climate forecasts. The resulting value of seasonal climate forecasts when choosing to allocate land either to quinoa or potatoes corresponds to 0.5 per land unit for a relative price of 2.2 for quinoa in comparison to potatoes. Thus, with the aid of seasonal forecasts, the expected revenue can be increased by 4.66%. In conclusion, the positive value of seasonal climate forecasts, found for a large range of relative prices, supports efforts to enhance the quality and availability of these forecasts. However, in order for this positive value to be utilised, not only is the provision of high quality forecasting necessary, but also the cautious integration of the information into the plans and actions of key decision-makers.

Contents

List of Figures

List of Tables

List of Abbreviations

CS Climate Services

ENSO El Niño-Southern Oscillation

GFCS Global Framework for Climate Services

SCF Seasonal Climate Forecasts

WMO World Meteorological Organisation

1 Introduction

1.1 Motivation

Agricultural production is directly exposed and therefore highly vulnerable to climatic variability. This vulnerability poses large economic risks, since farmers utilise a limited range of prevention and adaptation measures. One possible method to reduce these risks and enlarge the set of potential measures is to offer climate services (CS) to farmers. Climate services are defined by the World Meteorological Organisation (WMO) as climate information which assists the decision making of individuals and organisations. The Global Framework for Climate Services (GFCS) of the WMO provides a mechanism for coordinated actions aimed at "improving the scientific quality, accessibility and relevance of climate information to users" (WMO, 2014, p. 5). The GFCS defines four priority areas, one of which is 'Agriculture and Food Security'.

In developing countries, agriculture accounts for a larger share of the economy than in more developed countries, which means that relative economic losses from climate variability in agricultural production can be much more damaging. This underscores the importance of innovative and effective approaches to reducing farmers' vulnerability that can be readily employed in developing world contexts. Furthermore, WMO (2007) states that in developing countries, there is great potential for improving the provision of climate services. Parallel to this goes the frequent lack of awareness, on the part of potential users, of the climate services that are available; even the highest quality climate service does not create added value when it is not integrated into the decision making process.

Seasonal climate forecasts (SCF), a particular type of climate services, aim to reduce the vulnerability of farmers by recommending adaptation measures based on early information about the climatic conditions to be expected in the coming months. As Hill and Mjelde (2002) put it, the goal of SCF is to mitigate against the potential adverse effects of future climatic conditions while also taking advantage of the favourable impacts. In regions where the El Niño-southern oscillation (ENSO) and other large-scale inter-annual climate variations influence the local climate considerably, the improvement in the quality of seasonal climate forecasts over the last few years has been especially notable. Supporting this have been several studies, which have documented a link between ENSO and crop yields in southern Africa, North and South America, Australia, and India (Nicholls, 1986; Mearns et al., 1992; Cane et al., 1994; Mjelde and Keplinger, 1998).

Climate services in general and seasonal climate forecasts in particular exhibit the following two characteristics of a quasi-public good: partial non-excludability and non-rivalry. These characteristics arise from the fact that such services are usually provided by public institutions free of charge or at symbolic prices, which means that the market price cannot serve as a true indication of the actual value of a given climate service. Freebairn and Zillman (2002) find that these characteristics are the main cause for an underestimation of the value of CS and their resulting under-provision in many countries. By creating more knowledge about the value CS could potentially generate, decision makers may be more easily persuaded to avail of the quality information base provided by CS and thus the provision of CS itself could, ideally, be enhanced.

Various studies have been conducted to estimate the value of SCF, as will be discussed in more detail in Section 1.2. Most of the studies focus on management options for one crop only, and thus cannot be generalised to the management practices of other crops. In addition, these management options often require capital investments, which are sometimes out of reach for smallholder farmers. Adjusting land allocation is, however, a simple and often affordable measure to adapt behaviour (Phillips et al., 2002). As such, by focusing on adjusting the crop choice when SCF are available, this thesis provides insights on a simple cost effective management option, which is not only available to smallholder farmers with minimal investment capability, but also can be generalised for use with any number of crops for a one-year period.

The objective of this master's thesis is to estimate the value of SCF in the allocation of land by combining a theoretical framework (as it relates to an optimal crop choice for a representative farmer) with an application using statistical climate data and simulated yields for two crops, quinoa and potatoes, in the region of Puno, in Peru. Looking at both a scenario with and without SCF, the difference in expected revenue between the two scenarios gives an estimate of the benefit of SCF. While the theoretical framework enhances the understanding of how a positive value for a SCF is obtained, the procedure using simulated yields offers an estimate of the scale of the value of SCF for land allocation decision making in the region of Puno.

The remainder of this thesis is structured as follows: Section 1.2 provides a short review of the existing related literature. Section 2 describes the central theoretical model. Section 3 discusses the climatic data used, describes the yield simulation, runs a linear regression to find the most significant climatic indicators for the classification of yields, and then maximises expected revenue with and without seasonal climate forecasts. Section 4 discusses contributions and limitations of the approach proposed in this thesis and - to some extent - seasonal climate forecasts in general. Finally, Section 5 will offer a conclusion.

1.2 Related Literature

Comprehensive literature reviews on the topic at hand have been presented by Hill and Mjelde (2002) and Meza et al. (2008). Further, WMO (2015) offers a broad overview of the topic of valuing meteorological and hydrological services by conducting benefit-cost analyses.

Different approaches can be used to derive an estimate of the economic value of SCF. Most of the studies conducted in this field follow an empirical approach; studies using theoretical frameworks to simulate the optimal management of agricultural systems with SCF are still limited in number. Further, the studies vary on three different levels of analysis (Meza et al., 2008). The most common approach is analysis on the crop level, where practices to manage one single crop are evaluated. A second approach is to estimate the economic value of SCF on the farm level, e.g. by using crop simulation models to determine the effect of the forecasts on land allocation: the approach forwarded in this thesis falls into this category. The third possible level of analysis is the aggregate scale, where equilibrium models are used to determine an optimum between supply and demand of SCF. Studies which include an empirical assessment of the use, and resulting added value, of SCF are relatively rare. One example is Patt et al. (2005), where farmers in Zimbabwe indicated that they adjusted their farm management to SCF, with resulting positive effects on harvests.

According to Hill and Mjelde (2002), the common approach for valuing SCF for agriculture combines decision theory with Bayesian analysis. Then, two cases are distinguished; one without SCF, where farmers maximise expected utility with prior knowledge about past climate. The endogenous variable is a decision set D, which varies from study to study. Further, $h(c)$ represents the historical probability density function. The second case includes SCF, F, which changes the probability density function of climate conditions to $g(c|F)$. Subtracting the utility derived without SCF from the utility with SCF, the value of the forecast system is found. This can then be expressed in monetary terms using certainty equivalence dollars - or if risk neutrality is assumed, the value can be directly read in monetary units.

Analysis on Crop Level: An example for an analysis on crop level is provided by Meza and Wilks (2004). In this study, an intertemporal economic decision model is applied to derive the value of both perfect and imperfect sea surface temperature anomalies (SSTA) in the Equatorial Pacific for potato fertilisation strategies. It is interesting to note that the value of imperfect forecasts reaches about 40 to 60% of the value a perfect forecast would offer, depending on initial fertilisation levels. Hammer et al. (1996) determined the value of skill of SCF in improving wheat crop management by analysing the complex decisions farmers face, i.e. planting time, varietal development pattern, fertiliser strategy, etc. At that time they found that the skill of SCF was sufficient to justify its use in the tactical management of crops. Also McIntosh et al. (2007) investigated the potential value of different forecasting systems for wheat growth, and found that a perfect forecast of total rainfall in a growing season might provide only just less than half of the potential value of an ideal forecast system (which would e.g. include distribution of rainfall over time). Mjelde et al. (1988) determined the value of forecast characteristics in a dynamic programming model of corn production and found that the value is sensitive both to economic conditions and forecast characteristics. Lechthaler and Vinogradova (2016) conducted a study, combining theoretical and empirical work, to assess the potential value of climate services (i.e. early warning systems) for coffee farming in Peru. They found that there was a considerable willingness to pay for climate services. This willingness to pay, and as such the value of this climate service, was mainly dependent on service accuracy and geographic resolution. Further, Cantelaube and Terres (2005) developed a method for supplying seasonal forecast information for crop simulation models. Based on this, they simulated probability distribution functions, the spreads of which can be used to quantify the benefits and risks of making weather-sensitive decisions.

Analysis on Farm Level: On farm level, Jones et al. (2000) estimated the potential economic value of climate forecasts for farm scale management decisions in Tifton, USA. Crop simulation models were combined with simple economic decision models to find the crop mix that would maximise expected utility. Expected utility depends on predicted costs and prices, risk preferences, and crop yield simulations. The results derived were then compared to findings from Pergamino, Argentina, where a similar study was conducted (Messina et al., 1999). The derived values for Argentina were considerably higher than those for Tifton, USA, with a range of $9-35 compared to $3-6 per hectare for all years. The value of the forecast was found to increase where greater risk aversion was present, in particular at low initial wealth levels.

Analysis on Aggregate Level: The third level of analysis focuses on an aggregate scale. For example, Adams et al. (2003) conducted a study to model the changes in crop prices resulting from a shift in crop supply caused by different ENSO phases. Similar to this, Solow et al. (1998) analysed the effects of ENSO-based forecasting for the agricultural sector in the US. They found an increase in crop supply when forecasts are in use and thus an increase in social welfare over years. Another example is Chen et al. (2002) study, where the authors estimated the value of ENSO forecasts based on a multi-commodity and multi-country approach. In addition, they distinguished between different resolutions of the forecast, i.e. a three versus five phase information. Results indicated that a five phase forecast is nearly twice as valuable as a three phase forecast (\$754 million compared to \$399 million of total value for the US in the base year of the study, 1996). Also Mjelde et al. (1997) emphasised that different decisions need to be considered when assessing the value of SCF, because they are often interrelated. However, the study focused on medium to large sized farms (around 500 ha each), where potentially more management options are available than for smallholder farmers. Further, Roudier et al. (2016) combine different levels of forecasts by investigating whether a combination of a 10-days forecast and a seasonal forecast is more valuable for millet farmers in Niger than only one of the two forecast methods. Results indicate that seasonal forecasts alone are not really beneficial in this setting. However, in combination with 10-days forecasts, the mean income increases from +1.8% to +13%, depending on adaptation strategies.

Some studies also focus on more general aspects of the value analysis of seasonal forecasts. Letson et al. (2005) argue that even if SCF are perfectly certain, randomness remains important because the agricultural context, in which SCF are used, is highly variable and complex. Therefore, they base their analysis of potential value of ENSO forecasts on two assumptions: that the crop prices farmers are faced with are uncertain, and that within an ENSO phase, the climate is variable and thus influences yields. The authors find that even the value of perfect ENSO forecasts must be analysed in terms of probability distributions. Jagtap et al. (2002) went a step further and analysed the whole process of SCF; forecast generation, its communication, its use, as well as an implementation and evaluation component. One of their studies' main results was that SCF truly show their value only when trusted advisors engage in research and outreach efforts.

2 Theoretical Model

For the purpose of this study, a theoretical model on the farm level was developed to assess how seasonal climate forecasts can be used to adapt crop choice. First, in Section 2.1, the basic setting of the model is laid out in a general way for two scenarios, one without and one with SCF. Then, in Section 2.2, a numerical illustration will be provided.

2.1 General Setting of the Model

Let us consider one representative farmer, who owns a land resource normalised to unity. Further, they have seedlings of $i = 1, ..., n$ different crops at hand. At the beginning of an agricultural cycle, they can choose which crops to plant for the coming season, and how much of their land they are going to allocate for which crop. The fraction of land allocated to crop i is indicated by γ_i. The farmer allocates all of their entire land resources, thus $\sum_{i=1}^{n} \gamma_i = 1$. The target of the risk-neutral farmer is to maximise the expected revenue, which they achieve by choosing the optimal crop (mix) to plant. The crop yields per land unit are denoted by $Y_i(\overrightarrow{w})$, and thus depend on the weather conditions $\overrightarrow{w}$. The crop prices, denoted by p_i, represent global market prices and are taken as given by the farmer. Also the costs c_i are fixed and independent of the realised yields, marginal costs are thus constant and no economies of scale occur. The decision about what to plant, and to what extent to plant it, is based on the farmers' knowledge about past weather patterns. In our model, past weather is represented by the probability density function $\phi(\overrightarrow{w})$ of a weather index. This weather index is a vector containing different weather indicators as elements with $\overrightarrow{w} \in \mathbb{R}^m$, and thus represents the different weather conditions.

The decisions the farmer takes are optimal with respect to climatology, which does not necessarily mean they are optimal for the coming season. The problem the farmer faces is thus caused by the climatic variability, of which they are unable to take full advantage. This in turn leads to a revenue below the maximum achievable revenue, which would be feasible when choosing the exact optimal crop – and amount thereof – for the season at hand. SCF inform the farmer in advance about the climatic conditions to be expected in the coming season, and are thus a useful measure to assist the farmers' decision making. We introduce a SCF into our model, which informs the farmer in advance about expected climatic conditions for the coming season. We assume that the forecast is perfectly accurate, thus the farmer knows exactly which outcome of $\overrightarrow{w}$ will be realised in the coming season. This assumption poses limitations on the significance of the SCF's value; the value we obtain for this information indicates the upper limit, and as such a less accurate forecast would consequently be worth less.

The farmers' revenue function is given by:

$$\Pi(\overrightarrow{w}, \gamma_i) = \sum_{i=1}^{n} \left[\gamma_i \left(Y_i(\overrightarrow{w})p_i - c_i\right)\right] \tag{1}$$

In the scenario without seasonal climate forecasts, the farmer has no information about the climatic conditions of the coming season, thus $\overrightarrow{w}$ is not known. Therefore, the farmer maximises their expected revenue with respect to past climate, i.e. to the probability density function of the weather index:

$$E\left[\Pi(\overrightarrow{w})\right] = \int_M \Pi(\overrightarrow{w}, \gamma_i)\phi(\overrightarrow{w})d\overrightarrow{w} \tag{2}$$

where $M \subset \mathbb{R}^m$. Opposed to this, in the scenario with SCF, the farmer avails of the information available on climatic conditions for the coming season. Therefore, they are able to choose the optimal crop for each realisation of $\overrightarrow{w}$:

$$\Pi(\overrightarrow{w}, \gamma_i) = max\left[\sum_{i=1}^{n} \gamma_i \left(Y_i(\overrightarrow{w})p_i - c_i\right)\right] \tag{3}$$

Then, by taking the difference between the revenue derived with and without seasonal climate forecasts, the value of the forecast is obtained.

2.2 Numerical Illustration

A numerical illustration of the derived model will be shown for $n = 2$ crops. Let's think of quinoa and potatoes, for example. Thus, the farmer faces the same problem setting as laid out above, i.e. two different scenarios – with and without seasonal climate forecasts, and must maximise the expected revenue in each. The farmers' revenue for two crops is given by:

$$\Pi(w, \gamma) = \gamma(Y_1(w)p_1 - c_1) + (1-\gamma)(Y_2(w)p_2 - c_2) \tag{4}$$

Further, the yield functions for crops 1 and 2 are defined as follows: Crop 1 (quinoa) is assigned a step function

$$Y_1(w) = \begin{cases} d & \text{for } a \leq w \leq b, \text{ where } 0 < a < b < 1 \\ 0 & \text{otherwise} \end{cases} \tag{5}$$

with a and b being parameters of the yield function. Crop 2 (potatoes) is assumed to be very robust and to perform equally well over all possible realisations of the weather index; its yields are equally distributed with

$$Y_2(w) = e \tag{6}$$

with e being strictly smaller than d. Both yield functions are defined such that the respective yields are obtained per unit of land allocated. The weather index $\overrightarrow{w}$ is reduced to one dimension, thus denoted by w, and normalised to a range for 0 to 1, hence all weather conditions can be expressed within this range. The probability density function of the weather index $\phi(w)$ follows a normal distribution, which is truncated such that it integrates to one for the index range given by [0,1]: $\int_0^1 \phi(w)dw \equiv 1$, thus

$$\phi(w) = A\left(\frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2}\frac{(w-\mu)}{\sigma}^2}\right) \tag{7}$$

The parameters chosen are specified in Table 1.

Scenario without Seasonal Climate Forecasts: In this scenario, expected revenue is derived for both yield functions separately in a first step. Then, the results are compared and the optimal crop choice deduced.

Solving the integral over $Y_1(w)$ results in

$$\int_0^1 Y_1(w)\phi(w)dw = \int_a^b Y_1(w)\phi(w)dw = 1.61$$

Table 1: Parameters for numerical illustration.

Parameter	Value
$Y_1(w)$ lower bound: a	0.3
$Y_1(w)$ upper bound: b	0.7
$Y_1[a,b]$: d	5
$Y_2(w)$: e	3
Prices: p_i	\$1
Costs: c_i	\$1
Mean of $\phi(w)$: μ	0.5
Standard deviation of $\phi(w)$: σ	0.3
Scale parameter of $\phi(w)$: A	0.58

The integral over Y_2 has a straightforward solution:

$$\int_0^1 Y_2(w)\phi(w)dw = 3$$

After multiplying with the respective prices and subtracting the respective costs, we find that the expected revenue derived from crop 2 (\$2) is larger than from crop 1 (\$0.61). Therefore, all land available is allocated to crop 2.

Scenario with Seasonal Climate Forecasts: In the second scenario, the crops to cultivate are chosen using SCF. Since the forecast is considered to be perfectly accurate, the exact realisation of w is known in advance and thus the farmer is able to choose the optimal crop for each situation. We set up the revenue function for the two crops:

$$\Pi(w,\gamma) = max[Y_1(w)p_1 - c_1, Y_2(w)p_2 - c_2]$$

The farmer chooses the crop which returns the highest yields for each outcome of w. For example, taking $w = 0.5$, crop 1 would be chosen, since \$4 > \$2. By integrating over the yield functions and the probability density function, we derive the expected yields with SCF:

$$\int_0^1 Y_i(w)\phi(w)dw = \int_0^a Y_2(w)\phi(w)dw + \int_a^b Y_1(w)\phi(w)dw$$
$$+ \int_b^1 Y_2(w)\phi(w)dw = 3.63$$

Multiplying the derived expected yields with prices and subtracting costs results in the expected revenue of \$2.63.

2.3 Difference: Value

A comparison of the results in the previous section reveals that the expected revenue derived by using SCF is higher than the one without it. By subtracting the expected revenue without SCF from the one with SCF, we get the value (V) of SCF for this numerical illustration:

$$V = \$2.63 - \$2 = \$0.63$$

In the case without climate services, the more robust crop is favoured, which on average ensures higher expected revenue. However, when seasonal climate forecasts are available, the farmer is able to choose the optimal crop for each weather outcome. The value of the SCF thus arises from those weather outcomes, where through the use of SCF higher yields can be obtained. In our model, this is the case for values of w between a and b. Then, crop 1 is planted, based on SCF, as it is predicted to yield a higher revenue than crop 2.

3 Application to Puno, Peru

3.1 Motivation and Background

A simple decision mechanism for adapting land allocation using seasonal forecasts was deduced in the previous section. However, the yield functions used in the model do not represent effective crop behaviour, but rather serve illustrative purposes only. Therefore, a similar procedure to that in the theoretical part is applied to sampled yields, thus, a discretisation is derived. Two crops, quinoa (*Chenopodium quinoa* Willd) and potatoes (*Solanum juzepczukii* Buk.), are chosen as these are the most predominant crops in the region of Puno, Peru[1]. Yields are simulated by use of a crop model, which allows for the control of climatic influences. There will be a discussion about a comparison with statistical yields from this region later, in Section 4.1.

The analysis consists of the following: to begin with, a descriptive analysis of the statistical climate data and simulated yields used is performed; second, two important climatic indicators for yields are identified using linear regression; third, the two indicators are used to classify the occurrence frequency of climatic conditions and resulting mean yields in a two-dimensional grid, which allows one to make an inference about which crop performs better under which climatic circumstances; in a fourth and final step, the value of the seasonal climate forecasts, i.e. the difference in revenue between the scenarios with and without SCF, is estimated depending on relative prices.

3.2 Climate Data

The following analysis relies on historic climate data from the Puno region of Peru[2]. Data from three stations was chosen (see Figure 1), and a descriptive data analysis thereof will be performed in this section. These three stations were chosen because they have been homogenised within the course of the first phase of the project Cli-

[1]http://censos.inei.gob.pe/Cenagro/redatam/

[2]Climate data is provided by SENAMHI, the Peruvian National Meteorological and Hydrological Service.

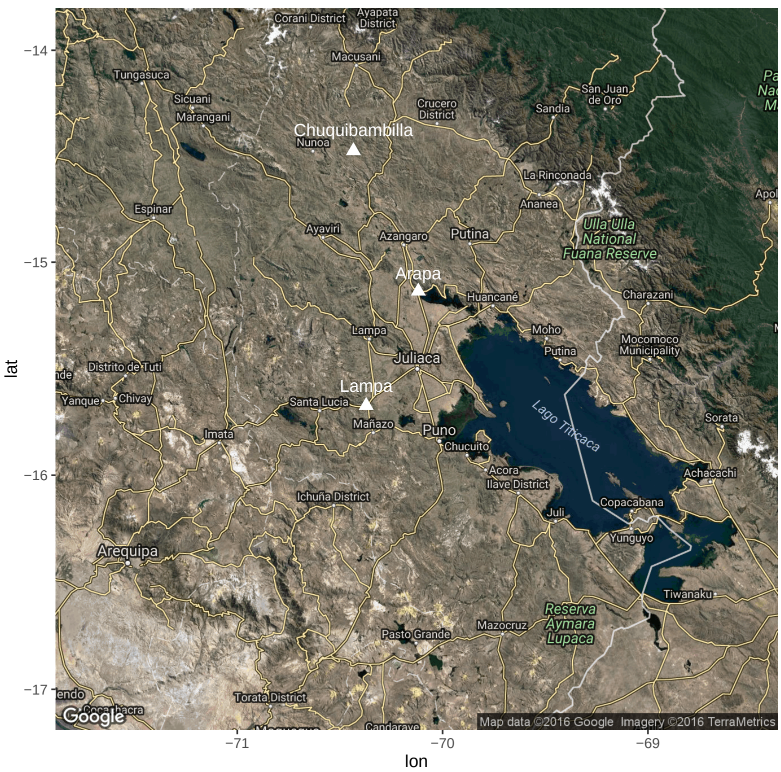

Figure 1: Location of the three weather stations in the region of Puno. (Source: Google Maps)

mandes (cf. Section 4.4), and thus consist of good data quality. The weather stations are located in the region of Puno in the Peruvian Andes in Arapa (3830 metres above sea level [masl]), Chuquibambilla (3910 masl), and Lampa (3892 masl). Their location can be seen in Figure 1. The stations Arapa and Lampa came into operation in 1964 and have measured the daily amount of precipitation and the minimum and maximum temperature ever since. The Chuquibambilla station started measuring daily minimum and maximum temperature in July 1965, and precipitation in 1971, as can be seen in Figure 2.

The values corresponding to a season of agricultural production in the chosen region, September until April, were extracted for all years at all stations. These values were then aggregated to get seasonal values, the seasonal precipitation sum, seasonal mean, minimum, and maximum temperature, and minimum temperature during flowering stage (January-February). For simplicity, a season is hereafter indicated by the year of harvesting, e.g. the season from September 1964 until April

Table 2: Climate characteristics of the stations Lampa (L), Arapa (A), and Chuquibambilla (C).

	Precipitation [mm]	Temperature [°C]
	L / A / C	L / A / C
Mean	694.50 / 647.30 / 615.80	9.29 / 10.02 / 8.28
Minimum	306.70 / 273.30 / 473.70	8.22 / 9.22 / 6.62
Maximum	1563.40 / 1234.10 / 964.80	10.74 / 11.42 / 9.67
Standard Deviation	218.40 / 176.80 / 275.62	0.50 / 0.47 / 0.62

1965 is referred to as 1965.

The mean, minimum, and maximum values of seasonal temperature and precipitation as well as the standard deviation are presented in Table 2. For the Lampa station, seasonal precipitation fluctuates around the mean value of 694.50 mm/a with a standard deviation of 218.40 mm. Seasonal mean temperature varies with a standard deviation of 0.50 °C around the mean value of 9.29 °C. In Figure 2, the seasonal precipitation sum and seasonal mean temperature values are displayed for the three stations.

3.2.1 Trends and Extremes

A short trend and extreme value analysis was conducted on the Lampa station dataset. The other two stations, Arapa and Chuquibambilla, show extremely similar results, and are therefore not presented individually.

Trend estimations are derived using two different techniques, so as to be less reliant on one method. Firstly, linear regression is used, which is a parametric test to find out whether data is linearly dependent on time. Secondly, an estimate is derived by the non-parameteric Theil-Sen trend estimate and Mann-Kendall test. The Theil-Sen trend estimate is a robust estimator for a linear trend, which is complemented by the Mann-Kendall trend test. This test assesses whether there is a monotonic, however not necessarily linear, trend in the data (Frei and Schär, 2001).

The temperature record seems to show a clear positive trend, as can be observed

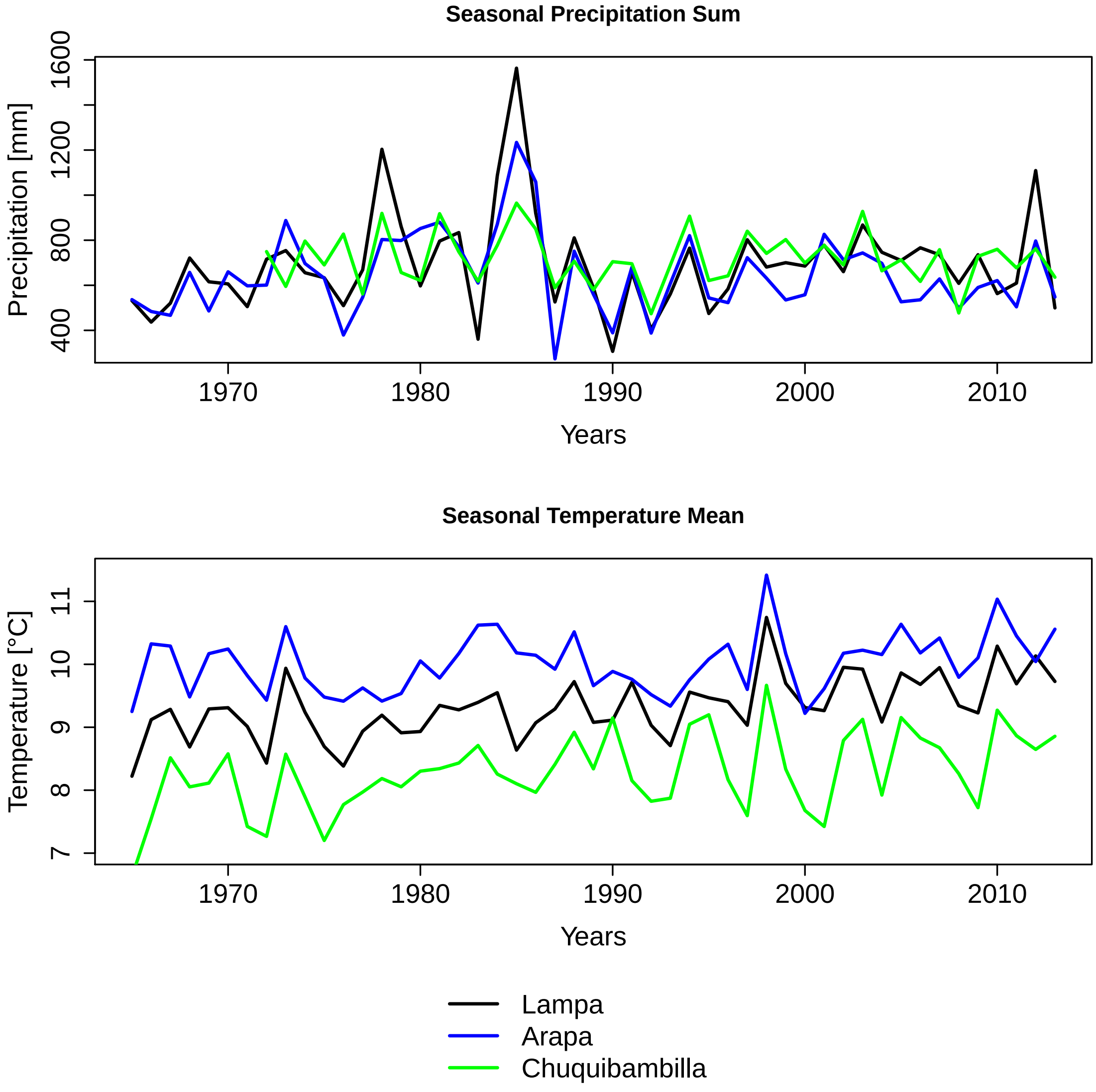

Figure 2: Temperature and precipitation time series of the three stations.

in Figure 12 in the Appendix. The linear regression technique reveals a trend of 0.02 °C per year and an absolute trend, i.e. the difference between the fitted value at the end and the beginning of the time series, of 0.99 °C for seasonal mean temperature. This is supported by the Mann-Kendall test, which finds a trend per year of 0.02 °C as well, and an absolute trend of 0.94 °C. Both p-values are significant on a level for $\alpha = 0.001$, thus the null hypothesis that there is no trend can be rejected and it is reasonable to assume that a positive trend exists. Residual analysis plots of the linear regression trend estimate for seasonal mean temperature is provided in Figure 13 in the Appendix. Both the QQ-Plot and the residual histogram indicate a right skew, which means that the residuals are not normally distributed. Further, the autocorrelation plot shows values which are larger than the critical values, thus there is evidence for serial correlation. Even though test results have to be looked at with care, the fact that similar results have been derived with the non-parametric test is a strong indicator that a trend exists.

Also for minimum temperature during flowering stage (January and February), both techniques agree on a slightly less pronounced positive trend of 0.016 °C resp. 0.013 °C (linear regression resp. Mann-Kendall test) per year and an absolute trend of 0.76 °C resp. 0.62 °C. The positive trend in mean temperature and minimum temperature during flowering is a potential reason for the upward trends in simulated yields of both quinoa and potatoes, as will be seen in the next section.

Visually, it is not possible to detect a trend or shift in the variance of the precipitation data, cf. Figure 2, and also the trend estimates do not show significant results. Thus, we cannot confirm the negative precipitation trend discovered by Morales et al. (2011) in the South American Altiplano. In that study, a persistent negative trend in precipitation since the 1930s could be observed by reconstructing precipitation based on tree-rings (*Polylepis tarapacana* tree-ring width series). However, the disagreement might also partly arise due to the difference in record length, since the record used in the study conducted by Morales et al. (2011) was longer than the one at hand.

The effect of the southern oscillation on precipitation patterns has been documented in a number of studies (Ropelewski and Halpert, 1987; Vuille, 1999). Ronchail (1998) conducted a study on said effects on precipitation patterns in the Andes. Although they found no clear relationship between strong ENSO events and very weak or strong seasonal rainfalls, their findings indicate that some El Niño events were characterised by negative rainfall anomalies. However, the temperature variance sign left by ENSO events seems to be clear in this region (Vuille et al., 2000); while El Niño events go along with above average temperature values in summertime (December, January, and February), La Niña is typically accompanied by colder temperatures.

From a visual analysis, temperature records of all three stations seem to be exceptionally high in the season 1997/98. Historical records[3] confirm that this was a very strong El Niño year. Further, also the years 1972/73, 1982/83, and 2009/10 were El Niño years, which can readily be seen in Figure 1 by the above average temperature values.

Precipitation sum was exceptionally high during the season 1984/85, which was a weak La Niña season. Further, the seasons 1982/83, 1986/87, and 1991/92 were El Niño years and showed in some parts strong negative anomalies of seasonal rainfall.

3.3 Yield Simulation

The yield simulations are run with climate data from the meteorological stations in Lampa, Arapa, and Chuquibambilla, using the crop model 'AquaCrop'[4]. Daily precipitation values and daily minimum and maximum temperature values of all the years from 1964 until 2012 were used as input. As crops, default quinoa (Bolivia) and default potatoes (Peru) were chosen. Default quinoa is well suited for the region of interest here. Geerts et al. (2009) set up eight calibration fields in the Bolivian Altiplano to calibrate AquaCrop for Quinoa (*Chenopodium quinoa* Willd), and achieved satisfying accordance between observed and simulated yields. In accordance with this study, the harvest index[5] was set to 0.49, which is a suitable

[3] See ggweather.com/enso/oni.htm and www.cpc.ncep.noaa.gov

[4] AquaCrop is a crop water productivity model developed by the Land and Water Division of FAO.

[5] Harvest index indicates the partition of biomass into yield part, where water and temperature stresses can have an influence on.

Table 3: Yield characteristics of quinoa and potatoes for the stations Lampa (L), Arapa (A), and Chuquibambilla (C) for the years 1964 until 2012.

	Quinoa [t/ha]	Potatoes [t/ha]
	L / A / C	L / A / C
Mean	4.98 / 4.57 / 5.12	10.71 / 10.72 / 10.68
Minimum	3.26 / 2.78 / 3.44	8.86 / 8.22 / 8.77
Maximum	6.41 / 5.92 / 6.16	12.23 / 12.21 / 12.00
Standard Deviation	0.79 / 0.84 / 0.67	0.84 / 0.84 / 0.74

value for quinoa in a rainfed environment at a comparable altitude. The default potato in AquaCrop has not been calibrated for the Altiplano or a comparable region, hence the accordance with the most predominant variety of potatoes in the Altiplano (*Solanum juzepczukii* Buk.) is not guaranteed, see Section 4.1 for further discussion of this topic. As soil type, the default profile 'deep loamy soil' is chosen, which can be used as an approximation for the average soil in the region of interest (Geerts et al., 2009). Furthermore, Geerts et al. (2009) find that Quinoa is only moderately sensitive to changes in soil type. Rainfed cropping is chosen in AquaCrop, which is in accordance with circumstances on-site, as local agronomists say that infrastructure is mostly not given in the region of Puno.

In the region of Puno, the beginning of an agricultural season is usually marked by light rainfall around September. From the end of September or October on, farmers typically start sowing after the first major rainfall. Therefore, the sowing criteria in AquaCrop was defined by at least 30 mm rainfall in a 7-day period, starting from the 1^{st} of September. This information was also provided by local agronomists of the regional agrarian office in Puno. The simulated yields for quinoa and potatoes of all three stations are displayed in Figure 3 and its characteristics described in Table 3.

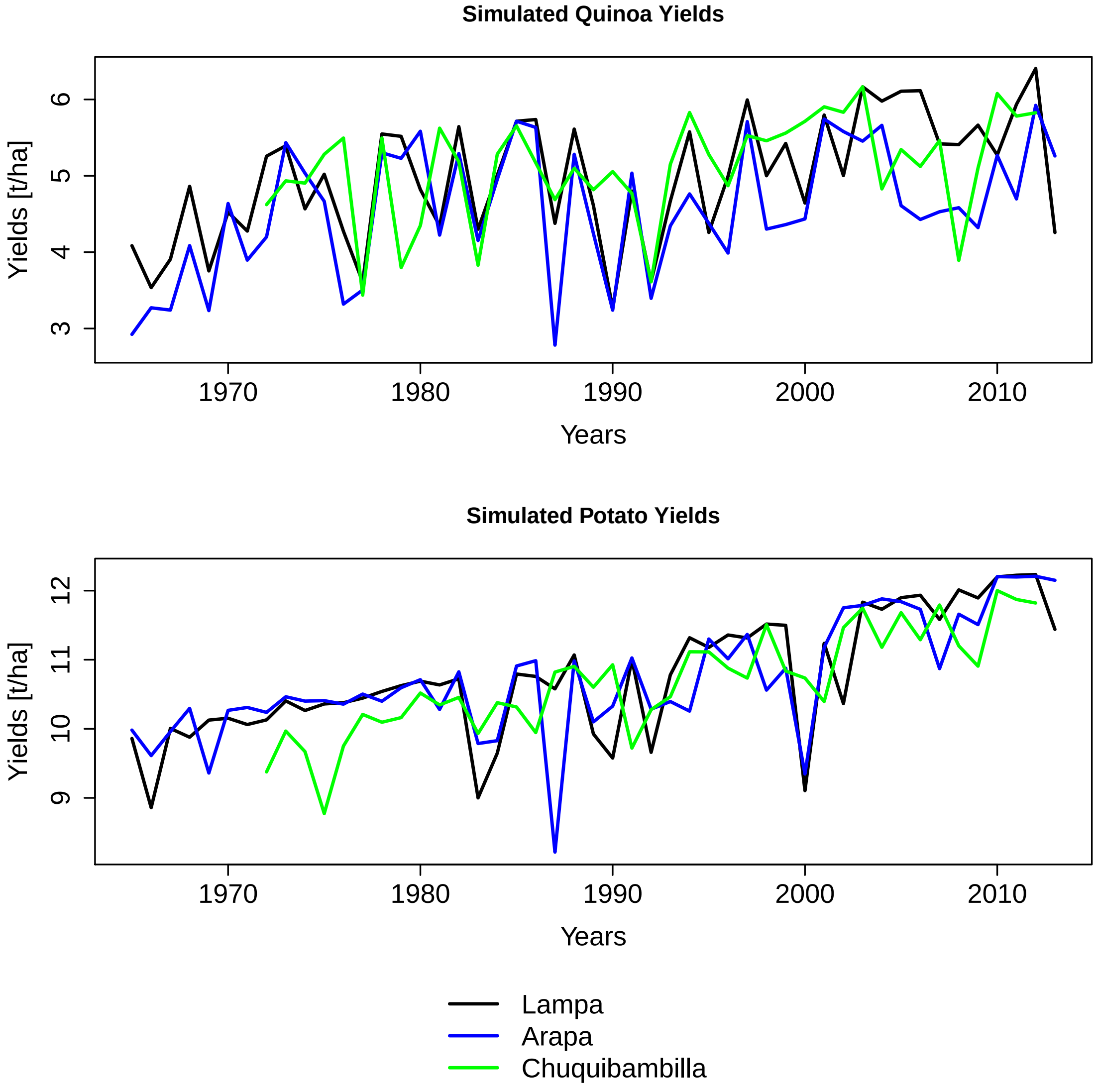

Figure 3: Simulated yields of the three stations.

3.4 Multiple Linear Regression

A multiple regression analysis was conducted to assess how climate data relates to simulated yields. The aim of this procedure is to identify the two most important climatic indicators for the yields of quinoa and potatoes. These two indicators are then used to classify yields in the analysis that follows. It is important to note here that the classification needs to be based on the same indicators for quinoa and potatoes, so only two indicators in total will be chosen. The regression analysis was performed with data from all stations involved. The following variables were chosen for the linear regression:

1. Seasonal precipitation sum: $\sum$ P(season)
2. Seasonal mean temperature: $\varnothing$ T(season)
3. Minimum temperature during flowering (January, February): $\varnothing \mathrm{T}_{min}(1, 2)$
4. Sum of days without precipitation during tuber initiation (December): $\sum \mathrm{d}_{P=0}(12)$
5. Beginning of rainy season with 30mm in 7 days: B_{RS}

The variables seasonal precipitation sum and seasonal mean temperature were chosen to get an impression of the influence of precipitation and temperature values over the whole season. Further, according to Vacher (1998), the minimum temperature during flowering stage is relevant for the yield outcomes of both potatoes and quinoa. This is the case because during the flowering process, plants are more vulnerable to low temperatures and thus frost, which can harm them severely during this formative stage. The flowering process for quinoa and potatoes in the region of Puno takes place in the months of January and February according to local agronomists. For potatoes, periods of water stress during tuber initiation can be harmful for plants as well; MacKerron and Jefferies (1986) even find this to be the most significant cause of effects on marketable yields. Due to this indicator's high relevance for potatoes, it is tested as well. Thus, the sum of days where precipitation is equal to zero during the month of December, which correspond to the tuber initiation stage, is defined. Finally, the beginning of the rainy season (30 mm in 7 days) is chosen as a possible indicator. This is potentially important for yields since a delay in the beginning of the rainy season prevents farmers from sowing early enough, which could lead to higher frost risk at the end of the growing period.

To begin with, a linear regression model is fitted for both quinoa and potato yields (Model 1), see Tables 4 and 5. Model 1 consists of the seasonal temperature mean and the beginning of the rainy season. Then, the seasonal precipitation sum is added to the model for quinoa, and the mean precipitation during tuber initiation stage to the model for potatoes, as these indicators are particularly important for quinoa and potatoes respectively. The seasonal precipitation sum is then tested logarithmically, which yielded better results than without the logarithm. The model formulation is the following:

$$Yields_{Quinoa} \sim \varnothing T(season) + B_{RS} + log(\sum P(season))$$
$$Yields_{Potatoes} \sim \varnothing T(season) + B_{RS} + \sum d_{P=0}(12)$$

The regression output of Model 1 for quinoa is presented in Table 4, and for potatoes, in Table 5. Then, for comparison, a second model (Model 2) is fitted to potatoes and quinoa in the same manner. This model consists of the seasonal precipitation sum, the beginning of the rainy season and the minimum temperature during flowering stage. The model formulation is described by:

$$Yields \sim log(\sum P(season)) + B_{RS} + \varnothing T_{min}(1,2) \tag{8}$$

The regression output of the second model is shown in Table 4 for quinoa and Table 5 for potatoes. Figure 14 in the Appendix presents regression plots for the final models (cf. Equation 8). These plots show four different graphs which can be used to check whether the residuals are distributed normally and, hence, to see whether a good model was fitted. The residuals are centrally distributed, but some outliers can be detected. For example the point for the 1982/83 season shows, when looking at the residuals vs. fitted or residuals vs. leverage plot of potatoes, a high Cook's distance. This means that the regression model is influenced strongly by this

Table 4: Regression output, quinoa (n = 136)

	Coefficient	Standard Error	p-value	R^2 adjusted
Model 1				0.59
$\log(\sum P(\text{season}))$	2.49	0.18	2e-16	
B_{RS}	0.003	0.001	0.03	
$\varnothing$ T(season)	0.13	0.05	0.05	
Model 2				0.60
$\log(\sum P(\text{season}))$	2.49	0.17	2e-16	
B_{RS}	0.002	0.001	0.03	
$\varnothing T_{min}(1,2))$	0.12	0.04	0.04	

data point. This season was characterised by a below average seasonal precipitation sum (360.70 mm as compared to the mean of 694.50 mm for the Lampa station), cf. Section 3.2.1. Apart from this, the residuals look to be acceptably distributed and we can conclude that two indicators from the final model can be chosen for the subsequent analysis.

3.4.1 Variables for Classification

The seasonal precipitation sum shows significant influence on the response variable (simulated yields) on a level for $\alpha = 0.01$ for both quinoa and potato yields. Also, the beginning of the rainy season reaches a p-value significant on a level for $\alpha = 0.05$, however, its significance level is, without exception, lower than the one from the seasonal precipitation sum. Thus, this variable will be omitted from further analysis. The mean temperature during the period of tuber initiation of potatoes does not reach a significance level below $\alpha = 0.05$ and as such will not be considered for further analysis either. In the first model with seasonal mean temperature, this variable performs well (on a level for $\alpha = 0.05$). However, the minimum temperature during the flowering stage in model two performs even better with a p-value of 0.04 resp. 0.0001. Therefore, the two variables (seasonal precipitation sum - the logarithm is dropped for simplicity - and minimum temperature during flowering stage) are chosen to be the two key identifying variables for the classification of

Table 5: Regression output, potatoes (n = 136)

	Coefficient	Standard Error	p-value	R^2 adjusted
Model 1				0.23
$\sum d_{P=0}(12)$	-0.016	0.009	0.08	
B_{RS}	0.005	0.002	0.008	
$\varnothing$ T(season)	0.35	0.08	5.29e-05	
Model 2				0.29
$\log(\sum$ P(season))	0.99	0.26	0.0002	
B_{RS}	0.005	0.002	0.004	
$\varnothing T_{min}(1,2))$	0.23	0.06	0.0001	

yields. In Figures 4 and 5, the yields are presented in accordance with the two chosen climatic indicators.

3.5 Frequency and Yield Grid

The two identifying variables chosen in the previous section will now be used to assign yields to different combinations of those variables. In a first step, grid levels for both variables are chosen. This is done by means of a sensitivity check, the aim of which is to reduce the standard deviation in each grid, cf. Figure 15 in the Appendix. The aim being to obtain grid cells which contain yield values as homogenous as possible. The levels for the precipitation sum are set as follows: 270-550 mm, 550-710 mm, and 710-1600 mm. The levels for the minimum temperature during the flowering stage are the following: 1.1-2.9 °C, 2.9-4 °C, and 4-6.7 °C. In Figure 6, the occurrence frequency of the different precipitation / temperature combinations is displayed. For each climate grid, the mean of all the yields which fall into this grid are taken for quinoa and potatoes respectively, as presented in Figures 7 and 8. Standard deviations of the yields are shown in Figure 15 in the Appendix. The yields for 136 years in total are allocated; 48 years (from 1964 to 2012) for both the Lampa and Arapa stations, and 40 years (1972 to 2012) for the Chuquibambilla station. Unfortunately, there is no climate data available for the

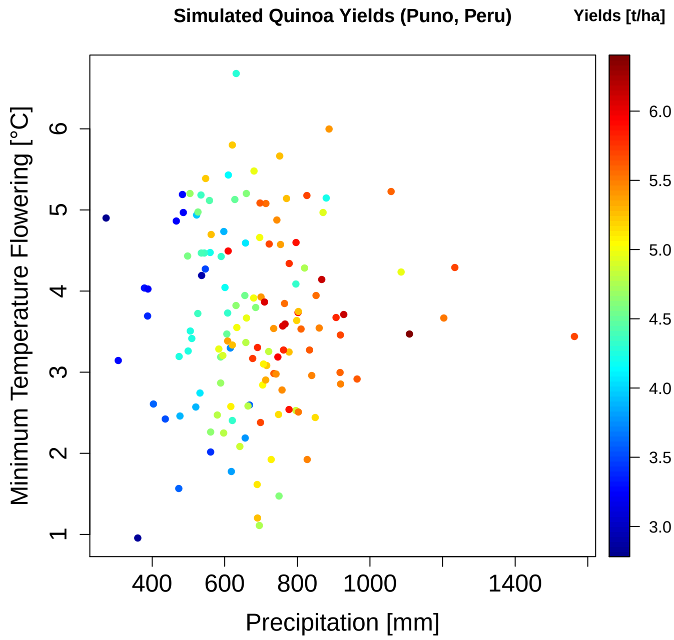

Figure 4: Quinoa yields plotted against temperature and precipitation values (Lampa, Arapa, and Chuquibambilla, years 1964-2012).

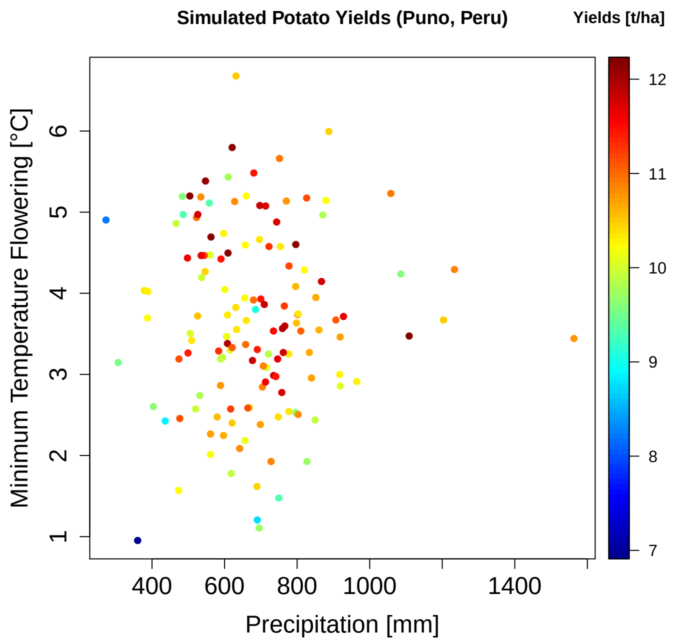

Figure 5: Potato yields plotted against temperature and precipitation values (Lampa, Arapa, and Chuquibambilla, years 1964-2012).

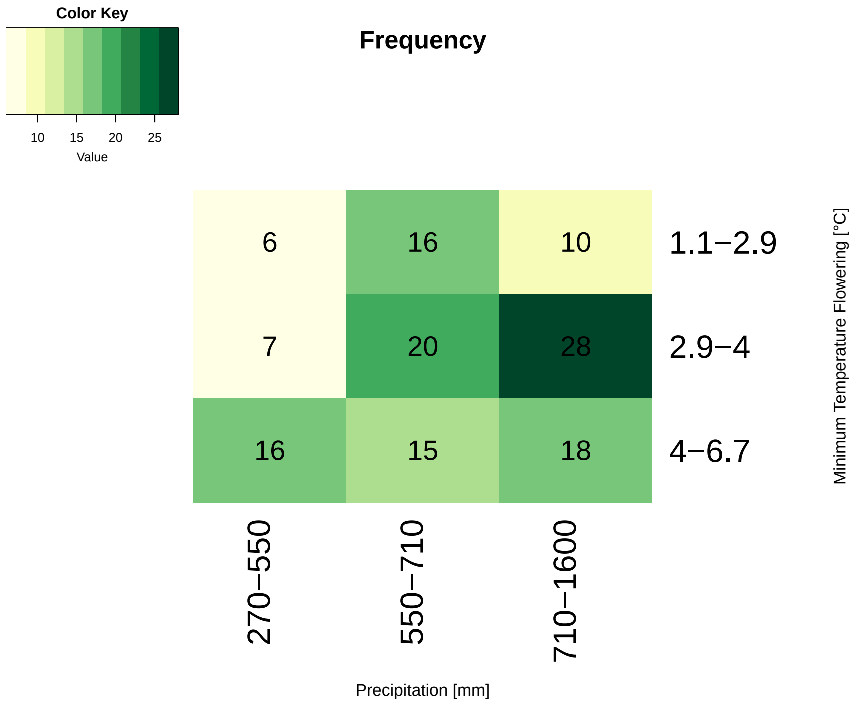

Figure 6: Frequency of precipitation and temperature realisations (n = 136).

Chuquibambilla station for the years 1964-1971 as mentioned in Section 3.2.

3.6 Value of Climate Services: Application

To derive an estimate of the value of SCF in helping to allocate land to either quinoa (crop 1) or potato (crop 2) in the region of Puno, we maximise expected revenue analogously as in the theoretical model, for the two scenarios, one with and one without SCF. Then, the difference found between the expected revenue of the two scenarios reveals the value estimation depending on relative prices.

Maximising expected revenue both with and without climate services requires a comparison of the revenues of the two crops. In Section 2.1, we defined revenue by multiplying quantity with prices and subtracting the costs. Since historic price and cost data is not suitable for this analysis (see Section 4.1 for further discussion on this topic), relative prices are introduced. These relative prices are seen as net-prices, i.e. price minus cost per unit, and correspond to the price ratio of crop 1 to crop 2. The economic interpretation behind these relative prices is based on the assumption concerning the indifference of the farmer: if the expected revenues

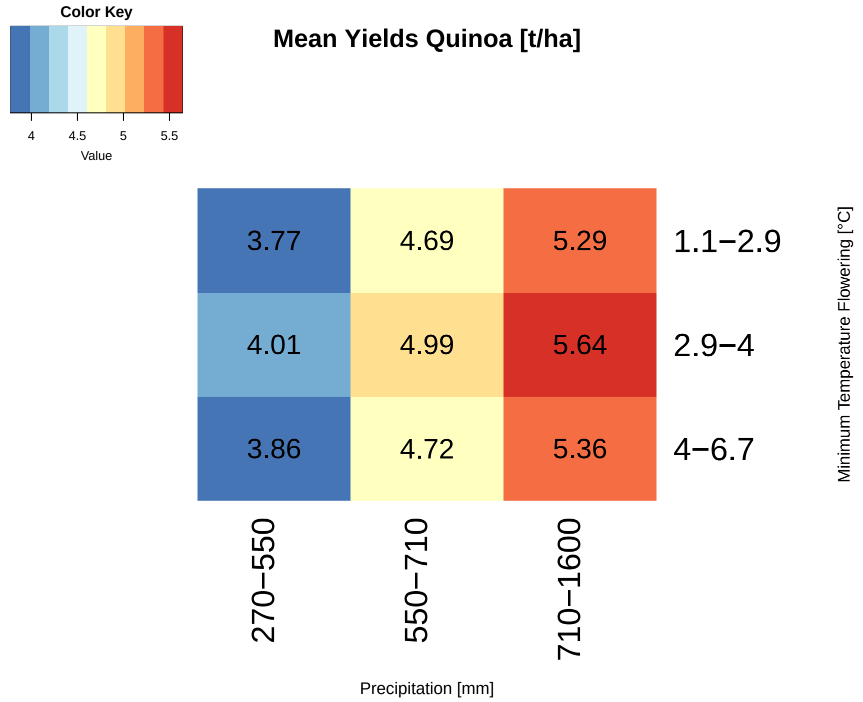

Figure 7: Mean quinoa yields per precipitation and temperature grid (n = 136).

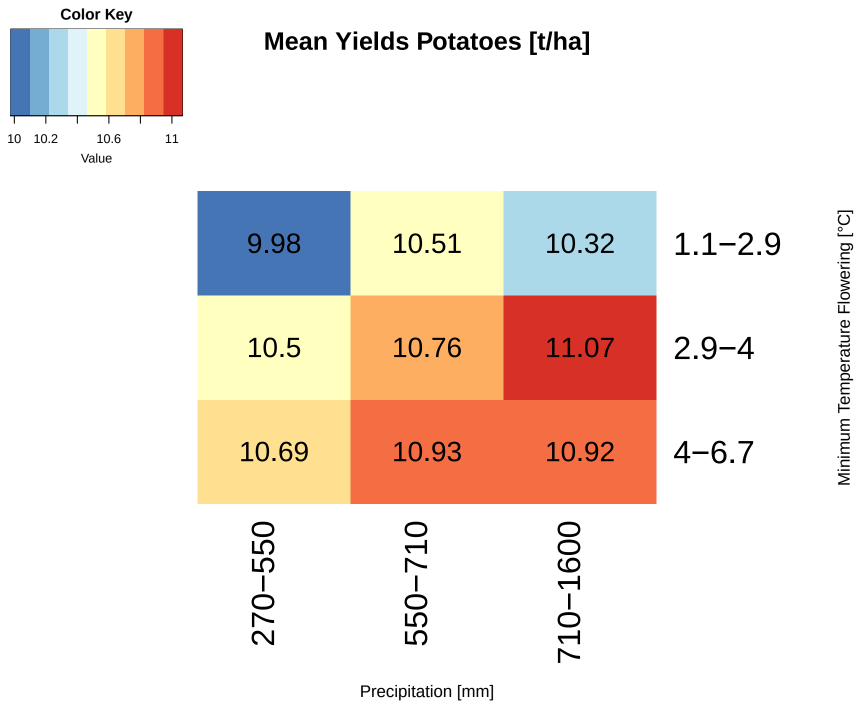

Figure 8: Mean potato yields per precipitation and temperature grid (n = 136).

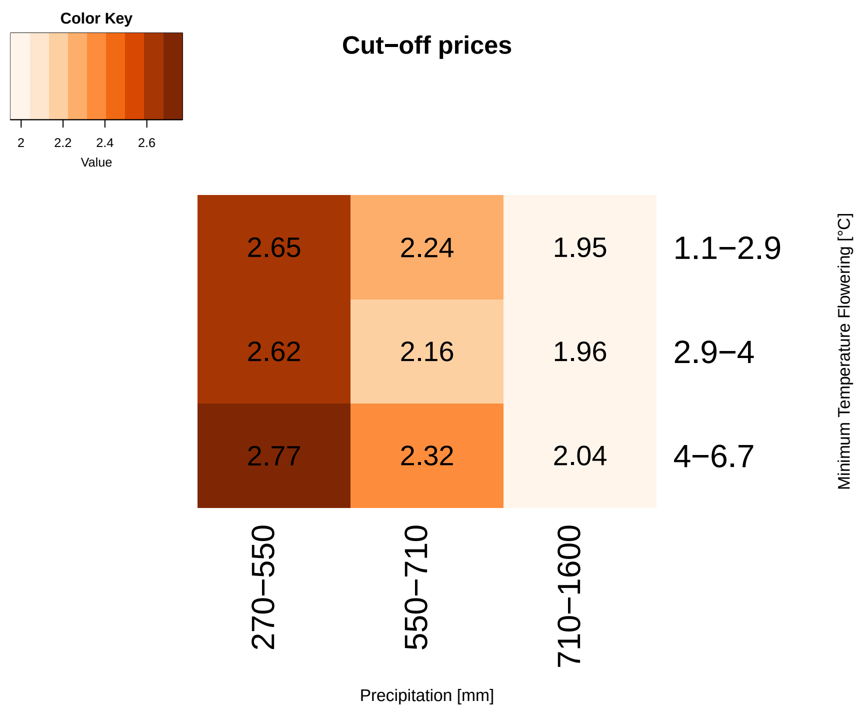

Figure 9: Cut-off prices per climate grid.

of the two crops are equal, they are assumed to be indifferent as to whether they cultivate quinoa or potatoes. Here, the cut-off prices come into play: they represent the relative prices with which the farmer is exactly indifferent in terms of allocating their land to either of the two crops at hand. Thus, the cut-off prices are defined as follows, where q_i indicates quantity and p_i prices for crops $i = 1, 2$:

$$p_1 q_1 = p_2 q_2 \rightarrow \frac{p_1}{p_2} = \frac{q_2}{q_1}$$

Following this definition, one cut-off price was calculated for each climate grid, as presented in Figure 9. The cut-off prices indicate the range of relative prices, within which an adjustment of crop choice when using SCF might be of interest. Taking the example of the grid cell with precipitation values between 270 and 550 mm and minimum temperature during flowering of 1.1-2.9 °C, this means that if the relative price of quinoa to potatoes is higher than 2.65 (e.g. 2.7), a farmer would choose to plant quinoa only. This is because the revenue they can earn by planting quinoa is higher than with potatoes, i.e. $2.7q_1 > q_2$, for this climatic condition. Now let us calculate the value of SCF based on relative prices. The relative prices are chosen such that they are close to, but never equal to, the cut-off prices. This ensures that we choose relative prices where a change of crops, between years with different climatic conditions, is of interest to the farmer. The cut-off prices are left out for simplicity, so that we do not have results where the farmer is indifferent to the two crops for a given climatic condition.

3.6.1 Maximisation without Seasonal Climate Forecasts

Maximisation without seasonal climate forecasts is conducted analogously to Section 2.1, by maximising expected revenue with respect to the probability density function of past climatic conditions. Note that in this applied part, the pdf has been discretised, cf. Figure 6.

We multiply the mean yields of quinoa for each climatic grid with a relative price. Subsequently, we multiply this product with the frequency of occurrence of each grid cell. Then we take the sum over all 9 results and divide it by the number of years, which in our case is 136 years. This procedure results in a frequency-weighted revenue for quinoa, depending on the relative price chosen. For the second crop, potatoes, we can directly multiply the mean yields with the frequency per grid cell, then also take the sum and divide it by the number of years. The next step is to compare the expected revenues of the two crops, and then to choose the higher value to allocate the whole land resource to. We do this for a large number of relative prices, to get an encompassing view of the influence of different relative prices on farmers' decisions.

The same procedure is carried out for the 2.5th and the 97.5th percentile of quinoa and potato yields, to derive the 95% confidence interval as an estimation of the error of the resulting value. The two percentiles are obtained by subtracting and adding 1.96 times the standard deviation, hence assuming a normal distribution. Figure 15 in the Appendix presents the cut-off prices for the upper and lower percentiles.

3.6.2 Maximisation with Seasonal Climate Forecasts

The procedure derived in Section 2.1 for the maximisation with SCF can also be directly applied to the simulated yields. As a reminder, the important difference to the maximisation without SCF is that now, the climatic conditions of the coming season are known perfectly in advance thanks to the seasonal forecast. Thus, we take the same relative prices as in the previous case, and conduct the maximisation for each grid cell. This is done by first multiplying the quinoa yields of each grid cell with a relative price. In a next step, the revenue of quinoa and potatoes for each grid cell is compared, and the higher value chosen. This then results in a new grid, which consists of the higher of the two revenues for each cell. In other words, for each climatic condition, the crop yielding the higher revenue is chosen and the whole land resource is allocated to it. This new grid is again weighted by frequency, as was done for the scenario without climate services. As a result we get the expected revenue which can be derived from SCF when they are available. Again, this is done for a large range of relative prices, and for the 2.5th and the 97.5th percentile values of quinoa and potato yields as well.

3.6.3 Difference: Value with the Application

The maximisation with and without SCF results in expected mean revenues depending on a range of relative prices, which are presented in Figure 10. Then, to get an estimation of the value of the SCF, for each relative price, the expected revenue without SCF is subtracted from the expected revenue with SCF. The value of the SCF depending on the relative prices is displayed in Figure 11. For the range between 1.95 and 2.77 of the relative prices, a positive value has been found. Below 1.95, potatoes are chosen, and above 2.77, quinoa is chosen - then, a change of crops is not worthwhile for any climatic condition, because the expected revenue of said crop is strictly higher than that of the other crop. The value peaks at the relative price of 2.2, with 0.5 per unit. This means that in the case with SCF, the expected revenue is 4.66% higher than without SCF. The 95% confidence interval in Figure 11 represents the values derived for the lower and upper percentiles, which serve as a robustness check of the derived value estimates. The value of the SCF for the lower

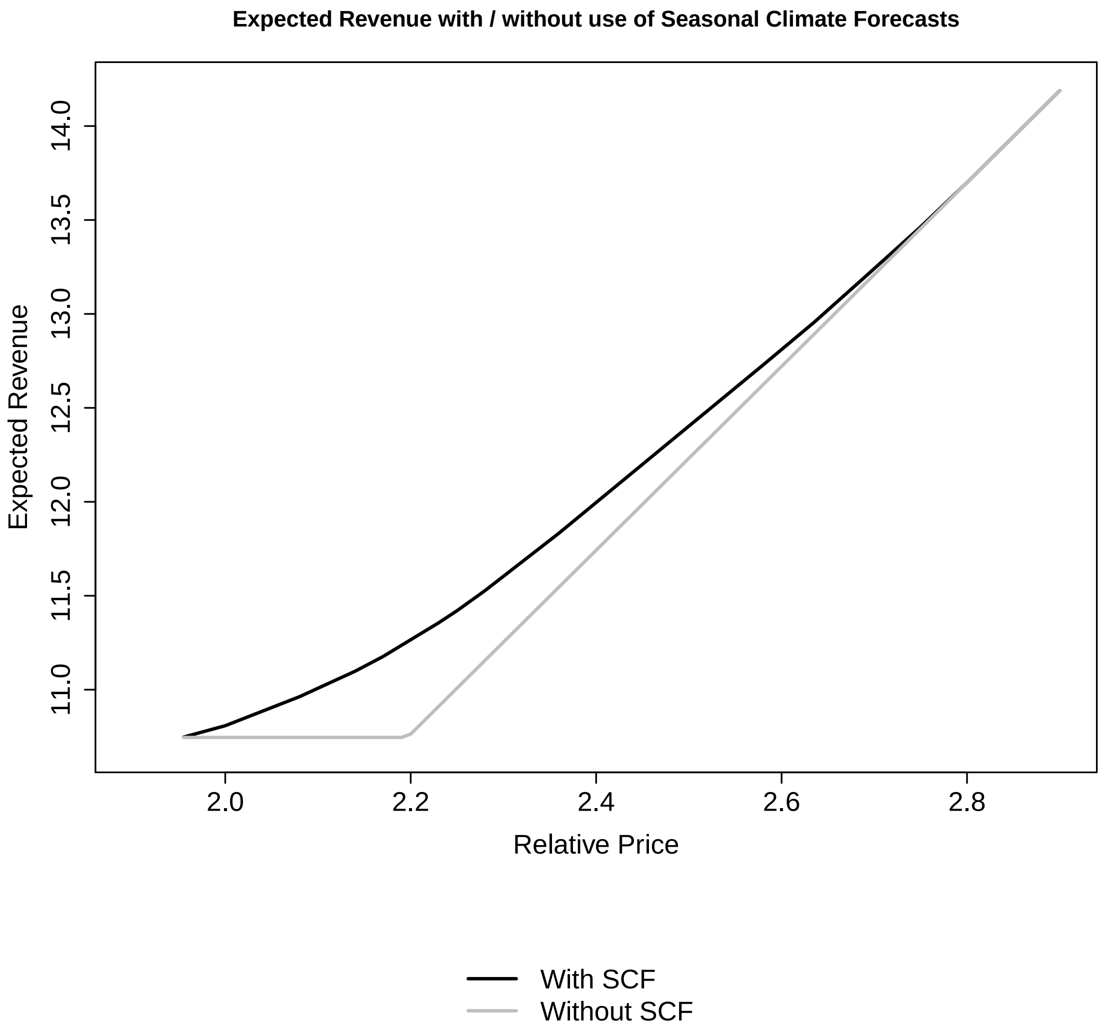

Figure 10: Expected revenue resulting from maximisation with and without seasonal climate forecasts, depending on a range of relative prices.

resp. upper percentile peaks at 0.45 (relative price of 2.08) resp. 0.65 (relative price of 2.4).

It is worth noting for which climate grids SCF are of relevance. These grids can be identified per relative price, which is done illustratively for the relative price 2.2, which yields maximum value (cf. Figure 11). Thus, the maximisation with and without SCF is performed. The grids where a deviation from the crop chosen without SCF (potatoes for a relative price of 2.2) occurs clearly correspond to those where SCF are most valuable. These grids encompass values of minimum temperature during flowering stage in the medium range (2.9-4 °C) for precipitation values of 500-1600 mm as well as all grids with the highest precipitation rate (710-1600 mm).

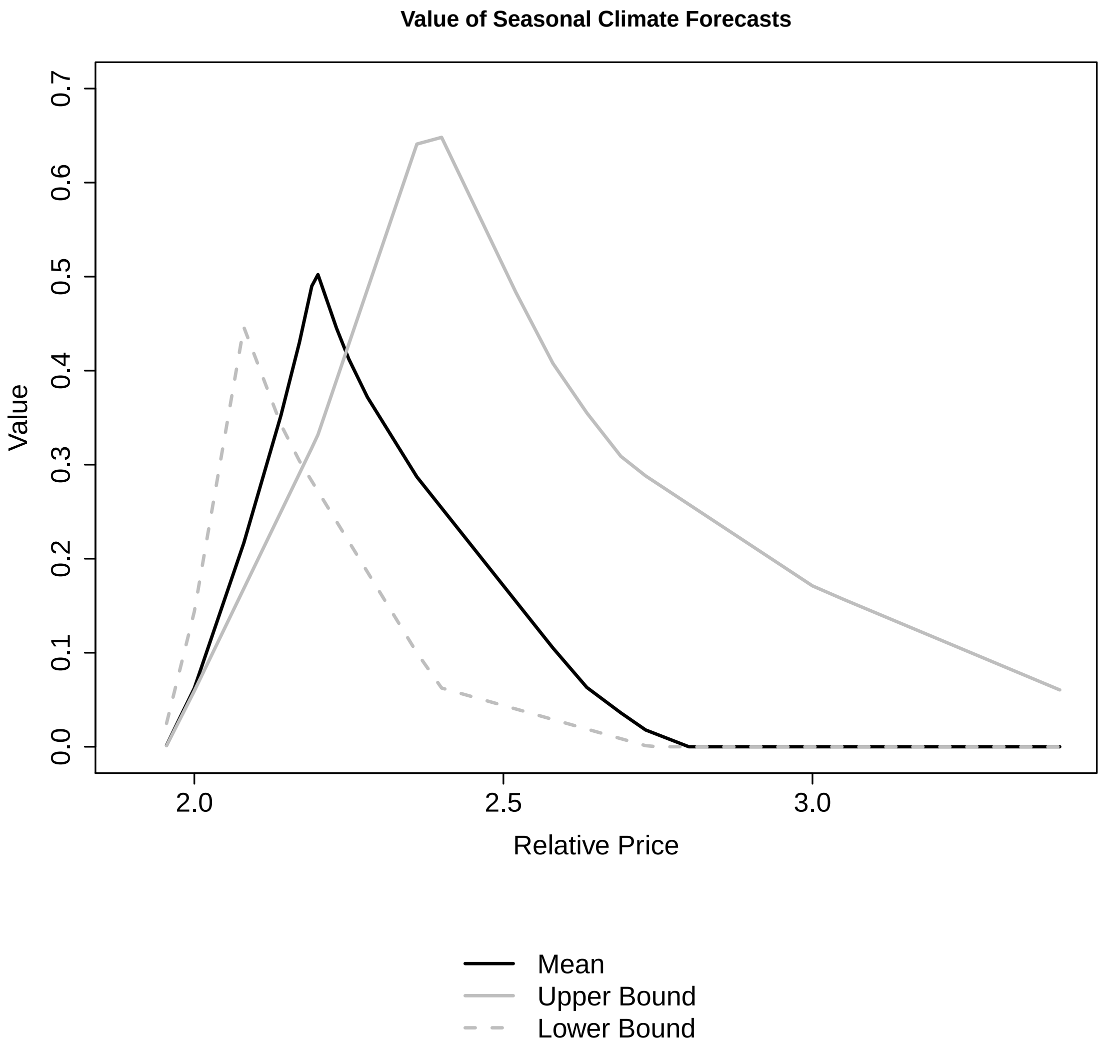

Figure 11: Value of seasonal climate forecasts depending on relative prices. The lower resp. upper bound indicate the 95% CI.

4 Discussion

In this section, the contributions and limitations of the approach developed in this thesis will be discussed. Then, the perspective will be broadened and the value of seasonal climate forecasts (SCF) in general will be focused upon. Further, SCF and constraints regarding their use will be discussed. Finally, the thesis will be put in its proper context within the Climandes project, as it was in collaboration with this project that the research question itself was developed.

4.1 Value of Seasonal Climate Forecasts for Land Allocation

On the one hand, the present approach to valuing SCF clarifies where SCF are most useful for optimal land allocation, i.e. in those years, where allocating crops with knowledge of past climatic conditions only results in lower yields than an allocation with knowledge of the climatic conditions in the coming season. This is, as shown in Section 3, the case in years where the minimum temperature during the flowering stage is in the medium range (2.9-4 °C) and the precipitation values are 500-1600 mm, as well as in all grids with the highest precipitation rate (710-1600 mm). For these climatic conditions, the value of SCF was found to be highest, assuming a relative price of 2.2. On the other hand, an estimation of the value SCF can generate was derived based on relative prices. This resulted in a maximum value of 0.5 per land unit for a relative price of 2.2 for quinoa to potatoes, which means that with seasonal forecasts, the revenue can be increased by 4.66% compared to the case when no forecasts are available.

Several limitations to this approach should be mentioned. First, only simulated yields were used for the analysis. A comparison of the simulated yields with statistical yields from the region of Puno for the same time span showed that the accordance was, with some exceptional years, rather low. On the one hand, the absolute values were much lower, and on the other hand, the variation mostly did not coincide. One point the simulated and statistical yields were in accordance on was the positive trend, which could - among other reasons - arise from the positive temperature trend identified in Section 3.2. Apart from this point of accord, the differences could arise from several socio-economic and environmental factors. Socio-economic factors arise mainly from external limitations on optimal crop management, for example a shortage in labour to work the land. Environmental factors could arise from the highly localised weather circumstances in this region. The simulations were run with climatic data from one station at a time, but the statistical yields are an aggregation of the whole region, which encompass a large variety of micro-climates and thus of yield levels. Another reason for the differences emerging for environmental reasons are soil specifications, which may vary among different locations and among the region of Puno and our simulations. For the scope of this analysis, we therefore decided to focus on simulated yields only, to emphasise the climatic influence.

A second limitation is connected to the costs and prices of the two crops. Within our approach, we have made use of relative prices, which can be seen as net prices, thus price minus cost, per unit. Although statistical price and cost data would be interesting to add, reliable cost data for the two crops for the respective time span and region was not available. As a consequence, only general statements on the differences in cultivation costs could be made. Price data for the required time period and region would have been available; however, the year to year fluctuations were immense, which can only be explained by famines or other extreme events. These extreme values would have distorted the result and would have been a distraction from the actual processes which were to be shown. Furthermore, too many data points in time were affected to remove them from the analysis. As another option, world market prices instead of local prices could have been used. This would have been possible for prices of potatoes, but not for quinoa prices. Since quinoa was produced only in Peru and Bolivia until recently, only price data from these two countries exists. Both countries have experienced the severe price instability of agricultural commodities in the past, hence, the result would have been similar to the one with local prices only.

Further, the possibility that crop prices and costs depend on the weather index could have been considered in the analysis. Potentially, if the harvest is low due to unfavourable conditions during the growing stage of a crop, supply decreases and prices would be expected to rise, and vice versa. This was noted by Keppenne (1995), who has shown a relationship between the ENSO phenomenon and commodity prices. Another issue associated with crop prices encompasses the relationship between farmers' land allocation strategies and prices. Thus, if in one year climatic conditions are more suitable for crop 1, most farmers will plant crop 1 only, and the price of this crop would be expected to decrease due to an excess in supply. This mechanism calls for management strategies which are able to offset such effects.

A third limitation arises from the assumption that the representative farmer is risk neutral, and thus maximises expected revenue. Evidence suggests that smallholder farmers tend to be especially risk averse, due to their high dependence on yields for their own, and their families, nutritional needs (Young, 1979; Lins et al., 1981; Pope and Just, 1991; Chavas and Holt, 1990). Tying this fact to our model leads to the suggestion that without SCF, farmers choose the less robust crops in fewer cases than the risk neutral farmer would, to reduce the risk of low yields. With SCF however, the risk averse farmer would also be able to choose the optimal crop for each situation, leading to a higher difference in yields for the two scenarios. This implies that for risk averse farmers, the value of SCF is even higher than for risk neutral farmers, as was also claimed by Messina et al. (1999).

4.2 Value of Seasonal Climate Forecasts in General

Farmers utilise a whole set of management options when seasonal climate forecasts are available. This set encompasses decisions that can be made at different points in time during the cultivation process. Before sowing, decisions about land allocation need to be made, which the present approach investigates. The time of sowing is a criteria which is dependent on the beginning of the rainy season and therefore, SCF can also prove very useful. Further, after sowing, decisions about irrigation, the application of fertilizer, herbicide etc. need to be taken. SCF can potentially also play a role in these vital decisions. Thus, the present approach only covers one part of the possible management options and thus of the potential value of seasonal climate forecasts. Mjelde et al. (1997) emphasise the importance of including a whole set of decision types into the analysis of the value of SCF. They argue that the interactions between decisions also play an important role, e.g. when decision A is taken based on SCF, then decision B also needs to be adjusted. However, Mjelde et al. (1997) analysis is based on the decision sets available to large farmholders, and these, as mentioned previously, are more wide ranging than those of smallholder farmers, who are the average farmer in the region of Puno. In conclusion, the value of seasonal climate forecasts arises from different management options being carefully used in unison; the present study has only covered one stage of the farming process where SCF could be of use, thus the true value of SCF is probably higher.

4.3 Uncertainty and User-Dialog

An increase in the time horizon of forecasts usually goes along with an increase in possible sources of uncertainty. Therefore, the quality of SCF is often too low to use for decision making. However, in regions where the El Niño-southern oscillation and other large-scale inter-annual climate variations have a direct influence on the local climate, the quality of SCF is often remarkably high. Jaksic (2001) reviewed several studies about the effect of ENSO on the climate in western South America, where many direct links have been found. Thus, Peru lies within a region where the quality of SCF is potentially high enough to base decision making upon, cf. Tapley Jr and Waylen (1990). This is further supported by Orlove et al. (2000), who found that the poor visibility of the Pleiades (star formation) in June indicates an El Niño year, which is characterised by reduced rainfall and thus reduced crop yield. This indicator is said to be a centuries-old method the Andean inhabitants have used to forecast the climate of the coming season.

In the theoretical model proffered in Section 2, the forecast is assumed to be perfectly accurate, which is of course a strong assumption. Then, in the applied part (Section 3) it was possible to slight relax this assumption, since the forecast only needs to be able to tell in which climate grid the coming season will fall. The assumption that this grid is always correctly predicted is, however, still a pre-requisite. The value found in this study therefore indicates the upper limit, and in consequence a less accurate forecast would be worth less.

The remaining uncertainty in SCF and their communication continues to be a challenge. For SCF to become valuable, they need to find their way into the decision making processes of farmers. Jones et al. (2000) stated that apart from providing information about the effects of climate variability and climate forecasts, feasible alternatives for adaptive actions based on forecasts must also be comprehended. Once accomplished, the currently existing gap between climate forecasts and their application in agriculture could be bridged. Further, Patt and Gwata (2002) found 6 constraints which limit the usefulness of forecasts: credibility, legitimacy, scale, cognitive capacity, procedural and institutional barriers, and the available choices of farmers. For the successful use of seasonal forecasts, these constraints would need to be addressed whenever possible. In addition, concerning the optimal timing of the forecast, the trade-off between the forecast skill and its relevance, depending on the timing of agricultural decision making, has to be kept in mind so that a useful balance between the two can be achieved (Haigh et al., 2015). Furthermore, in respect to other factors influencing decisions farmers make, careful coordination is required, to prevent crowding-out effects. Such effects could for example arise if farmers make decisions based on SCF, but then fail to take price fluctuations into account, which could lead to a reduction in total revenue despite their best intentions and efforts.

4.4 Context: Climandes Project

The project Climandes (Servicios climáticos con énfasis en los Andes en apoyo a las decisiones) aims to develop climate services, such as SCF, for decision-makers in the agricultural sector in Peru, with the Puno region as a pilot area. The project is coordinated by the World Meteorological Organisation and implemented jointly by the Peruvian National Meteorological and Hydrological Service (SENAMHI) and MeteoSwiss with many supporting partners. The project is divided into three different modules. One module is in charge of the development of the climate services, another for education and capacity building, and a third module focuses on user-dialogue and the socio-economic benefit of the climate services. My internship at MeteoSwiss was within the latter and therefore, the research question for this Master's thesis was developed in collaboration with the associates of this module.

This module encompasses various activities and approaches to deepen the knowledge of user needs in the context of SCF, such as a field study, recurring workshops, and the use of scientific methods to estimate the value of SCF. The field study intends to disclose the vulnerability of farmers to climatic variability and the management options that could reduce this vulnerability, while being based on SCF. The workshops were designed to facilitate the inclusion of the SCF into decision making. Further, the estimations of the value of SCF gained by different scientific methods, such as stochastic life cycle modeling and real option analysis, aim to enhance knowledge and consequently public perception of the value of such services. The scientific analyses will be focused on management options for the crop quinoa; hence, this Master's thesis provides a complementary analysis by looking at the optimal allocation of land.

4.5 Outlook

An extension of the theoretical model developed in this thesis could take into account decreasing (or potentially also increasing) returns to scale of the fraction of land allocated to crops. Therefore, one could for example assume that a representative farmer has a certain area of land which they can allocate to two crops, as was done in this thesis. However, the assumption of the land to be of homogeneous quality could be relaxed by assuming that one part of the land is particularly suitable for crop 1, and the other part especially suitable for crop 2. In this sense, in an 'average' year, crops would then be allocated where the land is most suitable for them. However, in a year where the climatic conditions are more suitable, for example for crop 1, it might be optimal to plant more of this crop than the suitable area allows for. The part of the less suitable land which is allocated to crop 1 would then yield decreasing returns to scale and hence an interior solution for the fraction of land allocated could be found.

A second possibility of further research in this area focuses on future climate. The analysis in this Master's thesis provides an estimation of the value of SCF for land allocation based on historical weather data. The same style of analysis could also be conducted for future climate scenarios based on different emission projections. The distribution of the occurrence frequency of climatic conditions (cf. Figure 6) would probably shift towards higher temperatures (IPCC, 2013). As a result, yields could be simulated for projected climatic conditions and the maximisation conducted based on the projected data. Comparing these results with the results obtained in this thesis would allow inferences to be made about how changing climate conditions affect the potential of reducing agriculture's vulnerability through the optimal allocation of land via SCF.

A third direction for further investigation is the issue of how to lower farmers' vulnerability to climate variability. Such a study could encompass measures beyond SCF. Such measures could for example be the use of insurances to flatten risk over time. Potentially, a combination of these measures, i.e. insurance and SCF, could be used to achieve a reduction in farmers' vulnerability.

5 Conclusion

The objective of this thesis was to analyse and estimate the value SCF could potentially generate when used to adjust land allocation in the agricultural sector. Therefore, a theoretical model was developed, and then applied to the region of Puno in Peru. The theoretical model consists of a representative farmer which maximises expected revenue. The farmer is set into two different scenarios; in one case, they choose the crops to plant depending on their knowledge of past weather conditions. In the other case, the farmer maximises revenue by using seasonal climate forecasts, which means they have perfect knowledge about the climatic conditions in the coming season. The thesis has shown that the revenue derived in the second scenario will be higher than in the first scenario, because in the first scenario, the farmer always chooses the more robust crop, while in the second, they are able to choose the crop which suits the coming climatic conditions best.

The practical application to Peru was intended to achieve a discretisation of the theoretical model derived by using statistical climate data with simulated yields from the region of Puno in Peru. By using multiple linear regression, two main climatic indicators to classify yields were found, namely the seasonal precipitation sum and the mean of the minimum temperature during flowering stage. Then, the yields were aggregated to a climatic grid, depending on their precipitation and temperature values, such that the mean yields per climatic condition were obtained. The next step involved the value of the seasonal climate forecast being calculated, analogously to the theoretical model, by maximising expected revenue with and without SCF, depending on relative prices, and taking the difference thereof.

Two main results could be obtained. First, an estimation of the value of SCF in allocating land to quinoa and potatoes was derived, which corresponds to 0.5 per land unit for a relative price of 2.2 for quinoa to potatoes. Thus, with the aid of SCF, the expected revenue can be increased by 4.66% for this case. Second, the areas where the SCF turns out to be useful for the relative price of 2.2 could be identified; this is the case in years with values of minimum temperature during the flowering stage in the medium range (2.9-4 °C) for precipitation values of 500-1600 mm as well as all grids with the highest precipitation rate (710-1600 mm) for an optimal allocation of quinoa and potatoes.

Finally, we can draw two main conclusions. First, the value of seasonal climate forecasts for land allocation has been found to be positive for a large range of relative prices. This supports efforts to enhance the quality and availability of these forecasts in regions where their predictive ability is high enough to justify their use in decision-making, and in particular, where a large fraction of the population is dependent on the agricultural sector. Second, in order for this positive value to be exploited, the provision of high quality climate services alone is not enough, the careful communication of SCF and its meaningful integration into decision-making processes is a must.

Acknowledgements

I would like to thank all those who – directly or indirectly – helped me to complete this Master's thesis. A special word of thanks goes to my supervisor, Prof. Dr. Ralph Winkler, who never got short of valuable advice and sparkling ideas. Then, I would like to thank the three advisors of my thesis: Prof. Dr. Lucas Bretschger, Dr. Alexandra Vinogradova, and Dr. Annelie Holzkämper, who assisted with complementary advice whenever possible. Thanks to Prof. Dr. Gunter Stephan for chairing my Master's examination. Further, I would like to express my gratitude to all the colleagues at MeteoSwiss for providing me with ideas, advice, and good spirits. Especially to Moritz Flubacher, Dr. Andrea Rossa, Sara De Ventura, and Dr. Gabriela Seiz, without whom this thesis would not have been possible. Thanks also to Aurich Jeltsch-Thömmes and Markus Zahner, for offering a helping hand whenever needed. Finally, thanks to Darragh Fingleton, Antti Peltonen, and Urs Frehner for their review.

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Appendix

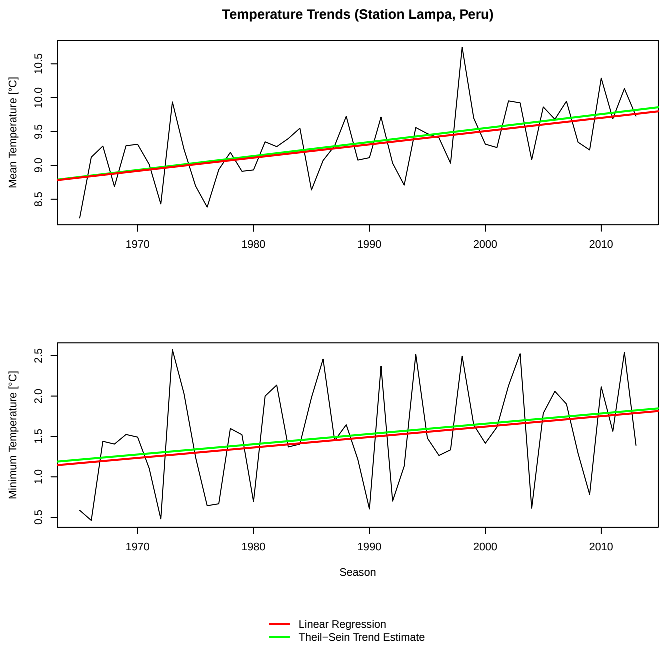


Figure 12: Temperature data plotted with trend estimates.

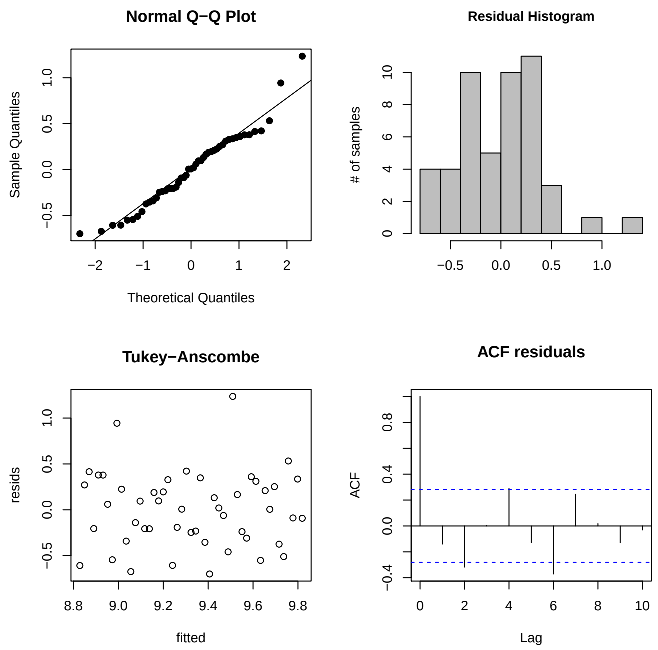


Figure 13: Residual plots of the linear regression trend estimate of seasonal mean temperature.

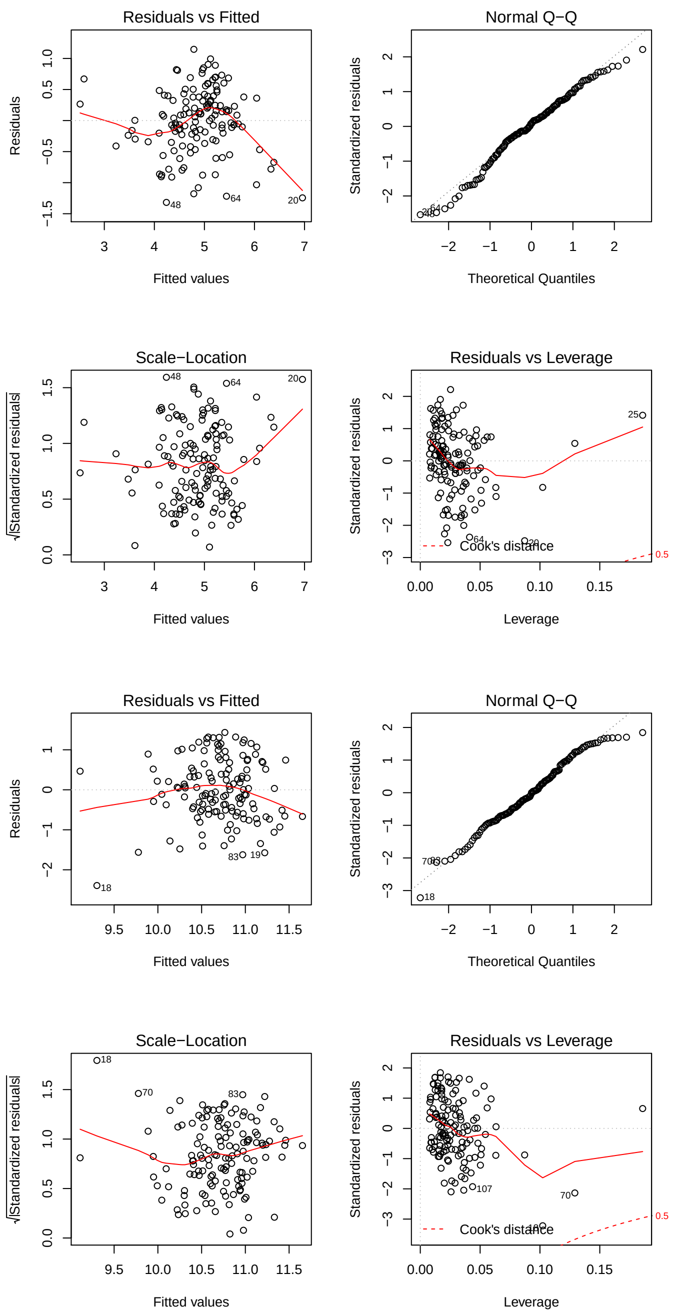


Figure 14: Regression plots of quinoa, Lampa (top) and potatoes, Lampa (bottom).

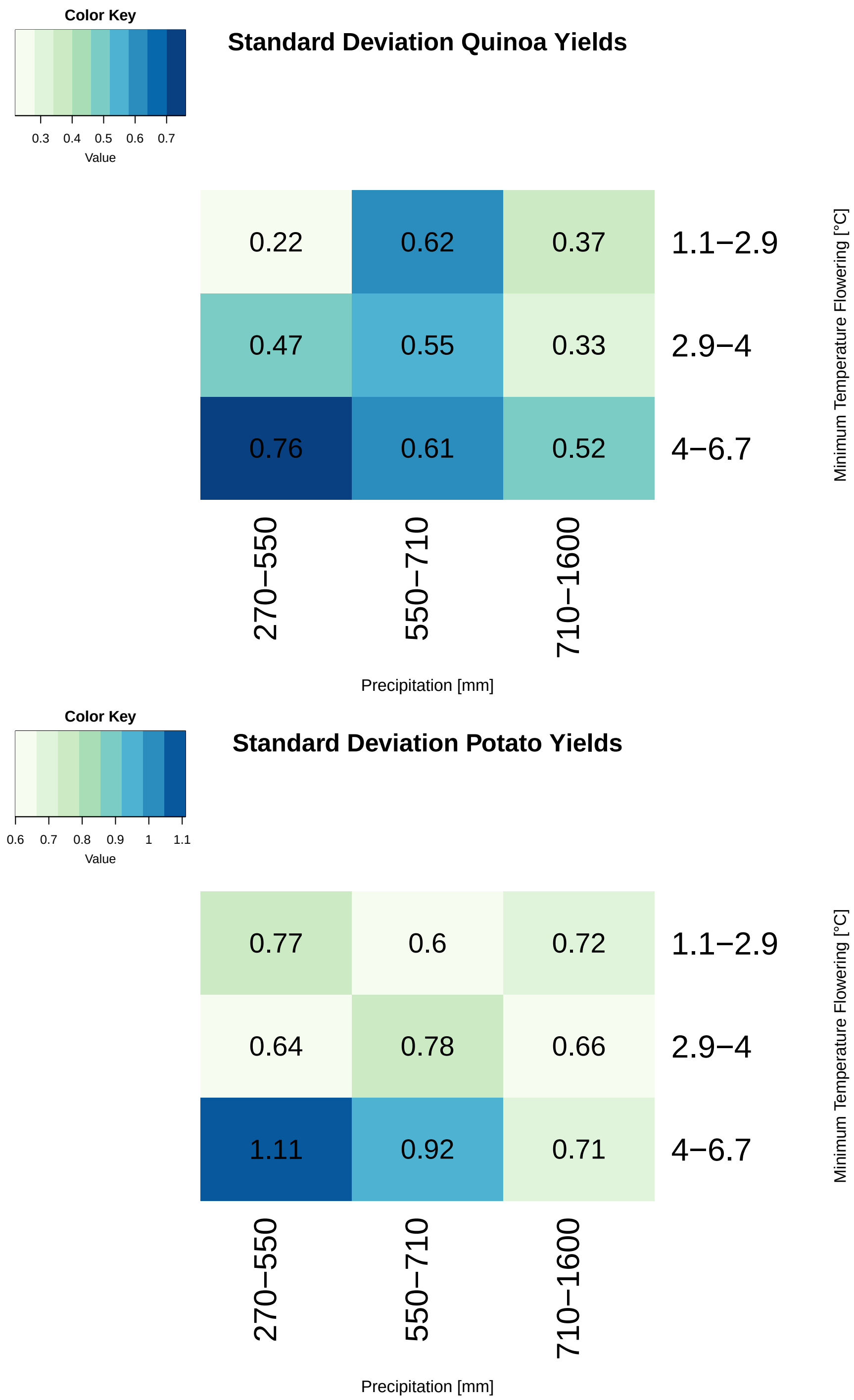
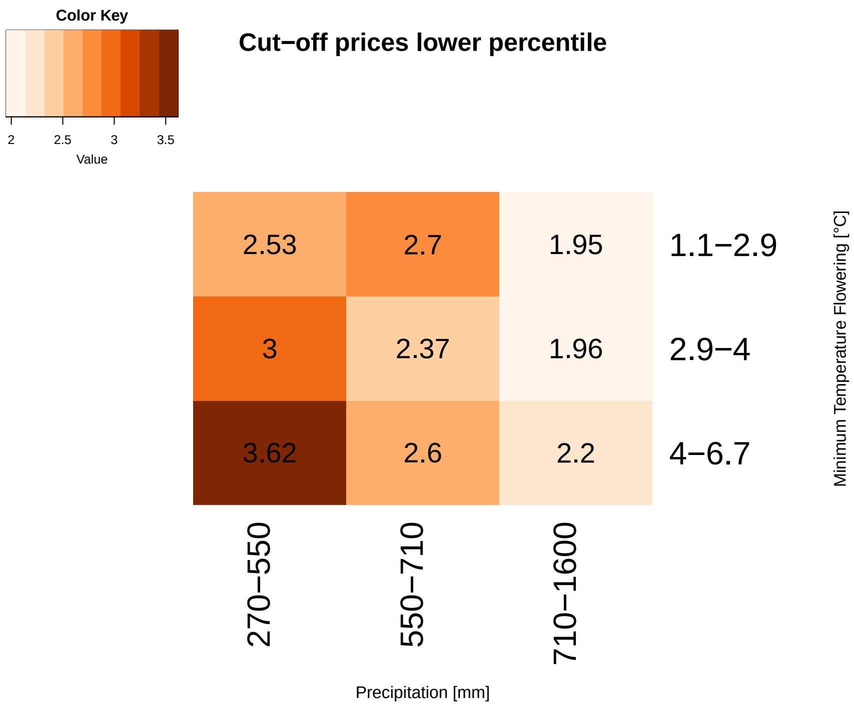


Figure 15: Standard deviation of quinoa and potato yields per climate grid.



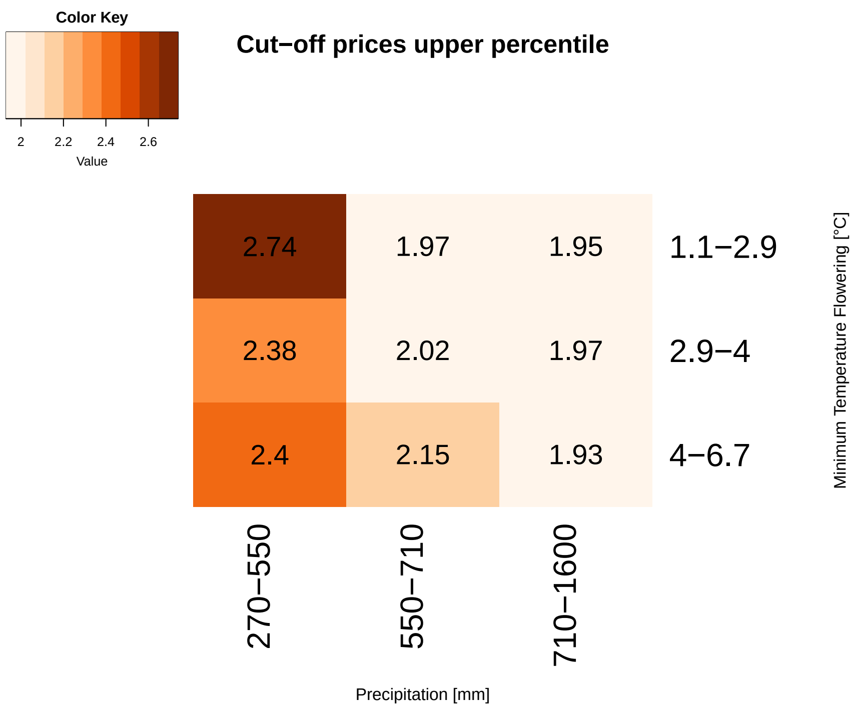


Figure 16: Cut-off prices of the lower and upper percentiles.

Declaration

under Art. 28 Para. 2 RSL 05

Last, first name: Frehner, Anita

Matriculation number: 10-111-706

Programme: Masters in Climate Sciences

Bachelor ☐ Master ☒ Dissertation ☐

Thesis title: Valuing Climate Services in the Agricultural Sector: Optimal Land Allocation using Seasonal Climate Forecasts

Thesis supervisor: Prof. Dr. Ralph Winkler

I hereby declare that this submission is my own work and that, to the best of my knowledge and belief, it contains no material previously published or written by another person, except where due acknowledgement has been made in the text. In accordance with academic rules and ethical conduct, I have fully cited and referenced all material and results that are not original to this work. I am well aware of the fact that, on the basis of Article 36 Paragraph 1 Letter o of the University Law of 5 September 1996, the Senate is entitled to deny the title awarded on the basis of this work if proven otherwise. I grant inspection of my thesis.

Bern, 08.12.2016

Signature