Review Article

Iván Beltrán Ccama*, Bruno Faccini Santoro, José Oliden Semino

Model predictive control for precision irrigation of a Quinoa crop

https://doi.org/10.1515/chem-2022-0264
received August 20, 2022; accepted December 4, 2022

Abstract: Traditional High Andean agriculture is rainfed, and irrigation is commonly carried out in an open loop, that is, without measuring variables such as soil moisture content or plant development to define water consumption. This article presents model predictive control applied to irrigation systems under real conditions, whose purpose is the efficient use of water in rainfed crops with improved yield and crop productivity at minimum water consumption. The article presents a control strategy applying a model of predictive control that calculates the optimal amount of water for daily irrigation under real conditions. The most important attraction of the model is the prediction and future behavior of the controlled variables as a function of the changes in the manipulated variables. The objective is to improve the yield of the crop at minimum water consumption, for this, it will be necessary to use models that link with the Aquacrop software and allow it to be a source of data, and for the prediction of future values. The predictive controller is evaluated in the Quinoa crop (*Chenopodium Quinoa Willdenow*), and the performance is compared against existing traditional irrigation data in the literature. The results indicate that the predictive controller can achieve higher crop efficiency and reduce irrigation water supplies considerably.

Keywords: model predictive control, precision irrigation, quinoa

1 Introduction

Agriculture is the sector responsible for most of the water consumption on the planet, corresponding to approximately 70% of the total use in 2020 [1]. An alternative to achieve the best use of water resources in agriculture is to apply control strategies with proven potential in the industry. Traditional irrigation methodologies are based on defining periods of time for the use of irrigation water, which do not take into account the real-time information that can be obtained from the crop, such as soil moisture, soil salinity, ambient temperature, need for water in the crop, and evapotranspiration.

Classic control methodologies, such as On/Off control and Proportional Integral Derivative control, are easy to implement and have proven effectiveness in the industry. However, given the complexity of agricultural systems (nonlinearity and multivariables), the model predictive control (MPC) has shown superior performance in processes of this type [2,3].

MPC performance is superior to classical control. The MPC can achieve high regulation accuracy with moderate complexity. Therefore, this method is very suitable for precision agricultural production.

The MPC is a strategy based on the numerical optimization of a cost function over a finite horizon that calculates the control input using a mathematical model to predict the responses of the process [4]. An MPC refers to a class of advanced computer-controlled algorithms that use an explicit process model to predict the future response of a plant. A series of control inputs are calculated at each sampling instant, but only the first calculated input is implemented in the process [5]. The first input of the optimal sequence is sent to the process, and the entire calculation is repeated at subsequent sampling times [4]. This controller is based on three ideas: the use of a prediction model, optimization in a sliding horizon, and feedback adjustment [6], and it also allows the introduction of restrictions. The literature mentions some MPC applications in irrigation systems [3,7–11].

The application of MPC to agriculture can generate significant productivity and efficiency benefits. However, no review has been reported in agricultural applications with high Andean crops.

The high Andean phytogeographic domain is characterized by presenting crops adapted to climatic rigor, both due to excessive cold and lack of water, specifically

* **Corresponding author: Iván Beltrán Ccama,** Department of Chemical Engineering, National University of San Marcos UNMSM, Lima, Peru, e-mail: ivan.beltran@unmsm.edu.pe
Bruno Faccini Santoro: Department of Chemical Engineering, Federal University of Sao Paulo, Sao Paulo, Brazil
José Oliden Semino: Departamento de Ingeniería, Universidad Tecnológica del Perú, Lima, Peru

the high plateau region of Puno presents a variable regime of well-differentiated rainfall: a wet season (November–February), a dry season (June–August), and transition periods (September–October and April–May). Due to this, the amount of water available is generally insufficient to cover the daily irrigation needs of high-value Andean crops on the world market, such as Quinoa (*Chenopodium Quinoa Willdenow*).

Due to the complexity of crop dynamics, their simulation plays a fundamental role in the evaluation of irrigation management strategies [12,13]. AquaCrop is presented as a suitable alternative for this type of crop [14] because it simulates the yield response of herbaceous crops to water and is particularly suitable for conditions in which water is a limiting factor in the production of crops [12].

In the present investigation, the predictive control based on models applied to the irrigation of the Quinoa crop will be evaluated, taking the AquaCrop-OpenSource (AquaCrop-OS) as a plant model and structure Auto Regressive with Exogenous Variables (ARX) as a prediction model. The results obtained were compared with the methods available in the AquaCrop-OS gallery. All simulations were performed in MATLAB.

The article is structured as follows: Section 2 describes the cultivation of quinoa and the characteristics of its irrigation. Section 3 describes the AquaCrop crop simulator, while Section 4 describes the implementation of the model-based predictive controller. Finally, in Sections 5 and 6, the numerical results, analysis, and conclusions are developed.

1.1 The cultivation of quinoa

Chenopodium Quinoa Willdenow, known as Quinoa, is a whole grain, native to the Andes of Bolivia, Chile, and Peru. It is a crop tolerant to abiotic and hydric stress; that is, it requires a small amount of water (200–300 mm) for its vegetative development [15], and it has extraordinary adaptability, in agroecological conditions from sea level to 4,000 m above sea level, being able to withstand temperatures from −4 to 38°C and grow with relative humidity between 40 and 70% [16]. The high Andean phytogeographic domain is characterized by presenting crops adapted to climatic rigor, both due to excessive cold and lack of water, specifically the high plateau region of Puno presents a variable regime of well-differentiated rainfall: a wet season (November–February), a dry season (June–August), and transition periods (September–October and April–May). Due to this, the amount of water available is generally insufficient to cover the daily irrigation needs of Andean crops with high value in the world market, such as Quinoa.

1.2 Irrigation

Quinoa in traditional cultivation presents critical phenological stages or phases of susceptibility and tolerance to the need for irrigation (Figure 1). According to the Puno-based National Institute of Agrarian Innovation (INIA-Puno), Quinoa must be sown in moist soil and must be kept for the first 15 days until germination, with the presence of rain or irrigation (sensitive stage). In the vegetative tolerant phenological branching stage of 15–70 days, quinoa supports the absence of water for up to 70 days. The flowering and milky grain stages are susceptible to the lack or absence of water; that is, between 70 and 120 days the water requirement is essential because they synthesize photosynthates and photoassimilates, which will be assimilated and will translate into the yield of Quinoa, and, in case of absence of rain, must be compensated with irrigation with a frequency of between 5 and 7 days. The last phenological stage of pasty grain and physiological maturation no longer requires water. Tolerant stages are marked with a red stripe and sensitive stages with a green stripe (Figure 1). The complete development of the crop takes place in 180 days.

2 Materials and methods

2.1 AquaCrop

The AquaCrop tool is a model that simulates crop growth. It was developed by the Food and Agriculture Organization (FAO) in order to improve water productivity in rainfed and irrigated conditions. It simulates the yield response of arable crops to water and is particularly suitable for conditions where water is a limiting factor in crop production [12]. It has been validated for various crops such as wheat [17] corn [13], quinoa [14], cotton [18,19], sugar cane [11], cassava [20], and potato [21].

It was developed in 2009, and its open-access version AquaCrop-OpenSource (AquaCrop-OS) is presented by FAO [22]. The program introduces crop information according to the various characteristics of climate, type of crop, type of

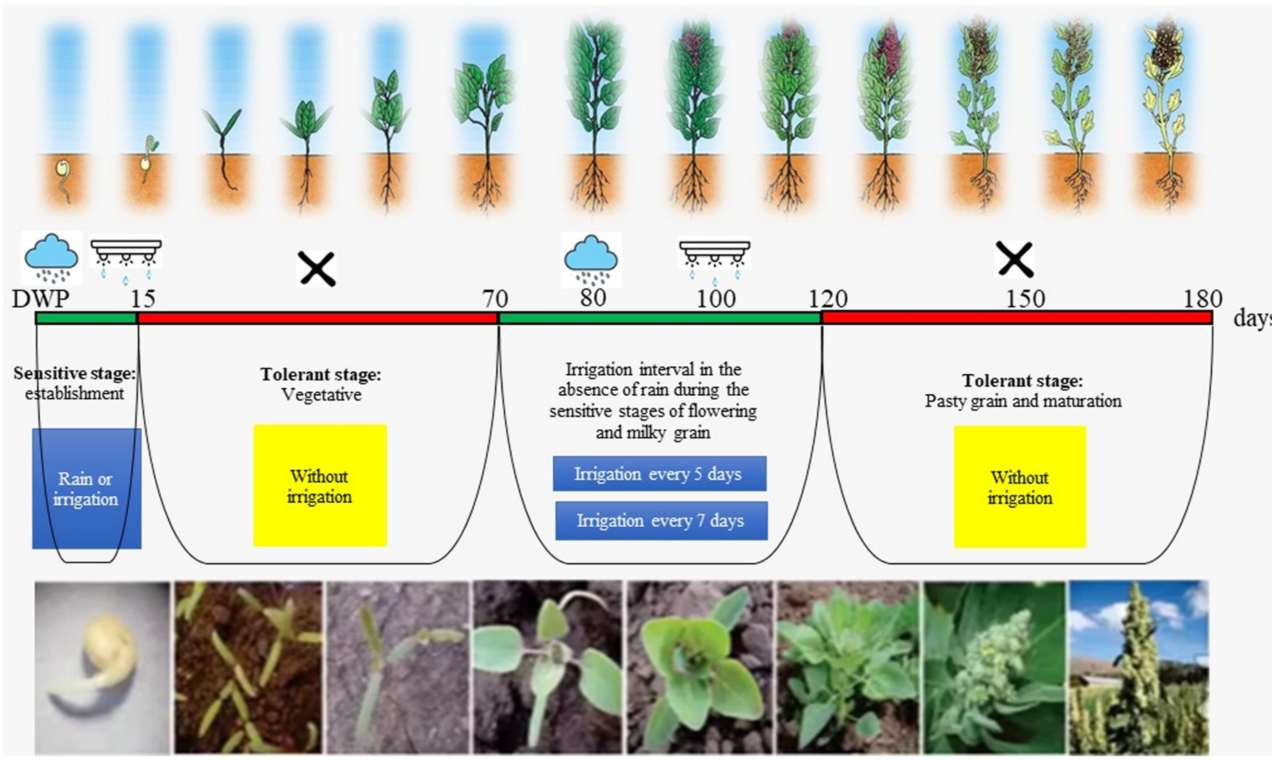

Figure 1: Critical phases tolerant to the need for irrigation in the cultivation of Quinoa taken from INIA.

irrigation, soil, and others. The results obtained from crop growth, water balance, water content in the crop, and others can provide solutions for various applications such as developing irrigation programs to optimize production, supporting decision making on water policies, and comparing potential yields and real [12].

2.2 Irrigation methods in AquaCrop-OS

AquaCrop has a gallery of irrigation methods for cultivation, and in AquaCrop-OS, the operation of these methods is encoded in the AOS_Irrigation file and the choice of method is in the IrrigationManagement.txt file. The methods provided are as follows:

1. Method 0: *Rainfed*: without irrigation
2. Method 1: *Soil moisture-based*: soil moisture is calculated each day, if it is less than a chosen value, irrigate to reach field capacity.
3. Method 2: *Fixed interval*: irrigation to saturation in a specified time interval.
4. Method 3: *Specified time series*: irrigation is given by a schedule specifying the day and the amount of water.
5. Method 4: *Net calculation*: it irrigates every day at field capacity, but this method takes into account the weather forecast and adapts the irrigation to this value.

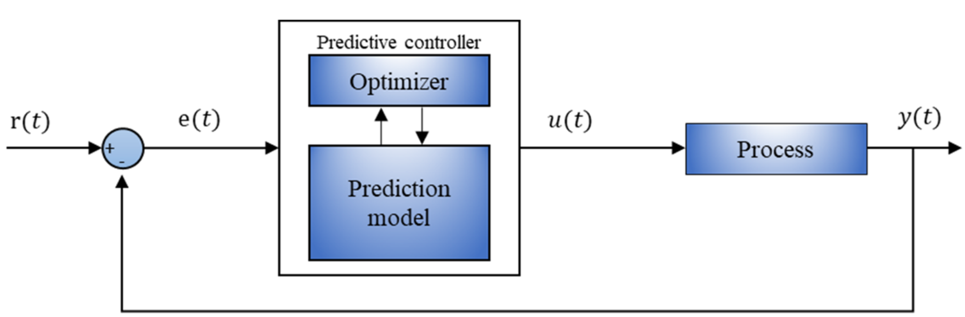

Figure 2: Predictive controller loop.

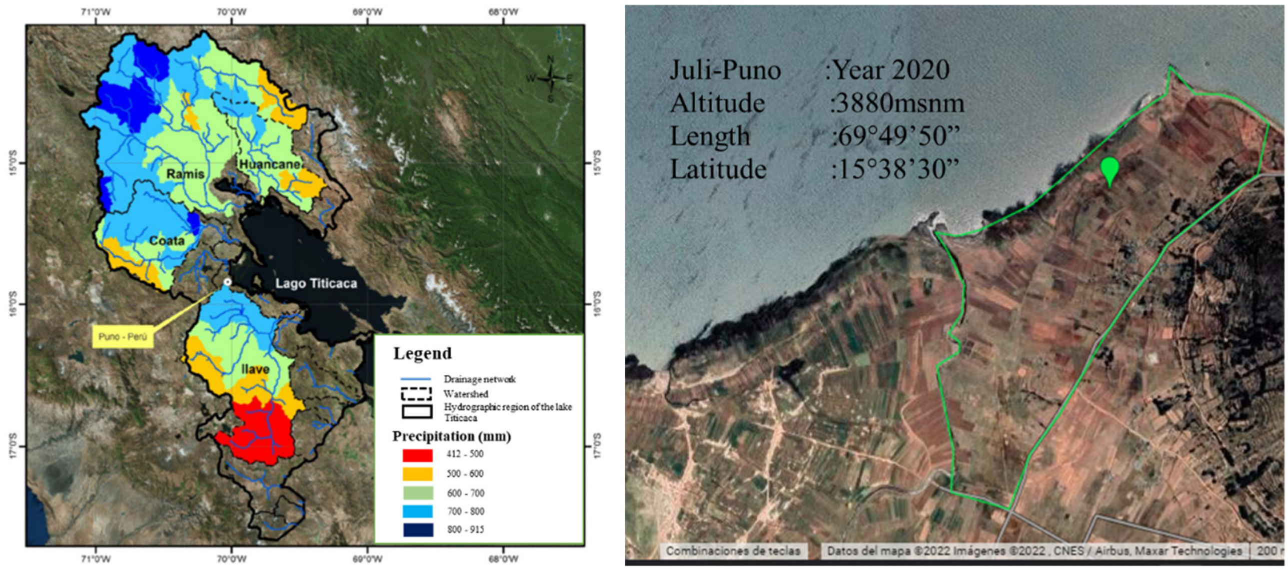

Figure 3: Location of the research site obtained from Google Earth Engine.

AquaCrop-OS, being an open-source gray box tool, can incorporate other user-defined irrigation methods.

2.3 Model-based predictive control

The usual MPC approach is described in the following objective function:

$$\min_{u(k),\dots,u(k+N-1)} \sum_{i=0}^{N-1} \|y(k+i-1) - r(k+i-1)\|_Q^2 + \|u(k+i)\|_R^2, \tag{1a}$$

which is subject to:

$$y(k+1) = f(y(k), u(k), v(k)), \tag{1b}$$

$$u_{\min} \le u(k) \le u_{\max}, \quad k = 0, \dots, N-1, \tag{1c}$$

where y is the control variable, u is the manipulated variable, v is the measurable disturbances, r is the reference, and Q and R correspond to the weight of each term of the cost function.

The function f defines the prediction model of the controller. This problem is solved at each sampling instant. Figure 2 shows the control loop.

2.4 Prediction model (ARX)

For the prediction of crop behavior, an ARX structure model or autoregressive model with exogenous input was used. To find the parameters, the method of least squares was used, which allows us to solve linear regression problems analytically and with a unique solution. The ARX model is represented in the form of a differential equation as follows:

$$A(z)y(k) = B(z)u(k-d) + e(k), \tag{2}$$

where $y(k)$ is the system output, $u(k)$ is the system input, $e(k)$ is the system disturbance, and d is the system delay.

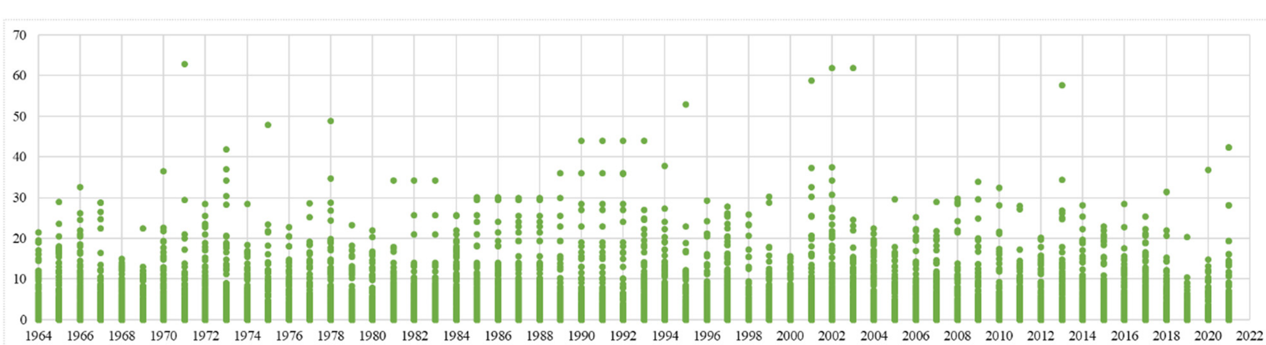

Figure 4: Average rainfall in the study area, between the years 1964 and 2021, obtained from SENAMHI-Puno meteorological station.

Table 1: Summary of results of the identification experiment

Years	NMSE Identification	NMSE Validation
Average of 1964 and 2016	0.0035	0.0039
Average of 2017 and 2021	0.0042	0.0047
1989	5.72×10^{-4}	5.99×10^{-4}
1984	0.0164	0.0202

3 Results and discussion

The research was carried out simulating the conditions of Quinoa (*Chenopodium Quinoa Willdenow*) cultivation in the high Andean phytogeographic domain in the Puno region, Peru. It is located in the southeastern highlands of the country, on the Collao plateau at 13°0066′00″ and 17°17′ 30″ south latitude and 71°06′57″ and 68°48′46″ west longitude. From the Greenwich meridian, it is located on the plateau between 3,812 and 5,500 m.a.s.l. In the Juli region, agriculture is developed with greater momentum on the shores of Lake Titicaca and the Coata and Ilave hydrographic basins (Figure 3).

For the development of the simulations, the input data were obtained from different sources. Figure 4 shows the climate information of the precipitation between the years 1964 and 2021 is obtained from the national service of hydrology and meteorology (SENAMHI). Likewise, information on the cultivation of Quinoa was obtained from the Ministry of Agriculture (MINAGRI) and the Puno-based National Agricultural Research Institute (INIA), public institutions of the Peruvian government. All of the aforementioned data are part of the inputs to the AquaCrop-OS model in MATLAB. All the simulations implemented were developed in the 2020a version of this programming environment.

3.1 Identification of the model for responding to the water deficit

The data for this experiment was obtained by simulation in AquaCrop-OS before a pseudorandom binary sequence (mm) irrigation input, with the real meteorological data taken from SENAMHI, and with the crop data (obtain from MINAGRI and INIA).

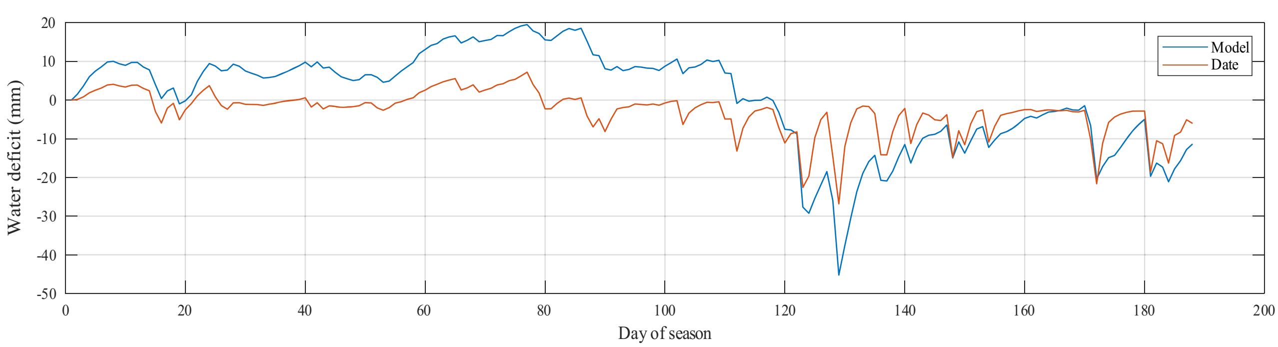

Figure 5: Model fit and data for data from the Year 1989.

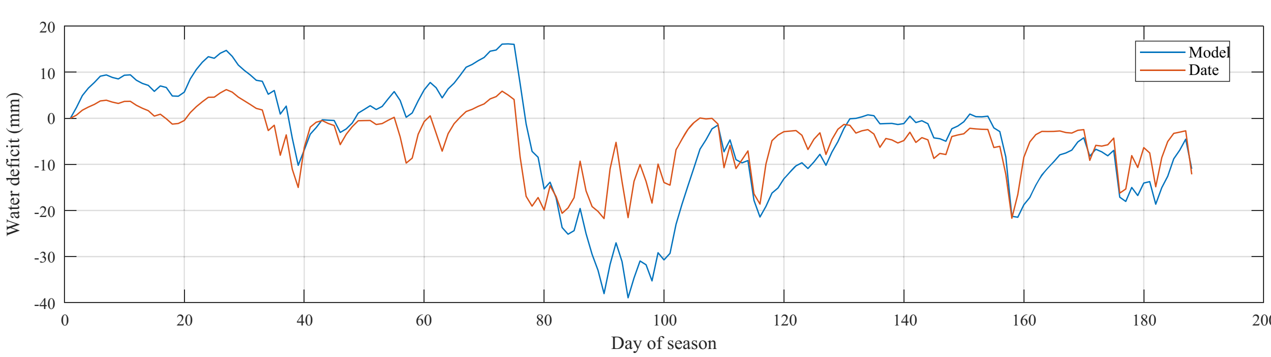

Figure 6: Model fit and data for data from the Year 1984.

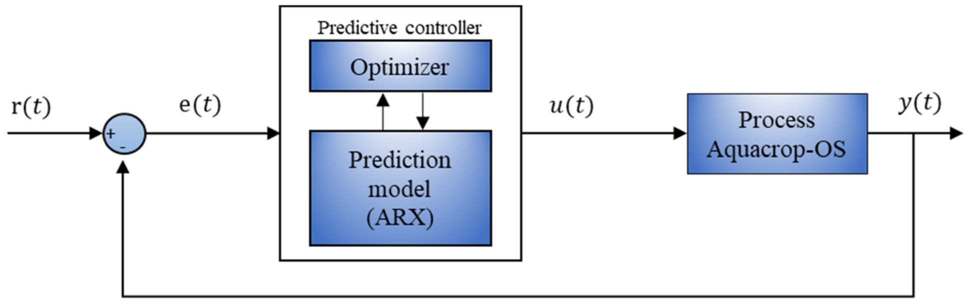

Figure 7: Predictive controller loop implemented in MATLAB.

The ARX structure model shown in equation (2) can be rewritten considering a system with multiple inputs and one output as represented by the following equation:

$$[1 + az^{-1}]y(k) = [b_1 \quad b_2 \quad b_3]\begin{bmatrix} u(k-1) \\ v_1(k-1) \\ v_2(k-1) \end{bmatrix} + e(k), \quad (3)$$

where $y(k)$ is the system output (water deficit), $u(k)$ is the system input that can be manipulated (irrigation), $v_1(k)$) is the measurable system input (evapotranspiration), $v_2(k)$ is the measurable system input (precipitation), and $e(k)$ is the system disturbance.

Normalized mean square error (NMSE) was used as an evaluation criterion, obtaining the best performance in 1989 (NMSE = 5.7212×10^{-4}) and the worst in 1984 (NMSE = 0.0164) for the identification experiment. For validation, the value of NMSE is 5.9894×10^{-4} and the value of NMSE is 0.0202, respectively. Table 1 summarizes the results.

In the identification of the system with the ARX linear structure, a better fit of the data is observed in years with little rain compared to years with abundant rain. As an example, the Year 1989 (little rain) and the Year 1984 (abundant rain) are shown.

Figures 5 and 6 show the results of the validation experiment for the years 1989 and 1984, respectively.

The following parameters were obtained: $a = -0.9808$, $b_1 = -0.5518$, $b_2 = 0.60810$, and $b_3 = -0.7516$.

3.2 MPC controller

The control variable for this work is the water deficit (mm), and the manipulated variable is irrigation (mm), while the measurable disturbances are evapotranspiration (mm) and precipitation (mm). Figure 7 shows the closed loop implemented in MATLAB that uses the ARX model calculated in the identification experiment to predict the behavior of the system, and this information is taken by the optimizer to calculate the value of the input. The process was simulated by the AquaCrop-OS model (Figure 7).

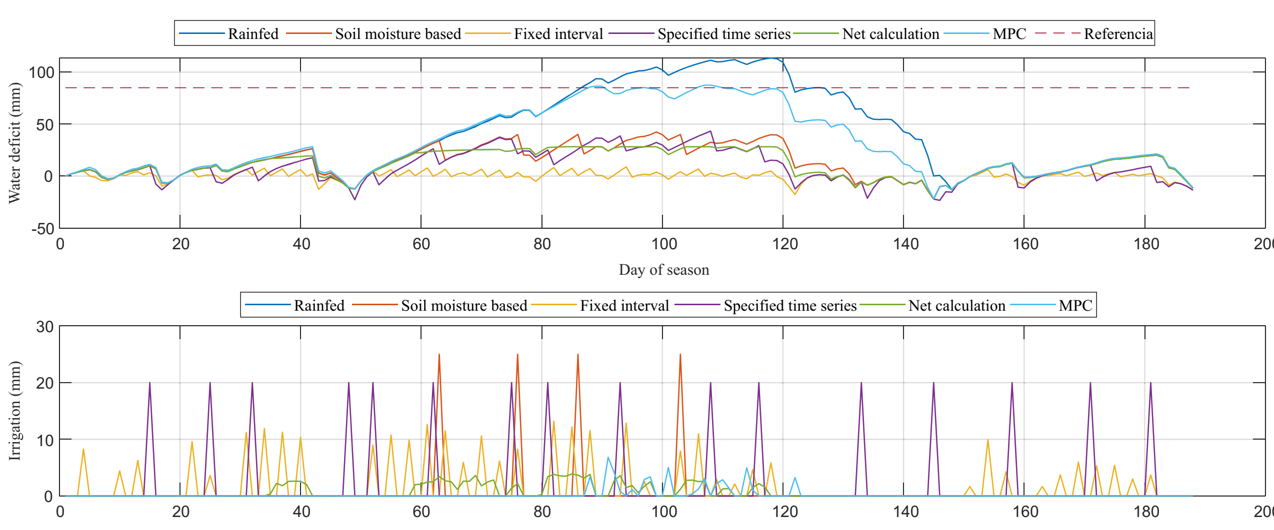

Figure 8: Comparison of the results of the irrigation methods for the Year 2017.

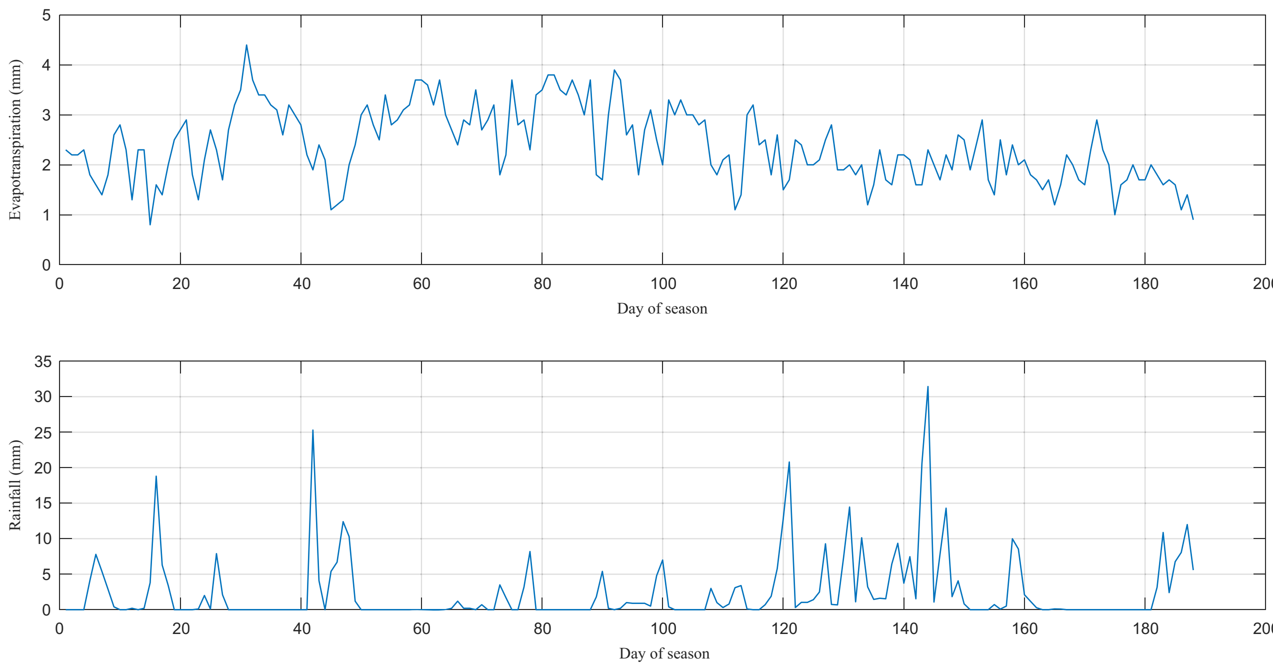

Figure 9: Precipitation and evapotranspiration in the Year 2017.

Table 2: Field yield and total irrigation for the Year 2017

Method	Yield (Ton/h)	Full irrigation (mm)
Method 0	4.04	0
Method 1	4.22	100
Method 2	4.22	293.1
Method 3	4.22	320
Method 4	4.22	115.89
MPC	4.22	48.19

Figure 8 shows the result of the simulation of the MPC controller for a simulation of the Year 2017. The evapotranspiration and precipitation of that year are shown in Figure 9. Table 2 shows the crop yield per hectare (ton/h) and the total irrigation (mm) of the simulated methods.

Figure 9 shows the relationship between rainfall and crop evapotranspiration loss; it is evident that on days without rain, the evapotranspiration values are high; these impacts are direct with respect to the water deficit suffered by the crop, and therefore, the irrigation requirement will be higher compared with other days (Figure 8). In the 2017 Quinoa cultivation campaign, using the MPC irrigation method, we obtain the most optimal water requirement and it is recommended between days 90 and 125 (months from November to December) of the season (Table 2).

Figure 10 shows the result of the simulation of the MPC controller for a simulation of the Year 2020. The evapotranspiration and precipitation of that year are shown in Figure 11. Table 3 shows the crop yield per hectare (ton/h) and the total irrigation (mm) of the simulated methods.

Tables 2 and 3 compare the results of the different irrigation methods. It is observed that the MPC controller presents a better performance taking into account the yield of the field and the total irrigation in a year with little rain as it occurs in the Year 2017. It achieves a performance equal to methods 1–4 with lower consumption of water (Table 2). In method 0, lower water consumption is obtained, but with lower field yield.

Table 3 shows that the MPC controller has the best performance, taking into account the yield of the field and the total irrigation in a year with a lot of rain, such as the one in 2020. It achieves a performance equal to methods 1–4 with less water consumption. Results similar to method 0 are obtained, with a major water consumption.

Figure 11 shows the trends in rainfall data and evapotranspiration for the Quinoa cultivation campaign in 2020, and the behavior is similar to that of the Year 2017 shown in Figure 9; however, the increase in rainwater presents in 2020, and it makes irrigation requirements minimal. Using the MPC irrigation method for this scenario, it will also be optimal and the irrigation recommendations would be between days 80 and 95 (months from October to November) of the season (Table 3).

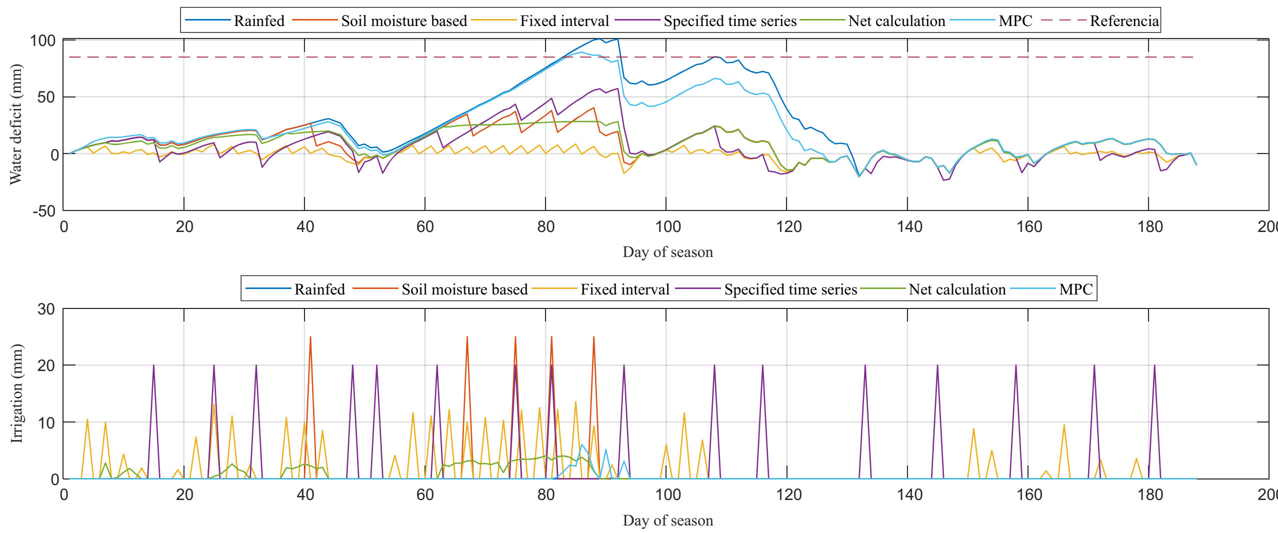

Figure 10: Comparison of the results of the irrigation methods for the Year 2020.

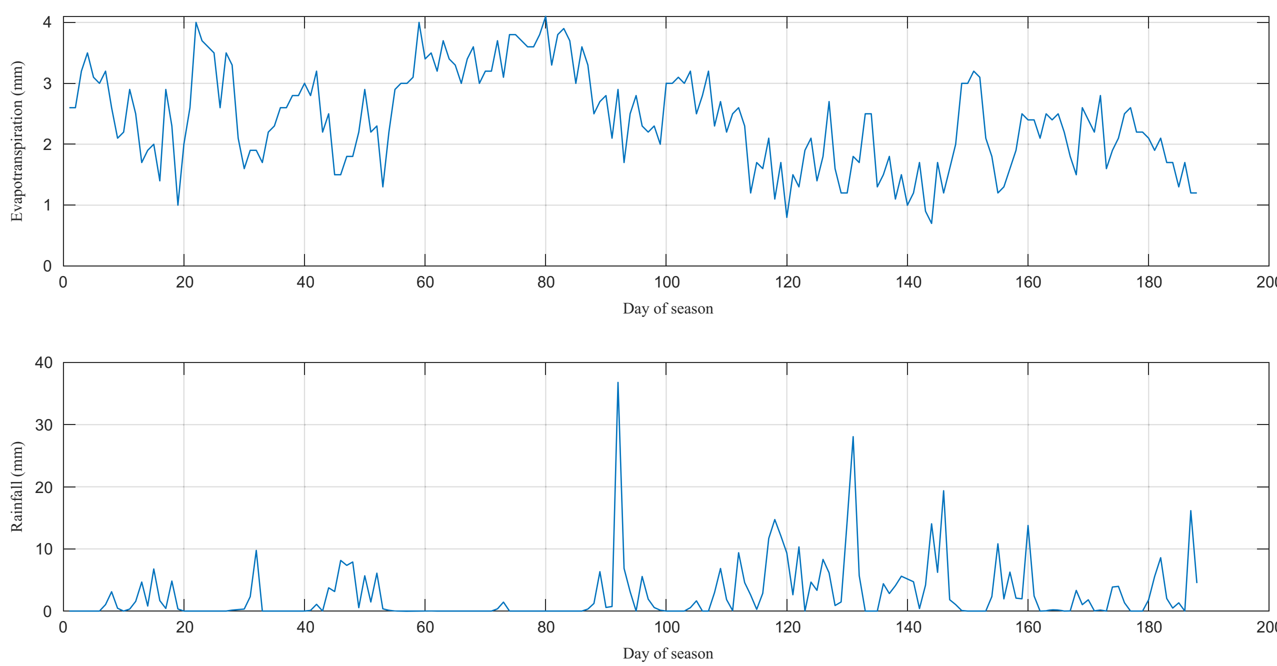

Figure 11: Rainfall and evapotranspiration in the Year 2020.

Table 3: Yield and total irrigation for the Year 2020

Method	Yield (Ton/h)	Full irrigation (mm)
Method 0	4.92	0
Method 1	4.92	125
Method 2	4.92	279.66
Method 3	4.92	320
Method 4	4.92	109.3
MPC	4.92	26.75

4 Conclusion

In this work, the problem of linear identification and MPC control of water deficit applied in a Quinoa (*Chenopodium Quinoa Willdenow*) crop model using AquaCrop-OS is presented. An ARX structure with multiple inputs and one output is proposed as a prediction model.

The structure proposed for the prediction model (ARX) presents a good adjustment for years with little rainfall, and its prediction capacity is lower for rainy years.

The proposed irrigation methodology presents the best performance among the simulated methods, both for rainy and dry years. This work aims to shed light for new studies and proposals that delve into the use of simulators to improve irrigation techniques in high Andean crop areas.

Regarding the link between MPC irrigation and crop yield, we can conclude that Quinoa is a drought-tolerant crop and that water yield has relative effects. For seasons with a rainy year (See Table 3), it reaches its maximum yield, there is no water deficit, so it does not require irrigation. In seasons with a dry year (See Table 2), the yield has increased with MPC irrigation, completing the need for crop water.

Acknowledgements: The results presented are part of the doctoral research project sponsored by the National Fund for Scientific, Technological Development, and Technological Innovation (FONDECYT), nowadays PROCIENCIA, one of the ten doctoral programs subsidized by PROCIENCIA in Peru – Contract 04-2018-FONDECYT/BM. The authors, therefore, acknowledge with thanks DSR for technical and financial support.

Funding information: This research has been financed by Concytec – World Bank Project "Improvement and Expansion of the Services of the National System of Science, Technology and Technological Innovation" 8682-PE, through its executing unit ProCiencia [contract 04-2018-FONDECYT/BM].

Author contributions: Iván Beltrán Ccama – conceptualization, data curation, formal analysis, funding acquisition, investigation, visualization, writing-original draft; Bruno Faccini Santoro – methodology, project administration, supervision, validation, writing-review and editing; José Oliden Semino – software, resources.

Conflict of interest: The authors declare no conflict of interest.

Ethical approval: The conducted research is not related to either human or animal use.

Data availability statement: All data generated or analyzed during this study are included in this published article.

References

[1] Pltonykova H, Koeppel S, Bernardini F, Tiefenauer-Linardon S. The United Nations World Water Development Report 2020: Water and Climate Change, 2020. https://unesdoc.unesco.org/ark:/48223/pf0000372985.

[2] Lopez-Jimenez J, Vande Wouwer A, Quijano N. Dynamic modeling of crop–soil systems to design monitoring and automatic irrigation processes: A review with worked examples. Water. 2022;14:889. doi: 10.3390/w14060889.

[3] Lozoya C, Mendoza C, Mejía L, Quintana J, Mendoza G, Bustillos M, et al. Model predictive control for closed-loop irrigation. IFAC Proc Volumes. 2014;47,(3):4429–34. doi: 10.3182/20140824-6-za-1003.02067.

[4] Rawlings JB, Mayne DQ. Model Predictive Control: Theory and Design. 4th edn. Madison, Wisconsin: Rawlings, Cheryl M.; 2014.

[5] Qin SJ, Badgwell TA. A survey of industrial model predictive control technology. Control Eng Pract. Jul. 2003;11,(7):733–64. doi: 10.1016/S0967-0661(02)00186-7.

[6] Camacho E, Bordons C. Control Predictivo: Pasado, presente y futuro. Rev Iberoamericana de automática e informática Ind (RIAI). 2004;1(3):1–28.

[7] Gu Z, Qi Z, Burghate R, Yuan S, Jiao X, Xu J. Irrigation scheduling approaches and applications: A review. J Irrig Drain Eng. 2020;146(6):1–15. doi: 10.1061/(asce)ir.1943-4774.0001464.

[8] Ding Y, Wang L, Li Y, Li D. Model predictive control and its application in agriculture: A review. Comput Electron Agriculture. 2018;151:104–17. doi: 10.1016/j.compag.2018.06.004.

[9] Abioye EA, Abidin MSZ, Mahmud MSA, Buyamin S, Ishak MHI, Rahman MKIA, et al. A review on monitoring and advanced control strategies for precision irrigation. Comput Electron Agriculture. 2020;173:1–22. doi: 10.1016/j.compag.2020.105441.

[10] Ayaz MA, Manzoor T, Muhammad A. MPC Based Soil Moisture Regulation of a Canal-Connected Crop Field. IFAC-PapersOnLine. 2020;53(5):170–5. doi: 10.1016/j.ifacol.2021.04.095.

[11] Kassing R, De Schutter B, Abraham E. Optimal control for precision irrigation of a large-scale plantation. Water Resour Res. 2020;56(10). doi: 10.1029/2019wr026989.

[12] FAO, AquaCrop, el modelo de productividad del agua de los cultivos, 2016.

[13] Shirazi SZ, Mei X, Liu B, Liu Y. Assessment of the AquaCrop Model under different irrigation scenarios in the North China Plain. Agric Water Manag. 2021;257:1–17. doi: 10.1016/j.agwat.2021.107120.

[14] Otiniano Mego GL. Calibración del modelo aquacrop para tres variedades de quinua, 2022, Tesis de pregrado, Universidad Nacional Agraria la Molina. https://repositorio.lamolina.edu.pe/handle/20.500.12996/5427.

[15] Apaza V, Cáceres G, Estrada R, Pinedo R. Catalogue of commercial varieties of quinoa in Peru; 2015. www.fao.org/publications.

[16] CIRAD and FAO. http://www.fao.org/3/contents/ca682370-10f8-40c2-b084-95a8f704f44d/i4042e00.htm.

[17] Zhang C, Xie Z, Wang Q, Tang M, Feng S, Cai H. AquaCrop modeling to explore optimal irrigation of winter wheat for improving grain yield and water productivity. Agric Water Manag. 2022;266. doi: 10.1016/j.agwat.2022.107580.

[18] García-Vila M, Fereres E, Mateos L, Orgaz F, Steduto P. Deficit irrigation optimization of cotton with AquaCrop. Agron J. 2009;101(3):477–87. doi: 10.2134/agronj2008.0179s.

[19] Aziz M, Rizvi SA, Sultan M, Bazmi MSA, Shamshiri RR, Ibrahim SM, et al. Simulating cotton growth and productivity using aquacrop model under deficit irrigation in a semi-arid climate. Agriculture. 2022;12. doi: 10.3390/agriculture12020242.

[20] Wellens J, Raes D, Fereres E, Diels J, Coppye C, Adiele JG, et al. Calibration and validation of the FAO AquaCrop water productivity model for cassava (Manihot esculenta Crantz). Agric Water Manag. 2022;263. doi: 10.1016/j.agwat.2022.107491.
[21] Wale A, Dessie M, Kendie H. Evaluating the performance of AquaCrop model for potato production under deficit irrigation. Air Soil Water Res. 2022;15:1–14. doi: 10.1177/11786221221108216.
[22] Foster T, Brozović N, Butler AP, Neale CMU, Raes D, Steduto P, et al. AquaCrop-OS: An open source version of FAO's crop water productivity model. Agric Water Manag. 2017;181:18–22. doi: 10.1016/j.agwat.2016.11.015.