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Evaluating the Yields of the Rainfed Potato Crop under Climate Change Scenarios Using the AquaCrop Model in the Peruvian Altiplano

Jesus Puma-Cahua [1], Germán Belizario [1,2], Wilber Laqui [1,2,*], Roberto Alfaro [1,2], Edilberto Huaquisto [1,2] and Elmer Calizaya [2,3]

[1] Escuela Profesional de Ingeniería Agrícola, Universidad Nacional del Altiplano, Puno 21001, Peru; jsyosef@gmail.com (J.P.-C.); gbelizario@unap.edu.pe (G.B.); ralfaro@unap.edu.pe (R.A.); ehuaquisto@unap.edu.pe (E.H.)
[2] Escuela de Posgrado, Universidad Nacional del Altiplano, Puno 21001, Peru; ecalizaya@unap.edu.pe
[3] Escuela Profesional de Ingeniería Topográfica y Agrimensura, Universidad Nacional del Altiplano, Puno 21001, Peru
* Correspondence: wlaqui@unap.edu.pe; Tel.: +51-990-088-187

Abstract: Ensuring global food security and adapting to the challenges posed by climate change, particularly in rainfed agriculture, are paramount concerns. This research investigates the impacts of climate change on the yield of the potato crop variety Imilla Negra (*Solanum tuberosum* spp.) under the extreme climatic conditions of the Peruvian Altiplano. From the experimentation in six crop plots under a rainfed agricultural system, periodic crop growth parameter measurements were obtained from 2017 to 2018. The results showed a good performance of the AquaCrop model in the calibration and validation, successfully simulating crop growth and yield parameters. Climate projections showed precipitation decreases and temperature and evapotranspiration increases for the representative concentration pathway (RCP), RCP 4.5, and RCP 8.5 scenarios in 2023–2050. A comparison of crop yields between the base period (2006–2021) and the period 2023–2037 showed no significant changes, whereas a more considerable decrease was observed for the period 2038–2050. It is concluded that climate change generates moderate impacts on potato crop yields under the rainfed agricultural system in the Peruvian Altiplano due to the average reduction in precipitation.

Keywords: climate change; crop yields; sustainable; AquaCrop; food security; rainfed agriculture; Altiplano

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1. Introduction

Global warming is the increase in the Earth's temperature and has a significant impact on water supply; over the last 33 years, water demand has increased considerably, while water supply has been precarious [1]. This distribution of water resources will be further unbalanced at the river basin level, where agricultural production will be influenced by these complex movements of the water deficit [2], by significant projected climate changes, including unprecedented global mean surface temperature increases since the mid-20th century (1.5 to 5.0 °C) [3], and reduction in precipitation rate in summer (−25%) [4], leading to a higher frequency of these extreme weather events [5] attributed to climate change, which is defined as the change in climatic elements in a given period [6].

Climatic variables, mainly precipitation and temperatures, are changing [7], affecting crop growth and productivity [8]. These effects mostly turn out to be adverse, becoming a major global threat during the dry season due to increased temperatures and decreased precipitation [9]. In developing countries, this situation is aggravated by the fact that agricultural activities are more sensitive and vulnerable to climatic conditions and climate change, as well as by different resource, technological, and institutional constraints [10].

In addition, climate change and precipitation shortages limit agricultural production and significantly impact rainfed crop production [11]. The increase in temperature threshold and water scarcity affect the development of the different phenological phases [12,13] in potato crops, mainly in the formation of tubers [12].

Climate change is one of the world's most crucial concerns. It is a significant threat to the global food supply, mainly in family or subsistence farming [13], because it influences the primary conditions of agriculture [14], which are carried out with scarce resources, directly affecting the quality of life of farmers [15]. Agriculture is the mainstay of the economy and contributes to the food security and employment of rural households [16]; however, under the conditions of climate change and variability in the availability of water resources, adopting efficient irrigation systems, cultivating crops better suited to withstand drought conditions, implementing sustainable agriculture practices, adopting the strategy of climate-resilient sustainable agriculture (CRSA), and reducing our reliance on rainfall will be necessary to address this challenge to ensure crop production and guarantee food security [1,17,18]. Also, sustainable agriculture provides a potential solution to enable agricultural systems to feed a growing population while successfully operating within the changing environmental conditions [19]. Rainfed agriculture is currently one of the main economic activities most affected by climate change due to its significant social and economic consequences for human well-being [20].

Many approaches have been used to investigate the impacts of climate change on agriculture [21] using the AquaCrop model in a variety of seasons and locales; in all of them, good model performances were obtained [22,23]. However, the Peruvian Altiplano has particular characteristics, where rainfed agriculture is the principal agricultural production system and most vulnerable to climate change [24], so it is essential to study the impacts of climate change and to develop and improve practical assessment tools, which are crucial to reducing uncertainty in agriculture [25]. Therefore, in this research, we propose and evaluate the yields of the rainfed potato crop under climate change scenarios using the AquaCrop model in the conditions of the Peruvian Altiplano.

2. Materials and Methods

2.1. Study Area

The experiment was carried out in the rural community of San Martín, in the district and province of Azangaro, in the department of Puno in the Peruvian Altiplano. The field is located at 14° 04′ 05″ S and 70° 25′ 25.6″ W, with an altitude of 4315 m above sea level (Figure 1). It has a semi-arid climate typical of the northern Altiplano, characterized by a short rainy season (December–March) and a long dry season (April–November) [26,27]. According to Azangaro station data, the annual total precipitation is 597.8 mm, 67% of which occurs in the rainy season and 33% in the dry season. The yearly average temperature is 8.8 °C, with the minimum temperature recorded in July at 5.6 °C and the maximum in November at 10.8 °C (Figure 2).

2.2. Experimental Details

Six experimental plots of potato cultivation, variety Imilla Negra *(Solanum tuberosum* spp.), with the characteristics detailed in Table 1, were determined. The sowing date was 4 November 2017, and the harvest date was 2 April 2018, with a vegetative period of 151 days. Given that potato cultivation in the Peruvian Altiplano is mainly developed under the rainfed agriculture system, a single treatment for potato cultivation called rainfed potato crop (RPC) was determined, as was also carried out in previous research [22,28,29]. Sixteen canopy cover assessments were made during the growing season, with six replicates, obtaining 96 canopy cover data during the crop growing season. At the end of the growing season, potato crop yields in fresh weight (t ha^{-1}) were determined. The soil sample was collected from the study area, and the soil properties laboratory analysis is presented in Table 1.

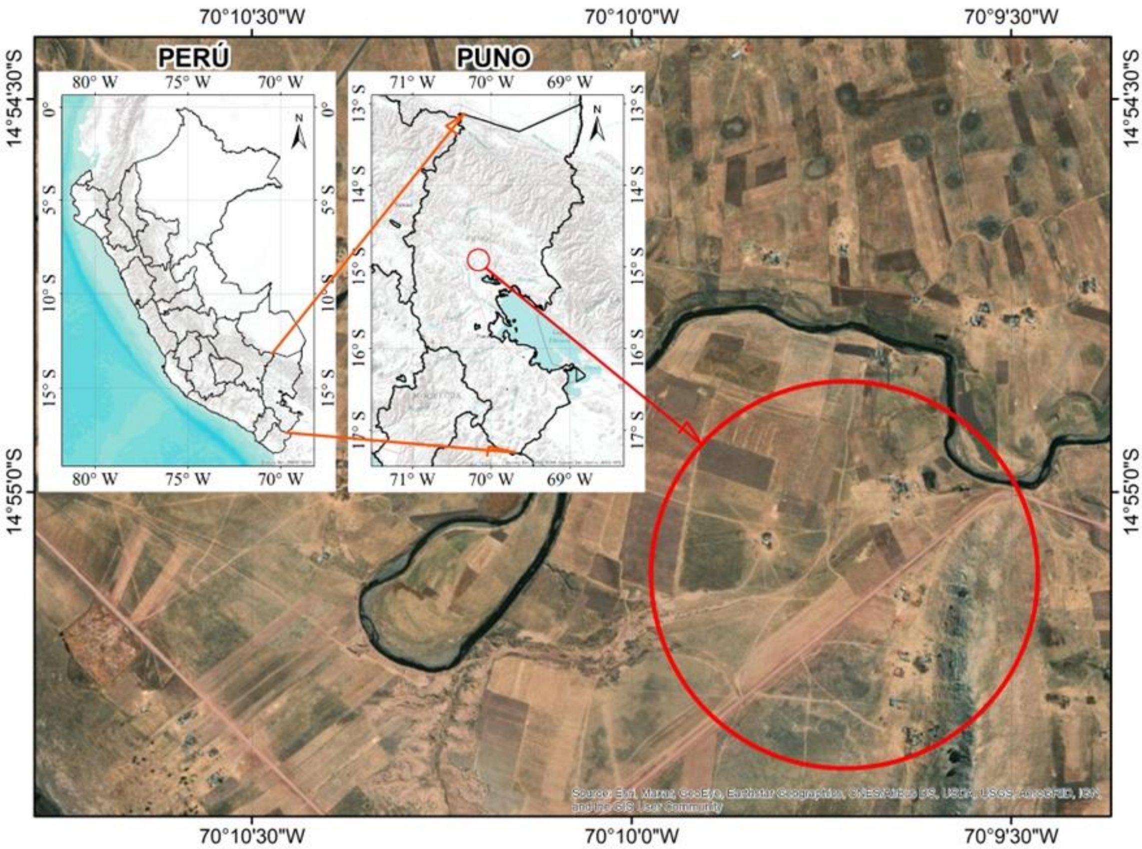

Figure 1. The location of the study area in Altiplano, Peru.

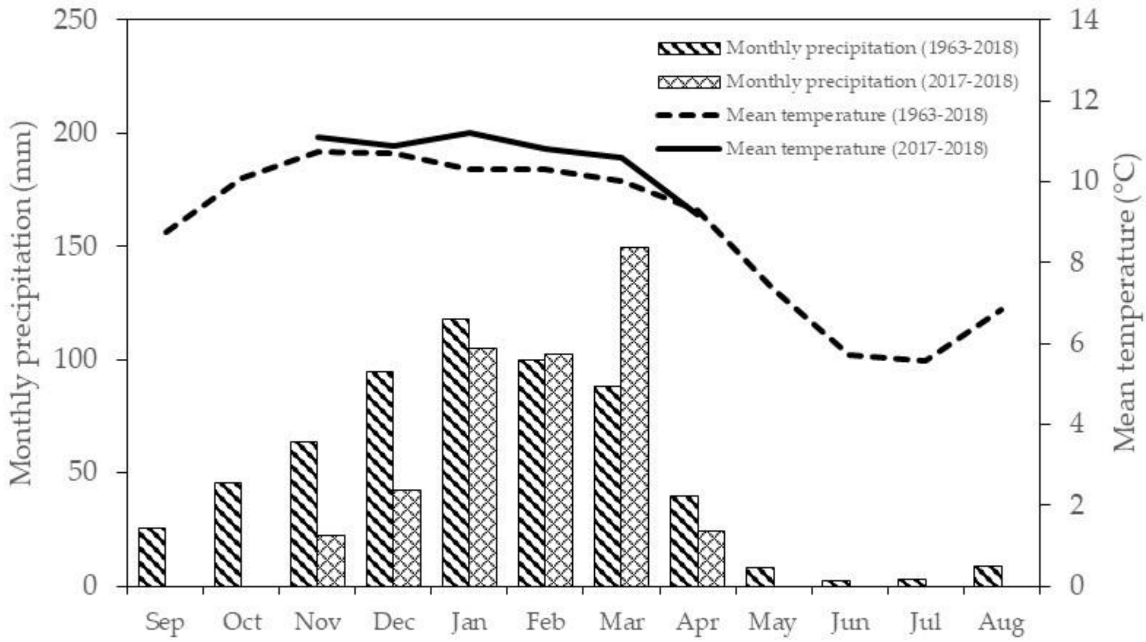

Figure 2. Historic monthly precipitation and mean temperature at the Azangaro station and data during crop growth period 2017–2018.

Table 1. Characteristics of experimental potato crop plots and soil properties.

Characteristic	Values
Total area	150.0 m^2
Number of plots	6
Plot area	25.0 m^2
Number of rows per plot	6
Furrow length	10.0 m
Row spacing	0.42 m
Plant spacing	0.40 m
Number of plants per row	25
Soil texture	sandy loam
Field capacity	27.6%
Permanent wilting point	14.2%
Bulk density	1.6 g cm^{-3}
Saturation percentage	42–49%
Hydraulic conductivity	400 mm day^{-1}
Soil depth	0–60 cm
pH	5.8
Organic matter	3.15%
Total nitrogen, phosphorus, and potassium	0.15%, 8.6 ppm, 119 ppm

2.3. Climate Data

Daily climatic data on precipitation and maximum and minimum temperature were obtained from the Azangaro station of the National Service for Meteorology and Hydrology of Peru (SENAMHI), located at 14° 54′ 52.2″ S and 70° 11′ 27.1″ W. Due to the limitation of climatic data, the Hargreaves method was used to estimate the reference evapotranspiration [30–33]. Figure 2 shows the monthly behavior of temperature and precipitation during the vegetative period of the potato crop (2017–2018).

2.4. Field Data Collection and AquaCrop Model Input Data

The setup of the AquaCrop model needs input data containing climatic parameters, crop, soil, field, and irrigation management data [23]. The daily precipitation and temperature values of Azangaro station were entered into the model, and evapotranspiration (ETo) values were also calculated using AquaCrop (ETo calculator) daily meteorological data. The canopy cover values were obtained through aerial images of plants from each repetition. The images were analyzed and processed in AutoCAD 24.2 to obtain the canopy cover. Final biomass and crop yield were obtained following maturity using samples from the experimental plot. The final aboveground biomass samples were collected by cutting the crop at the ground level and finally weighed digitally. The final yield samples were also harvested and weighed on the digital scale. Photographs of the process are shown in Supplementary Materials.

The physical and chemical properties of the soil characterized in samples taken from the study area (Table 1) were entered into the AquaCrop model. No irrigation management data was entered because it was considered a rainfed potato crop. The field management components include the soil fertility levels and weed infestation, which are the main agricultural activities in the study area [23]. Likewise, the model requires a set of soil and crop input parameters that were subsequently adjusted in the model's calibration.

2.5. AquaCrop Model Calibration and Validation

The AquaCrop model was calibrated with the observed field experiment values obtained from 2017–2018 for the rainfed potato crop (three experimental plots), according to the procedure described [34]. The field data were input variables to simulate rainfed potato crop growth and production. The fit of three growth parameters, such as canopy curve (CC), biomass (B), and crop yield (CY), obtained from the AquaCrop model, was evaluated with the field measurements made for the period 2017–2018, as also performed by [35], as well as statistics of the average annual yield of the potato crop obtained by the Regional Agrarian Directorate Puno for the period 2005–2017, using statistical evaluation criteria such as the Nash–Sutcliffe efficiency coefficient (NE), Pearson's correlation coefficient (r), normalized root mean squared error (NRMSE), and Willmott's aggregation index (d) [36].

The model was validated with the measurements of the field experiment for the 2017–2018 period (the other three experimental plots). The previously calibrated parameter values were used for the validation stage, and their evaluation was carried out using the NEC, r, NRMSE, and d performance criteria. The optimal value of NE is 1, representing a perfect fit; values of r close to 1 indicate a good association between the variables, while values below 30% are considered acceptable, and values of d close to 1 indicate a good fit [35,37,38].

2.6. Development of Climate Change Scenarios

Climate scenarios project gas emissions and temperatures for the future; the IPCC developed four climate scenarios called Representative Concentration Pathways (RCPs) (RCP2.6, RCP4.5, RCP6.0, and RCP8.5) [39]. For this research, two climate change scenarios were defined, RCP 4.5 and RCP 8.5, used in IPCC AR5. The RCP4.5 scenario corresponds to a medium stabilization scenario, and the RCP8.5 scenario corresponds to a very-high-emissions reference scenario. The precipitation and temperature projections used in this research correspond to data generated by CPTEC/INPE that are available on the climate change project platform for South America regionalized by the ETA Model (PROJETA), available at "https://projeta.cptec.inpe.br/ (accessed on 6 November 2022)" [40–42]. The projection database considers the CANESM2-ES, HadGEM2, and MIROC5 models regionalized at a 20 × 20 km spatial scale. The base period was defined as 1975–2005 and the projection period as 2023–2050.

Bias correction for daily precipitation maximum and minimum temperature projections was performed according to the procedure suggested by [43,44] for bias correction of regional climate models. From the corrected temperature projections, reference evapotranspiration was estimated using the Hargreaves method for the historical period (2006–2021) and the projected period (2023–2050). The reference evapotranspiration and precipitation were used as inputs to the AquaCrop model previously calibrated for the estimation of historical and projected potato crop production, as detailed in Figure 3.

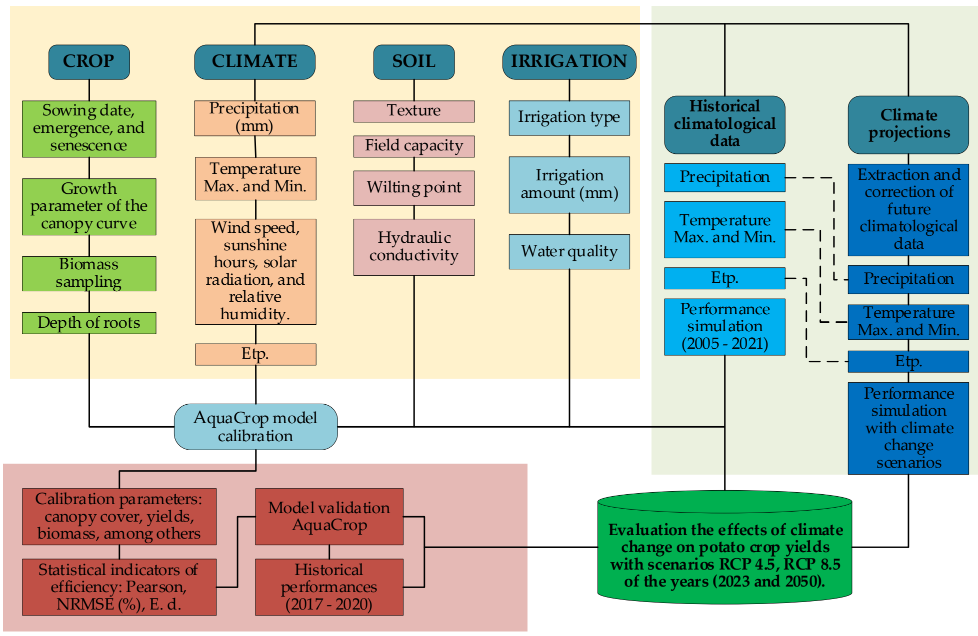

Figure 3. Methodological sequence for calibration, validation, and simulation of potato crop yield in the AquaCrop model.

3. Results

3.1. Calibration and Validation of the AquaCrop Model

The simulated canopy cover was compared with the potato crop canopy cover measurements recorded in the 2017–2018 season (Figure 4). It was observed that the values simulated with the AquaCrop model present consistency and a good fit with the field measurements of the canopy cover, obtaining an R^2 value of 0.95. Table 2 shows the performance statistics of the AquaCrop model for the calibration and validation phase. It was observed that the r, NRMSE, NEC, and d values had magnitudes of 0.98, 17.8, 0.86, and 0.96, respectively.

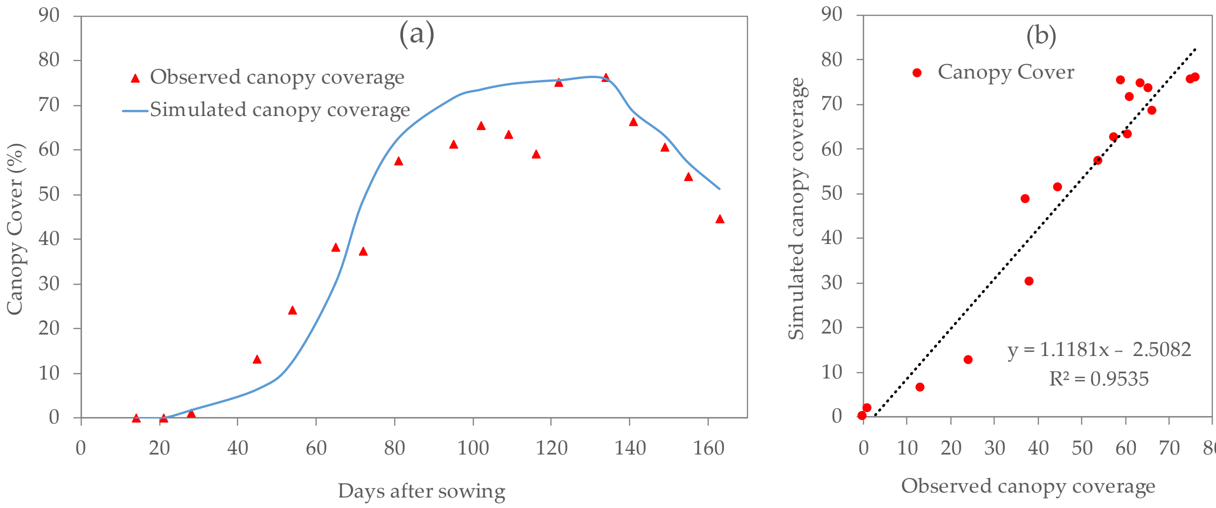

Figure 4. Calibration model: (**a**) comparison of the canopy cover simulated in the AquaCrop model and observed in the 2017–2018 period of the potato crop; (**b**) simulated vs. observed values of canopy cover.

Table 2. AquaCrop model performance statistics for canopy cover in calibration and validation phases.

Stage	r	NRMSE	NEC	d
Calibration	0.98	17.8	0.86	0.96
Validation	1.00	26.9	0.72	0.95

In the validation phase, good approximation was observed between simulated and observed canopy cover values for the 2017–2018 period recorded on 19 dates after planting. R^2 fit values of 0.99 were obtained, while the efficiency statistics of r, NRMSE, NEC, and d presented values of 1.00, 26.9, 0.72, and 0.95, respectively.

Concerning comparing observed and simulated dry aerial biomass with the AquaCrop model (Table 3), in the calibration stage, the performance statistics r, NRMSE, NE, and d presented values of 0.98, 6.4, 0.97, and 0.98, respectively, while in the validation stage, r, NRMSE, NE, and d were obtained with magnitudes of 0.96, 9.6, 0.96, and 0.98, respectively. Table 4 compares potato crop yield in dry weight observed and simulated by the AquaCrop model. In the calibration stage, a percentage difference of −0.44% was determined between the observed and simulated yield, while in the validation stage, the percentage difference was 0.87%.

Table 3. AquaCrop model performance statistics for dry aboveground biomass in the calibration and validation phases.

Stage	r	NRMSE	NEC	d
Calibration	0.98	6.4	0.97	0.98
Validation	0.96	9.6	0.96	0.98

Table 4. Comparison of observed and simulated crop yields at the harvest stage.

Stage	Performance (t ha^{-1})		.5 Difference	
	Observed	Simulated	Absolute	Percentual
Calibration	11.73	11.78	−0.06	−0.44
Validation	11.12	10.57	0.53	0.87

In Figure 4, it can be seen that for the period between the emergence and tuberization stages (27 to 60 days after planting), a marked underestimation of the simulated canopy cover was observed. In comparison, an underestimation of the simulated canopy cover was observed for the period between the lodging and fruiting stages (69 to 126 days after planting). Likewise, the model slightly overestimated the canopy cover values for the period from the onset of senescence to crop maturity (134 to 175 days after sowing). Therefore, the AquaCrop model in the calibration stage overestimated canopy cover compared to the observed values. As for the validation stage (Figure 5), it was observed that in the hilling stage (69 days after planting) and the period between the yield formation and fruiting stages (91 to 126 days after planting), the AquaCrop model generated a slight overestimation of the canopy cover values. These results are consistent with the error statistics (NRMSE) obtained for the calibration and validation stages, which in both cases were positive, which is an indicator of overestimation of the simulated canopy cover values. For biomass (Table 3), the performance statistics (NRMSE) showed that the AquaCrop model slightly overestimated the simulated biomass values. At the same time, for yield, it was observed that in the calibration stage, the model slightly underestimated the simulated yield values, and the opposite for the validation stage, as can be seen in the difference values in Table 4.

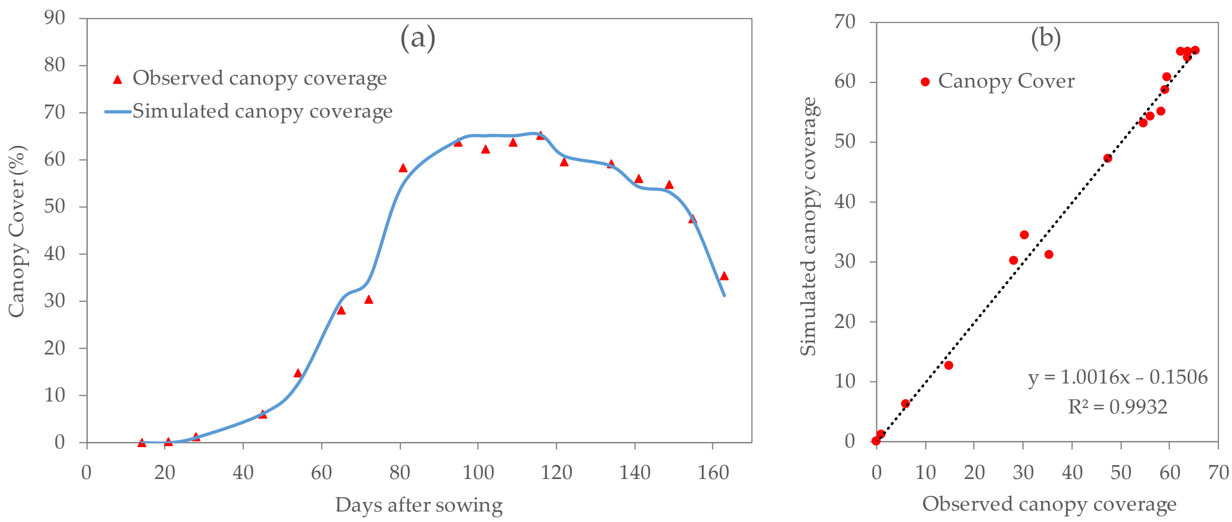

Figure 5. Validation model: (**a**) comparison of the canopy cover simulated in the AquaCrop model and observed in the 2017–2018 period of the potato crop; (**b**) simulated vs observed canopy cover values.

3.2. Precipitation Changes

The historical total annual precipitation (2006–2021) in the study area reached 610.5 mm, with yearly variations (Figure 6). For the projected period (2023–2050), using the CANESM2 model, it reached 687.07 mm and 743.66 mm per year, respectively, in the two scenarios RCP 4.5 (Figure 6a) and RCP 8.5 (Figure 6b). The average of the projected values shows a decreasing trend from December to April concerning the observed historical average values. It is deduced that the CANESM2 model behaves as an optimistic model in the two projected routes (RCP 4.5 and RCP 8.5) because its values favor the months of the agricultural season.

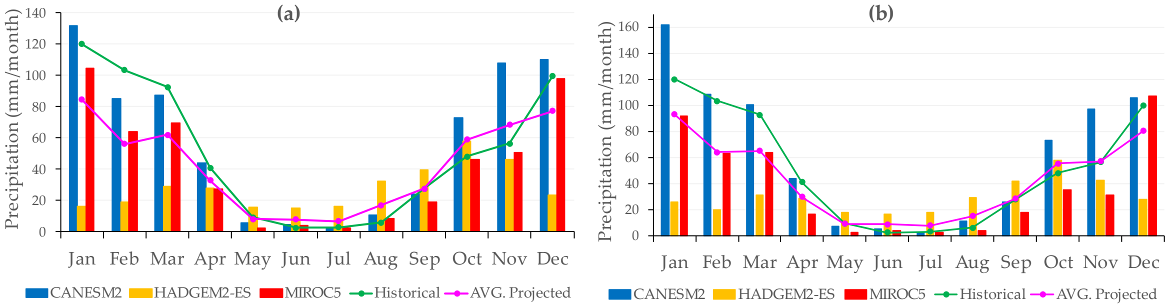

Figure 6. Projected average monthly precipitation (2023–2050) in scenarios (**a**) RCP 4.5 and (**b**) RCP 8.5. The curved lines show historical monthly precipitation summaries from January 2006 to December 2021 at the Azangaro station and the average of projected precipitation.

The values of the projected annual cumulative precipitation estimates correspond to the RCP 4.5 and RCP 8.5 scenarios (Figure 7); the former are represented by the solid lines and the latter by the dashed lines on the right margin, while the bar on the left side represents the observed historical precipitation. The vertical gray band marks the end of the observed historical precipitation graph and the beginning of the projections. The CANESM2 model in the two concentration paths (RCP 4.5 and RCP 8.5), which is represented as the most optimistic, shows relatively stable values above the historical by 120 mm per year throughout the projections; the highest peaks show the RCP 8.5 scenario. CANESM2 for the years 2023 and 2036 exceeds 900 mm per year; on the contrary, the RCP 4.5 CA-NESM2 scenario shows reductions for the year 2048, when it only reaches 350 mm per year (Figure 7). In general, the results of the average precipitation projections (2023–2050) made in the RCP 4.5 scenario estimate a decrease in precipitation from December to April, with reductions of 21.5%. For the RCP 8.5 scenario, the total rainfall for evaluating the period value reduces by 22.6% in relation to the base period.

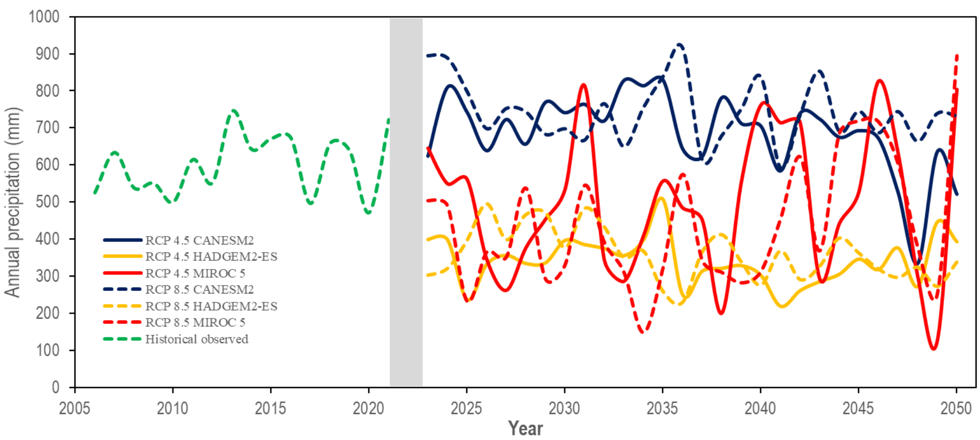

Figure 7. Historical annual precipitation (2006–2021) and projections with six climate change models for 2023–2050.

3.3. Analysis of the Change in Maximum and Minimum Temperature

Figure 8 shows the monthly behavior of the average monthly maximum temperature of the general circulation models under the representative concentration pathways RCP 4.5 (Figure 8a) and RCP 8.5 (Figure 8b) for the period 2023–2050 concerning the historical monthly maximum temperatures (2006–2021), noting that the overall projected maximum temperatures are in an average range of 17 °C to 19 °C in the case of the RCP 4.5 scenario and 17.5 °C to 19.3 °C for the representative concentration pathway RCP 8.5.

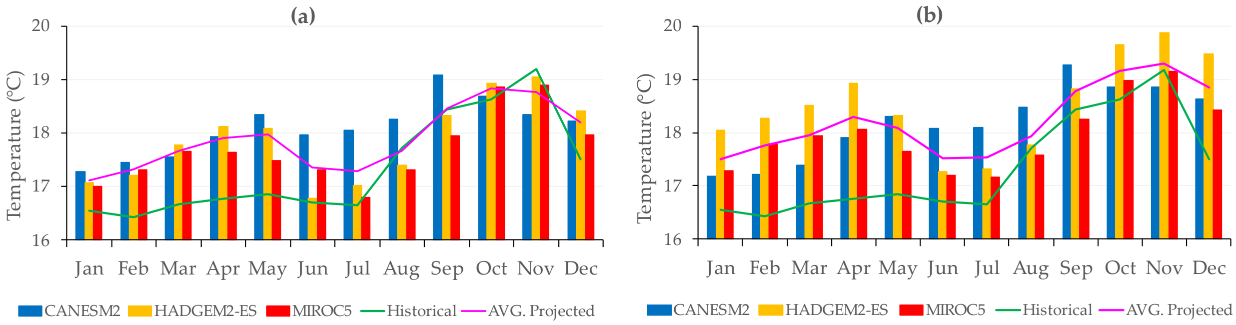

Figure 8. Average monthly maximum temperature for 2023–2050 for climate change scenarios (**a**) RCP 4.5 and (**b**) RCP 8.5, compared to historical values 2006–2021.

In general, they show more significant temperature variations because their scenarios project an increase in the average temperature of up to 13% compared to historical temperatures. The middle launched in the three models of the RCP 4.5 and RCP 8.5 routes show higher values than those recorded (Figure 8), except for November in the RCP 4.5.

For the minimum temperature, the RCP 4.5 and RCP 8.5 concentration pathways show greater increases between October and April; the CANESM2 model shows higher values in the RCP 8.5 pathway because its RCP 4.5 and RCP 8.5 scenarios project a higher average increase of up to 16% concerning the historical ones. This section indicates that all the scenarios under study are favorable since the minimum temperatures will have a relative increase, mainly in the months of the agricultural season (Figure 9). Regarding changes in mean temperature, it was observed that 2023–2050 temperature increases of 0.54 °C for the RCP 4.5 scenario and 0.88 °C for RCP 8.5 in the experimental area were observed.

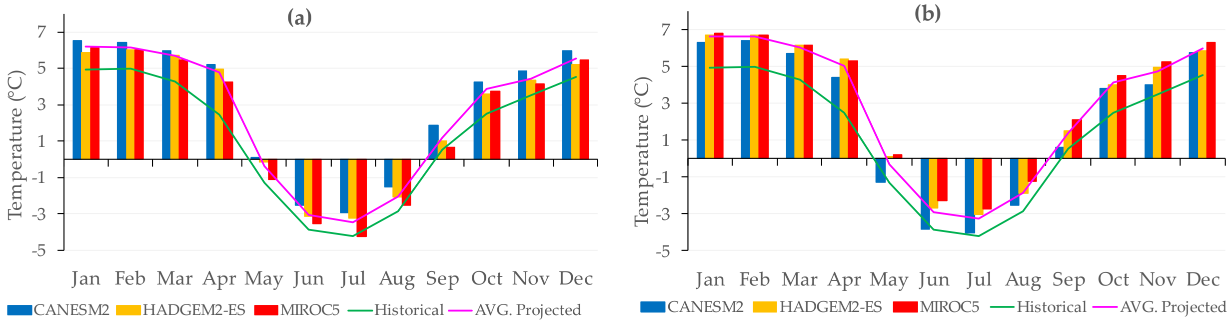

Figure 9. Average monthly minimum temperature in the period (2023–2050) in scenarios: (**a**) RCP 4.5 and (**b**) RCP 8.5 and historical (2006–2021) at the Azangaro station.

3.4. Crop Yields under Climate Change Scenarios

Figure 10 shows the simulation results using the AquaCrop model for the fresh weight yields in the concentration routes RCP 4.5 and RCP 8.5 for the period from 2023 to 2050; once these yields were adjusted in the process of calibration and validation of the AquaCrop model with the values observed during the 2017–2018 crop year, the fresh weight yields were simulated for the period 2006–2021. The new weight yields obtained remained relatively stable from 2023 to 2027 under two concentration pathways, RCP

4.5 and RCP 8.5, achieving an average annual result of 11.26 t ha^{-1}. For the second half (2038–2050), a decrease in potato crop yield is observed for the six future climate change scenarios, according to the AquaCrop model, reaching an annual average of 10.84 t ha^{-1}. In most years, it can be indicated that precipitation forecasts help to moderate the effects of temperature increases; however, there is a tendency for yields to fall in the most extreme years.

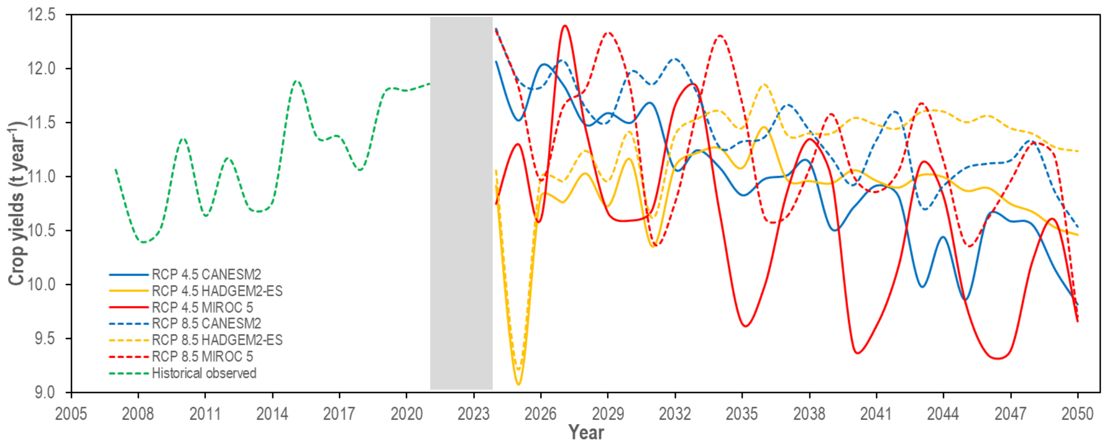

Figure 10. Annual crop yields for 2023–2050 in the climate change scenarios RCP 4.5 and RCP 8.5, compared to historical values 2006–2021.

The highest potato crop yield is in the RCP 4.5 MIROC 5 scenario (12.382 t ha^{-1}) and the lowest is for the RCP 4.5 HADGEM2-ES scenario (9.077 t ha^{-1}), where the trends of the results are favorable for the RCP 8.5 scenario and harmful for the RCP 4.5 scenario (Table 5). Under these future climate conditions, a slight negative impact on potato crop production in the Peruvian Altiplano was observed.

Table 5. Percentage change in simulated yields (2023–2050) compared to historical (2006–2021).

Routes	Scenarios		
	CANESM2	**HADGEM2-ES**	**MIROC 5**
RCP 4.5	−1.90%	−2.93%	−5.40%
RCP 8.5	2.30%	0.92%	0.49%

4. Discussion

The efficiency results of the simulation of rainfed potato crop development and production in the AquaCrop model in the calibration and validation stages showed satisfactory results. Despite slight over- and under-estimates of the model in canopy cover, biomass, and yield, which were also reported by other studies for the cultivation of potatoes [23,35], these results suggest that the AquaCrop model can satisfactorily simulate the development and production of rainfed potato crops under the extreme climatic conditions of the Peruvian Altiplano, since it simulates canopy cover, dry aerial biomass, and crop yield very closely to the observed values. The results obtained are consistent with previous research, which showed excellent performance of the AquaCrop model for simulating the work of different crops in different regions [34,35,45]. For example, in Ethiopia [23], coefficients of determination values (r^2) greater than 0.92 were found for the relation between observed and simulated values of canopy cover for potato crops under deficit irrigation, which are similar to those determined in this study (>0.95). In relation to the values of NRMSE, NE, and d, we found identical values to those obtained for Ethiopia, which suggests a high degree of adaptability of the AquaCrop model to different climatic conditions, soils, and crops.

Once the AquaCrop model was calibrated and validated, potato crop yields were simulated for the extended period (2005–2017). The simulated average annual yield results (Table 6), when compared with the yield statistics of the Dirección Regional Agraria Puno (DRA) for the province of Azangaro [46], show a good approximation. The mean difference analysis (t-Student) performed on the observed and simulated potato yields indicates no significant differences at a 5% significance level (t-statistic = 0.47 and t-tabular = 1.81). It suggests the AquaCrop model can adequately simulate potato crop yields for periods other than those used in the model calibration and validation. However, differences in potato crop yields can be attributed to various factors, including crop variety, local climatic conditions, irrigation rates, fertilization, and agricultural activities [34,47].

Table 6. Observed and simulated yields for the extended period 2005–2017.

Fuente	**Average Annual Performance (t year^{-1})**												
	2005	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**
Simulated	10.21	10.39	10.49	10.57	10.66	10.77	10.91	11.00	11.12	11.23	11.33	12.91	12.49
DRA	9.58	9.69	9.08	7.13	8.56	9.38	10.11	9.53	10.34	9.66	11.57	10.60	11.07

Potato yield statistics for the province of Azangaro averaged 9.72 t yr^{-1} (Table 6), which is compared to regions with similar climatic and geographical conditions, such as the Mantaro Valley in the central Andes of Peru, where higher yield values of up to 18.9 t yr^{-1} were observed [48]. The vital difference in yields could be attributed to the annual rainfall amounts, which are higher in the Mantaro Valley (833 mm) compared to Azángaro (597.8 mm), as crop yield is directly related to biomass, and biomass is directly related to the amount of water available, which generates a more significant expansion and coverage of the foliage [49]. Therefore, dependent on annual rainfall amounts, potato cultivation under rainfed production systems causes crop water stress periods, significantly influencing the potato crop's phenology, growth, and productivity. Therefore, it is necessary to practice irrigated agriculture by implementing irrigation systems that allow the timely provision of water to crops and reduce periods of water stress to obtain better yield levels [23,28,50].

According to projections for the period 2023–2050, changes in precipitation in Azángaro were not as significant as in other regions of the Altiplano [51,52]; therefore, it is expected that the conditions of the Peruvian Altiplano, such as hailstorms, snowfalls, frosts, and droughts that are persistent [53], affect productive activities in a negative way [53]. However, contrary to the results obtained in this research [54], it found a positive trend for the projected period (2071–2100), with an increase of up to 2 mm day^{-1}, agreeing with the results of [55]. This behavior would be attributed to the scarcity of meteorological information in the region, the geographical conditions of the Altiplano, and the uncertainty of projections obtained from global climate models, among others [56], which could be improved with the use of regional climate models [57].

The changes in mean temperature projected for the experimental area are conservative in comparison to previous research that determined rates of increase of 0.8 to 2.7 °C century^{-1} [58]. Furthermore, in the projections made by [54], the increases would be between 2 °C and 4 °C and up to 6 °C in the north of Lake Titicaca (2071–2100). Likewise, Galera and González [59] indicate temperature increases of up to 4 °C, generating favorable conditions for certain crops, with production increases due to changes in the climate. The temperature has a significant effect on the yield of the potato crop. The optimum maximum and minimum temperatures are in the range of 13.52 °C and 3.75 °C, respectively. Values above and below this range would negatively affect the crop yield because these are extremely sensitive to environmental changes. Values above the optimum modify the growth mode according to the duration of the different phenological phases, which would significantly affect the yield achieved due to the decrease in the number of tubers [60,61].

The changes in potato crop yields found in this research for the RCP 4.5 and RCP 8.5 scenarios showed differentiated behaviors for the periods 2023–2037 and 2038–2050, with minimal reductions for the former and more significant decreases for the latter periods; these results are in line with those found in previous studies [60,62–64]. Changes in rainfall and temperature modify the different phenological stages of the crop, affecting yields by reducing the number and size of potato tubers in rainfed crops [7,60,64,65]. Since the potato crop requires 400 mm to 800 mm of rain per agricultural campaign for adequate production [29], values slightly lower than this range were obtained in this research: 382 mm for RCP 4.5 and 390 mm for RCP 8.5, which generated a minimal reduction in crop yield under a rainfed agriculture system. Likewise, droughts represent a severe threat to agricultural development and food security [45] due to the deficit in precipitation and the increase in temperature, generating a tendency for production to decrease in the coming years, which would require the implementation of irrigation systems, resulting in higher water demand, according to [66].

Under these current conditions in the Peruvian Altiplano, the introduction of heat-tolerant and drought-resistant potato genotypes [67,68], as well as the cultivation of bitter potato varieties [69], the development of irrigated agriculture reversing the loss of traditional knowledge [47], the adoption of sustainable agricultural practices [17], the adoption of strategies for climate-resilient sustainable agriculture (CRSA) [18], and techniques to reduce crop water loss [70], are required as an essential strategy for adapting to climate change and variability, as these are issues of current global concern due to their impact on agricultural production [71].

5. Conclusions

In general, the AquaCrop model performed well in simulating the development and production of the potato crop variety Imilla Negra (*Solanum tuberosum* spp.) under the extreme climatic conditions of the Peruvian Altiplano, adequately enacting the observed values of canopy cover, aerial dry biomass, and crop yield for the period 2017–2018.

Climate projections showed decreases in precipitation and increases in temperature and evapotranspiration for the RCP 4.5 and RCP 8.5 scenarios in 2023–2050. Projections for potato yields in the Peruvian Altiplano under the climate scenarios showed a minimal decrease in the first half of the projection period (2023–2037). In the second period (2038–2050), the reduction increased due to climate change.

In addition, further research and field experiments are needed to determine the influence of other factors, such as potato crop variety, local climatic conditions, irrigation doses, fertilization, and agricultural activities, on potato crop yields in the Peruvian Altiplano, from which to promote strategies to adapt to climate change and ensure the food security and well-being of the communities of the Peruvian Altiplano.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/su16010071/s1, Figure S1. We obtain aerial images of the potato crop in different phenological stages to calculate canopy coverage. Figure S2. Scaling and delimitation of canopy coverage of the potato crop in AutoCAD. Figure S3. Monitoring the development of the potato crop in different phenological phases. Figure S4. (A) quantification of aboveground biomass of potato crop, (B) quantification of root biomass (without tuber).

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