Water Resources Optimization using Receding Horizon Control and a Weather Generator: A Case Study of the Elqui Basin, Chile

THESIS REPORT

CIE5060-09 MSc Thesis

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Embarking on a MSc journey after years of work experience isn't exactly the norm here in the Netherlands. While my fellow students were usually a decade younger, I've wholeheartedly cherished this incredible and joyous experience. It has allowed me to meet extraordinary individuals and relish the refreshing role of being a student again.

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Abstract

The integrated management of river catchments is a challenge to be addressed by many water authorities, where some of them even today do not yet incorporate the aquifers' status in decision-making. This situation has led to the depletion of many aquifers, deeply affecting the drinking water supply, agriculture, and industries. This challenge is combined with the difficulty of decision-making under highly uncertain long-term weather forecasts.

This thesis research proposes a new water management methodology for the Elqui River basin in Chile by using an optimization model aligned with the water authorities' main objectives and additionally incorporating the aquifer criteria. The optimization model is validated by comparing the results obtained over the 2010–2020 period with the water management practices employed during the same period.

Furthermore, an analysis of the performance of the model using different moving window lengths is executed by the implementation of a Receding Horizon Control (RHC) methodology, evaluating how well the solution is by comparing it with the historical simulation over the same period. The latter is done by looking at the performance of the key optimization goals and using a RMSE and R^2 analysis.

Finally, a weather generator was used to randomly generate weather data, based on the 30-year period between 1990 and 2020. The random weather conditions are incorporated in a hydrological model to translate weather data into water volume into the reservoir. Making use of the optimization model, the RHC methodology, and the weather generator, the proposed methodology is tested, enabling the simulation of the decision-making processes. The results are again compared with the water management practices employed over the simulation period.

The research concludes that the proposed methodology brings significant benefits to the aquifers' status, with neglectable impact on the *Desmarque* values. Receding horizon (RH) length plays a crucial role, with a balance between achieving optimal results and avoiding computational delays, recommending a RH length of 360 days for best results. The stochastic weather generator effectively replaces unpredictable forecast data, yielding comparable results to real future weather conditions, with temperature and accumulated snowpack playing important roles.

Keywords: Integrated water management, surface water, groundwater, optimization, receding horizon, aquifer recharge, weather generator.

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1. Introduction

1.1. Context

The increasing demand for freshwater together with the effect of climate change has been exerting enormous pressure on the water resources of the entire planet, both on the surface and in the subsurface. Consequently, this has led to the depletion of many aquifers (Konikow & Kendy, 2005) and the emptying of some accumulation reservoirs.

At the same time, precipitation patterns have been changing all over the world, most noticeably in arid and semiarid regions, where the precipitation events have become less frequent, but also more intense when they occurs. This new pattern can often exceed the capacity of reservoirs and result in significant losses of water resources. The change in precipitation patterns is especially critical for this type of region where "*water availability and timing are key factors*", controlling primary productivity and agricultural production, among others (Feng, Porporato, & Rodriguez-Iturbe, 2013).

The joint interaction use between reservoirs and aquifers is an Integrated Water Management (IWM) discipline that has not yet been deeply explored, and there may be a possibility of improving the integrated use of their capacity, by taking advantage of the water storage potential of aquifers.

This issue takes special importance in catchments where the primary activity is agriculture, and existing reservoirs and groundwater abstractions are the main source of water.

1.2. Problem statement

The adaptation and mitigation of adverse effects on water resources are urgent matters. The main challenges involve firstly halting and, if possible, restoring water levels in affected aquifers, while also safeguarding ecosystems dependent on surface waters. Secondly, there is a need to meet water demand, be it for basic population needs, food production, or use for industrial purposes.

For successful water resources management, (1) reliable forecast data is needed in order to be one (time) step ahead, but in some climates, forecasting is tremendously challenging for medium and long-term periods. This also brings the need for quick adaptability of management decisions when facing unexpected conditions, like sudden precipitation events, weather seasonality and other climatic phenomena (El Niño - La Niña).

This lack of information is currently addressed by using average data over the past years and by applying large safety factors to the decisions so that the uncertainty can then always be controlled. The result of this is a suboptimal solution, since safety factors limit the range of the different water management decisions. Therefore, (2) the decisions taken by authorities rarely or never associate with any statistical criteria about the confidence interval of made decisions.

Furthermore, when irrigation planning and water allocation of a catchment is realized, (3) rarely the aquifer conditions are considered. By including them, decision-makers are able to have an overall understanding of the catchment water resources. This also represents an improvement opportunity: the possibility of considering both surface water and groundwater as part of the same equation, getting close to an integrated water resources management.

These three problems make the water resources planning complex for many regions. These are addressed in this research by:

i. Proposing a new methodology for optimizing the water resources allocation that do incorporate the groundwater status in decision-making.
ii. Making use of a weather generator to model the proposed methodology, so confidence intervals are part of the decision-making information.

1.3. Proposed Solutions and Objectives

1.3.1. Proposed Solutions

For a good representation and assessment of the available water resources in the catchment, physical models were developed and used: a hydrological model for the precipitation-runoff processes, and a groundwater model for the aquifer's representation.

To represent how the water is allocated inside the catchment, a water allocation model is also needed, providing simple rules that acknowledge the physical constraints of the system and the routing of the water, described in Chapter 5.2. This model addresses water allocation in a general way, leaving the detailed allocation out of the scope of this research.

Then, using the water allocation model as the backbone and the physical model results as primary inputs, an optimization model can be implemented to compute the destination of water resources at each timestep considering the different goals, priorities, and constraints.

Undoubtedly, this approach would be the best if all the information is certain and no changes are expected. However, it is important to acknowledge that such ideal conditions do not exist, and to address the rapidly changing weather, this research includes the implementation of a Receding Horizon Control strategy (RHC), described in Chapter 4.2.

Finally, a weather generator is used for addressing the uncertainty of future weather conditions from a stochastic approach, replicating on the obtained resampling the probability of occurrence and statistical properties of the historical records, in terms of both temporal and spatial dimensions. With that, the optimization model can be run for multiple generated weather conditions and results can be presented associated with a probability of occurrence. This is described in Chapter 4.4.2.

1.3.2. Objectives

The main objective of this research is to add to the available methodologies a new approach for improving water management strategies in catchments where future conditions are volatile and highly unpredictable.

With regards to the RHC methodology, the longer the receding horizon is, the better the solution. But two things must be considered: the further in the future, the lower the forecast skill; and the longer the receding horizons, the higher the computational effort. This trade-off might change from one catchment to another, depending on the available information, skill of the forecast data, weather conditions, and the size of the catchment.

Evaluating the optimal solution for different receding horizon lengths and then comparing these results with the historical optimization results makes it possible to draw up the relationship between the performance of the solution in terms of the length of the receding horizon, so a specific RHC length can be recommended. The goal is then finding the most suitable RH length to be used at a specific catchment.

Once the RHC length is specified, and a large number of weather forecasts of that same length are generated, the optimization model can be run for an "unknown" but most probable future weather condition, implementing the obtained results for the first timestep. This process can be repeated for each timestep, updating first the initial state with the actual conditions. This method has great adaptability for sudden changes (thanks to the RHC methodology) and also delivering a robust result over decision making (thanks to the stochastic approach over future conditions).

2. Case study: Elqui catchment

2.1. Description

Chile is well known for being a long and narrow country, trapped between the Pacific Ocean and the Andes mountain range. Because of this atypical shape and location, you can find all types of climates across the country. This is of special interest for the region of Coquimbo, located on the edge of the division line between the semi-arid climate to the south and the desertic climate to the north.

Coquimbo region is then placed in this highly sensitive location. Due to climate change and a long and continuous drought over the last 10 years, enormous pressure has been put on the scarce water resources available, with no sufficient water in the surface resources and continuous depletion of the aquifers.

The main catchment of the region is the Elqui River catchment, which runs from the top of the Andes to the Pacific Ocean in an east-west direction, having a total surface area of 9,829 km^2. The topography of the catchment corresponds mainly to a mountain region with altitudes that range from above 4,000 m.a.s.l. to 0 m.a.s.l. This is part of the reason that inside the catchment it is possible to find Tundra (ET) to Semi-arid (BSk-BSh) and Desert (BWk) climates, based on the Köppen climate classification.

The catchment has only one recognizable glacier, known as the "*Tapado*" glacier, with an average altitude of 4,970 m.a.s.l. and having only 1.67 km^2. There are some other smaller and unnamed glaciers that can be neglectable due the small size of them.

There are two reservoirs inside the catchment, La Laguna and Puclaro reservoir, both described in Table 1. A general overview of the catchment is shown in Figure 1.

Table 1: Reservoirs data (Elqui catchment, Chile)

Reservoir	**Location (approx.)**		**Altitude (m.a.s.l)**	**Volume (Mm^3)**	**Main use**
	Lat (°)	Lon (°)			
La Laguna	-30.2	-70.0	3,130	50	Agriculture. Mainly permanent plantations (vineyards, olives, citrus, etc.)
Puclaro	-30.0	-70.8	435	210	Horticulture agriculture, drinking water supply, energy generation.

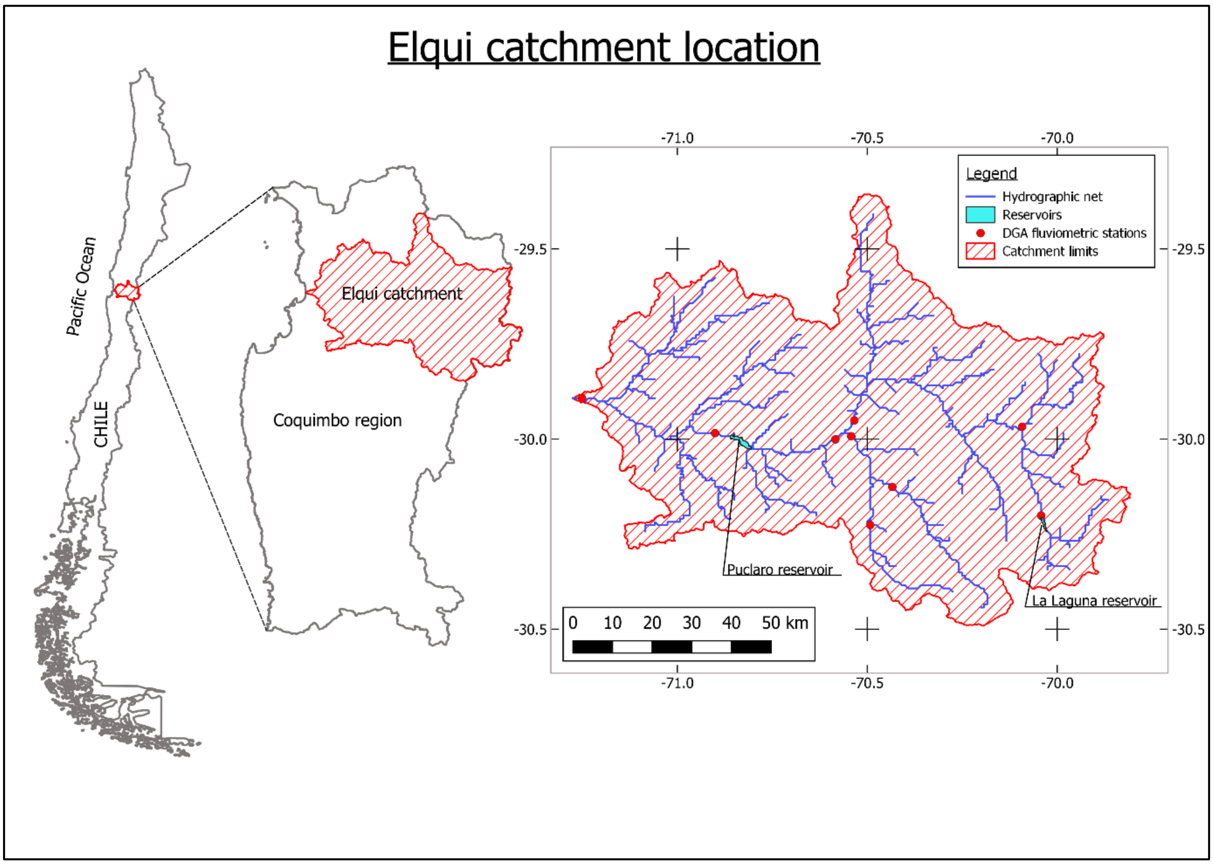

Figure 1: Elqui Catchment location.

The precipitation in the Elqui catchment is quite variable throughout the year, especially during the rainy season where the statistical spread is large. Temperature is expected to have a seasonal variability with a smaller deviation than precipitation. In the upper part of the catchment snow accumulation plays an important role in the water availability of the catchment, being the source of water during the irrigation season. Using average values over the entire catchment, Figure 2 shows how the precipitation and temperature change during the year, for a station at the coast (left) and a station in a high-altitude subcatchment (right – one of the stations used for calibration of the hydrological model).

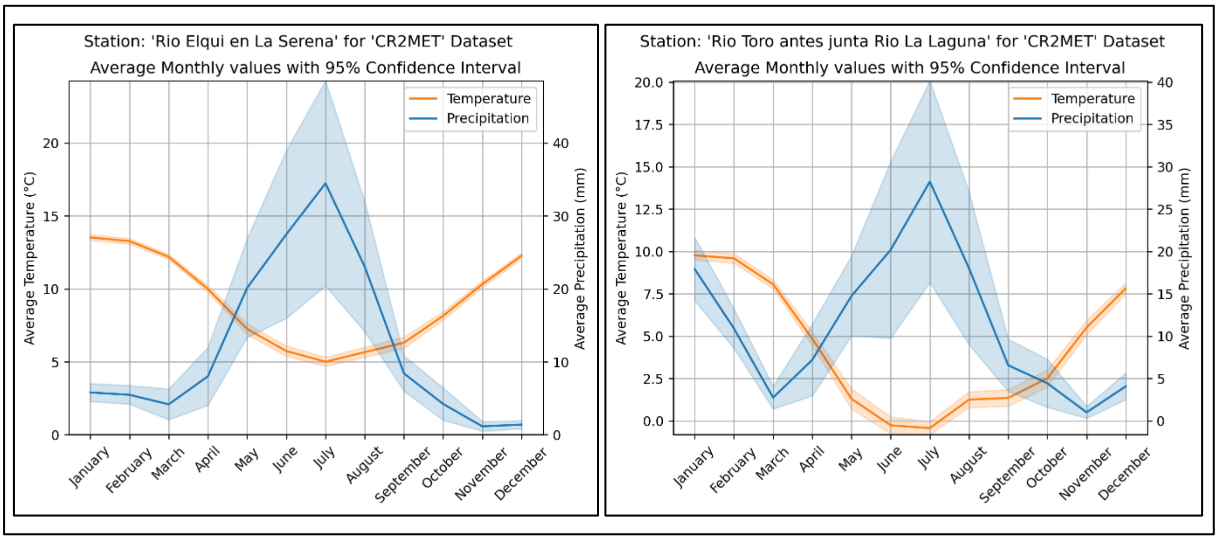

Figure 2: Walter Lieth diagrams for the whole catchment at "Rio Elqui en la Serena" station (left) and for a high altitude subcatchment (right) at "Rio Toro antes junta Rio La Laguna" station averaged over the years 1979-2020. Source: Own elaboration, based on data from CAMEL-CL.

During the last 10 years, extreme precipitation events have occurred more frequently, generating a lot of surface flow in the upper part of the catchment that sometimes cannot be used since there is not enough storage capacity in the reservoirs, which causes the water to drain to the ocean. [1,2,3]

[1] https://www.biobiochile.cl/noticias/nacional/region-de-atacama/2017/01/25/las-imagenes-que-deja-la-evacuacion-de-los-360-aislados-tras-el-desborde-del-rio-chollay.shtml

[2] https://www.24horas.cl/regiones/zona-norte/coquimbo/valle-del-elqui-cayeron-10-milimetros-de-agua-en-30-minutos

[3] https://www.emol.com/noticias/Nacional/2022/07/15/1067035/alcalde-coquimbo-emergencia-lluvias.html

2.2. Water allocation system

Chile's water allocation system is based on a legal framework that recognizes water as a tradable commodity and allows for private ownership of water rights. Water shares, or "water rights", are the cornerstone of Chile's water allocation system. Water rights are property rights that allow their holders to use and exploit water resources at a specific location, for a specific purpose, and for a specific amount of time.

Water rights in Chile are allocated through a permit system that is administered by the General Directorate of Water (DGA), a government agency responsible for regulating and overseeing the use and management of water resources in the country. The DGA grants water rights based on the availability of water in a particular basin or aquifer and the needs of different users and sectors. Water rights are always stated in terms of flow rates. Once a water right is granted, the holder has the exclusive right to use and exploit the water resource, subject to certain conditions and limitations. The holder can use the water for their own purposes, such as irrigation or industrial processes, or they can lease or sell their water rights to others.

In the most important catchments, there are also private and non-profit organizations called "*Juntas de Vigilancia*" (JdV) or Surveillance Boards that represent the interests of the water users in each specific basin, where "users" mean any natural or legal person that owns water shares in the basin.

The main role of a JdV is to manage the distribution of water among its members and to ensure that each user is complying with the terms of their water rights. They are responsible for monitoring water use, enforcing regulations, resolving disputes, and overseeing the maintenance of infrastructure. In the case of water scarcity, the JdV is responsible for declaring water scarcity, establishing shifts for the use of water, and adopting extraordinary measures for the fair distribution of water, being the *Desmarque* methodology one of them (see below).

2.2.1. Desmarque

The *Desmarque* concept simply refers to the percentage (%) of the nominal water shares flowrate (or volume) that the users are allowed to use in periods of scarcity, in order to assure that all users receive what corresponds to them in a fair way, according to the available water. The *Desmarque* was used for the first time in the catchment in 1911.

But a proper usage of the *Desmarque* value has only been done based on hydrological criteria since 2012, considering the stored water in the catchment and the hydrological projections. The full time series of the historical *Desmarque* values can be observed in Figure 3.

In order to assure water users can plan ahead their activities, an annual program of the *Desmarque* is realized for all irrigation sectors. Monthly variation is allowed but must always respect the annual (total) value.

The definition of the annual Desmarque value (since 2012) is based on a heuristic methodology that consists of two phases:

1. The hydrological projection for the next 12 months, for which four different methodologies are used:
    a. Hydrological model projection
    b. Meteorological decision tree projection
    c. Hydrological decision tree projection
    d. Hydrometeorological decision tree projection
2. Application of the operational binary decision tree rule developed by the JdV, for each of the previous four methodologies.

The detail of the complete methodology is described in The Operational Manual of the "*Junta de Vigilancia del Rio Elqui y sus Afluentes*" (JVRE) developed by Universidad de La Serena (Junta de Vigilancia Rio Elqui y sus Afluentes, 2019).

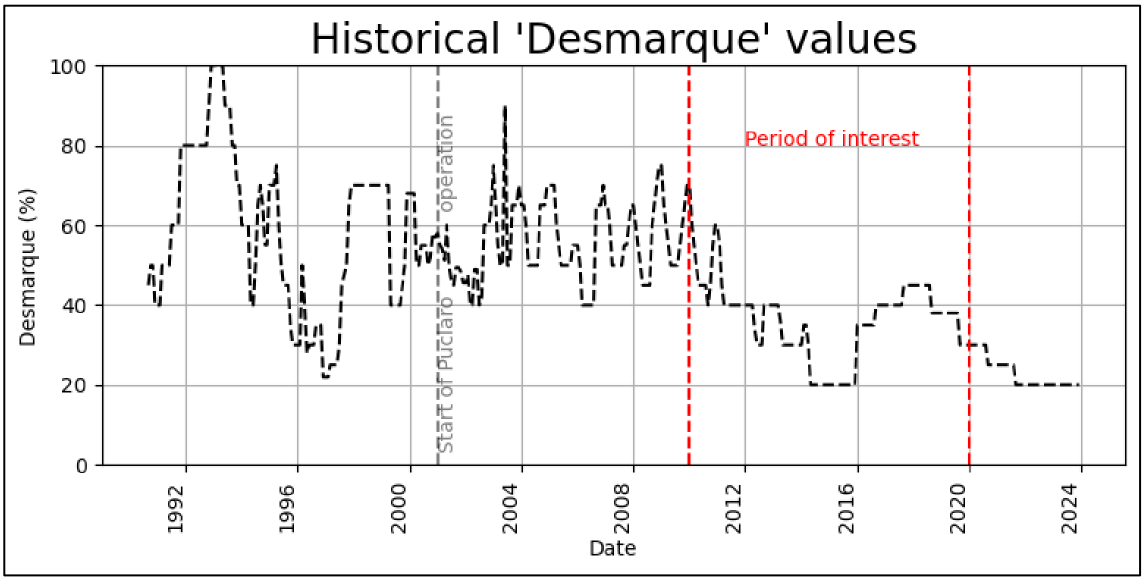

Figure 3: Historical values for the Desmarque value
Source: Own elaboration, based on data from Universidad de La Serena (ULS)

3. Research questions

Considering the research objectives stated in Chapter 1.3.2 and the specificities of the presented case study, intriguing questions arise that can guide this research. Given the heuristic nature of the current methodology used in the catchment to determine the annual Desmarque, it is worthwhile to explore a more scientific, direct, and precise approach for its calculation and compare it with historical Desmarque values. Additionally, since the existing methodology in the basin does not account for aquifer infiltration, the question arises whether the proposed new approach in this research can enhance the Desmarque values while simultaneously improving aquifer conditions. This provides an avenue for addressing Research Question A.

A. **How suitable is an optimization model for defining the yearly *Desmarque* value in a reservoir-aquifer catchment?**
    - How well does the historical simulation model reproduce the historical *Desmarque* data?
    - What are the contributions of incorporating the groundwater component (criteria) in the simulation to a change in the historical *Desmarque*?

If an optimization model is intended to be implemented for the water resources in the catchments, it is important to define the horizon with which the model should work. The longer this horizon, the greater the challenge for generating future conditions in a reliable way with good skill. So, the objective here is to determine the minimum length of this optimization horizon that gives acceptable results, formulating then Research Question B.

B. **What is the impact of the different receding horizon lengths on the optimized water management parameters in basins where there is an interaction between reservoirs and aquifers?**
    - How close is each receding horizon optimization results when comparing them with the historical simulation results?

And finally, when implementing a weather generator to be used in forecasting future weather conditions, a large number of weather time series can be generated, based on the statistical distribution of the different parameters. In theory, the optimization model could be run for each weather time series generated, but a more efficient way needs to be used due to computational effort. So, what if one of the most probable weather scenarios is used for each timestep? This is formulated in Research Question C.

C. **How well does the stochastic approach of the weather generator work when replacing the unpredictable and low skill forecast data with these highly probable weather conditions in the RHC optimization model?**

4. Methods and materials

4.1. Research methodology

The research process has been divided into four phases, which are described in Table 2 and schematized in Figure 4.

Table 2: Research phases

Research phase	Description	Milestone
Phase 1	Development of an optimization model able to calculate the *Desmarque* value (see Chapter 2.2.1) and as such, help with the annual water resources planning in the catchment. Is an improved version of the optimization model developed during the internship (see Chapter 4.5.3).	Acceptably good optimization model that correctly calculate *Desmarque* values.
Phase 2	Development of a hydrological model able to translate the weather parameters (precipitation, temperature, and potential evapotranspiration) into run-off data for the catchment.	Acceptably good hydrological model that replicates the precipitation-runoff processes in the catchment.
Phase 3	Firstly, incorporating groundwater infiltration into the optimization model. Secondly, the implementation of the RHC methodology over the historical data and then evaluating how good each solution is compared to the historical simulation.	Receding horizon length recommendation to be applied in a regular operation of the optimization model.
Phase 4	Firstly, the generation of a long synthetic weather time series with the same statistical parameters as the historical records, by daily resampling of historical data. Secondly, being able to randomly select a generated weather time series, implement the RHC methodology using the synthetic random weather and test its performance over the historical period between 2010 and 2020.	Performance analysis of the new methodology.

A detailed description of each model is provided in Chapter 5.

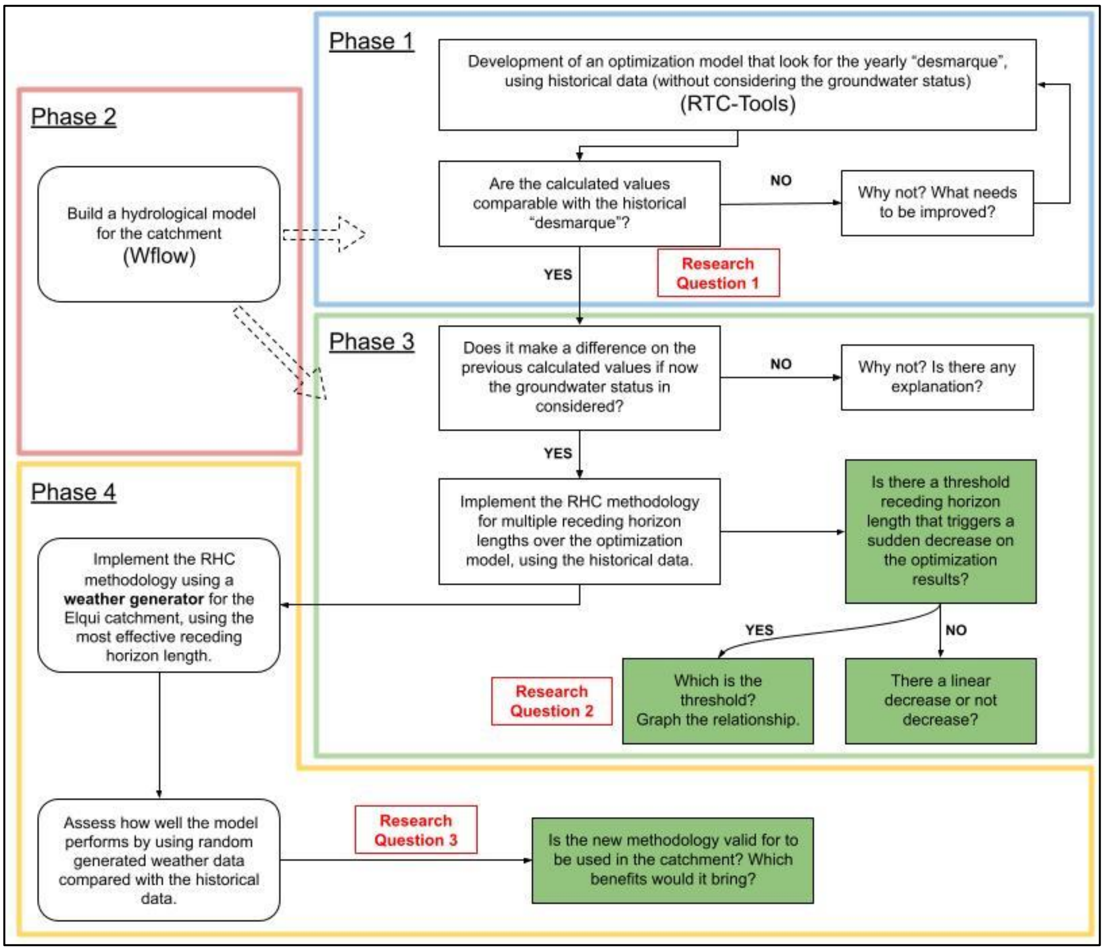

Figure 4: Research methodology

4.2. Conceptual model of the Elqui catchment

To simplify the domain of the problem, the allocation and the optimization model comprehend the Puclaro reservoir and the downstream area. This definition of the model is based on the fact that the area upstream of the Puclaro reservoir is mainly used for permanent plantations, as was stated in Table 1, and their irrigation needs are satisfied by the operation of the La Laguna reservoir.

To add to this, the administrative section downstream of de Puclaro reservoir (3rd section)[4] is the most important of the catchment in terms of the number of canals, the number of water shares, and the irrigation surface (Dirección General de Aguas, 1995).

Finally, since the relevant aquifers of the catchment are also downstream of the Puclaro reservoir, this assumption will not have an effect on the results of this research. The conceptual model schematization is shown in Figure 5.

[4] The Elqui river is administratively divided in three sections. The third section is located downstream de Puclaro reservoir.

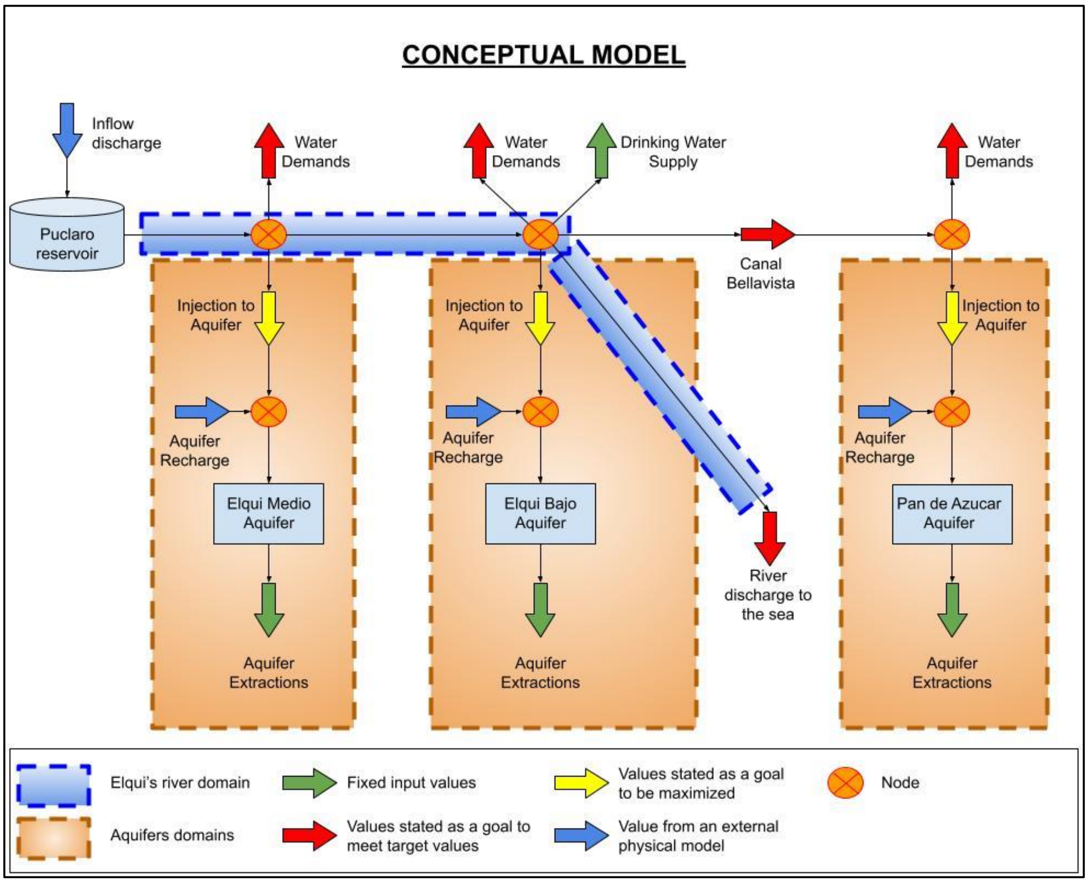

Figure 5: Conceptual model of the Elqui catchment water allocation and optimization process, downstream of the Puclaro reservoir.

The inflow discharge to the Puclaro reservoir will be calculated with the developed hydrological model, while the aquifer net recharges will be taken from the existing groundwater models (iMOD).

Finally, since this research has more interest in the change of the aquifer's volume instead of the total aquifer volume, and because there is not available information about the total water volume for each aquifer, a fixed volume of 4,000 Mm^3 was used as initial condition for the three aquifers.

4.3. Receding horizon control methodology (RHC)

The RHC methodology involves solving an optimization problem over a finite time horizon, but only implementing the first part of the solution trajectory. At the end of each control interval, the optimization problem is solved again, considering any new information or changes in the system state. This process is repeated iteratively, with the optimal solution being updated at each control interval, based on the latest available information.

This kind of methodology has been used in many fields, Optimal Energy Management being one of them (Alasali, Haben, Foudeh, & Holderbaum, 2020). As defined by Alasali et al., the RHC methodology uses a rolling forecast model for the period between t (current time step) and $t + k$, where k corresponds to the predictive horizon or receding horizon length, as shown in Figure 6.

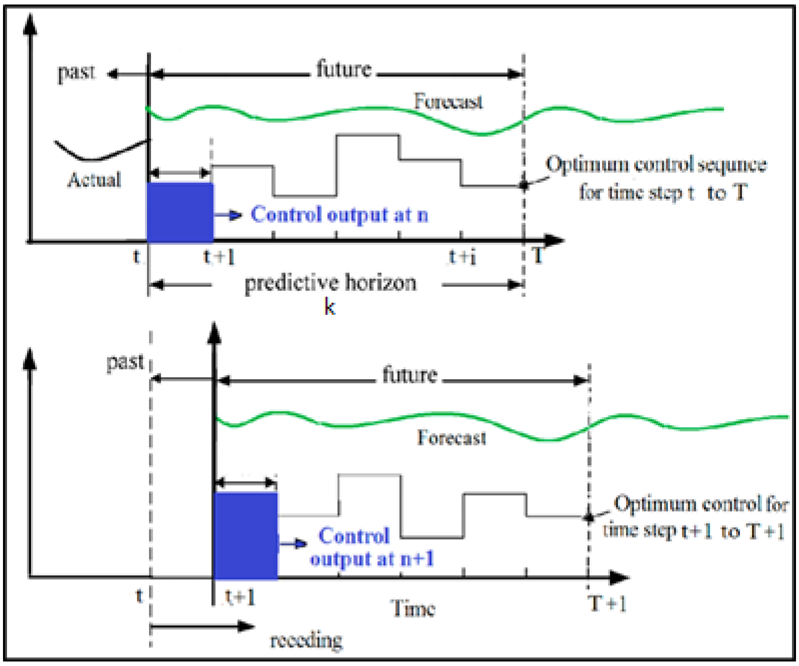

Figure 6: Simple illustration of the RHC methodology
Source: (Alasali, Haben, Foudeh, & Holderbaum, 2020)

For our specific case, the receding horizon length to be used will be determined by the present research. The forecast will correspond to the output of the weather generator (precipitation, temperature, and potential evapotranspiration), and the optimum control sequence corresponds to the result of the optimization problem for each timestep.

This method implementation is described in Chapter 5.4 and is important for answering Research Question B.

4.4. Future discharge flows

4.4.1. DGA discharge flows forecast

At the beginning of each irrigation season (September), the DGA releases a monthly forecast for the coming year with the snowmelt discharge flow for several fluviometric stations in the country to be used for better planning by the water users. The observed discharge flows and the DGA forecasts are shown together in Figure 7, for the period 2010-2020.

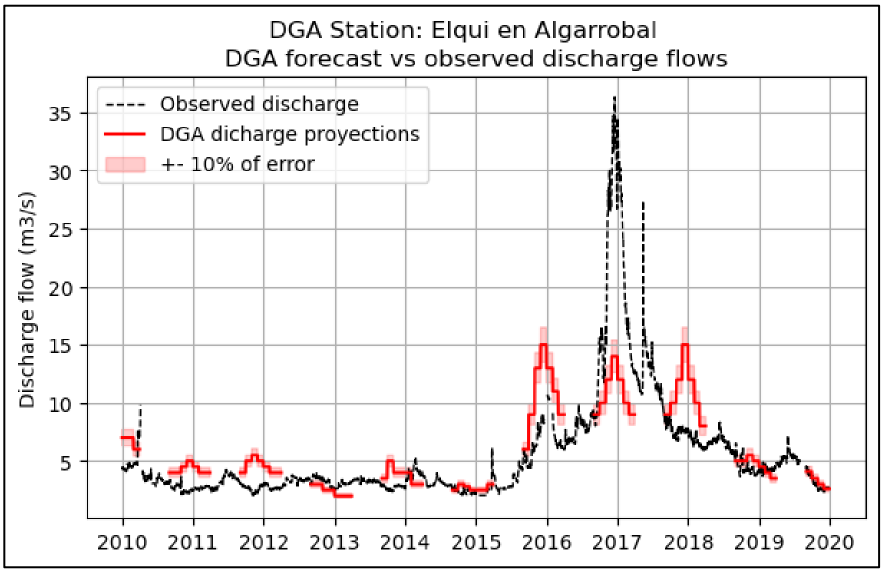

Figure 7: DGA forecast flows vs observed discharge flows at "Elqui en Algarrobal" DGA fluviometric station
Source: Own elaboration, based on DGA data.

From this figure it can be seen that for at least six out of the ten years shown, the DGA projections are not very accurate. Therefore, this data will not be used to assess the new methodology presented in this study; instead, only the weather generator predictions will be used for the methodology assessment.

4.4.2. Weather generator methodology

The weather generator methodology used in this research is based on the Gridwegen R-code developed at Deltares[5]. This code is a simplified and scalable implementation of the semi-parametric stochastic weather generator developed by Steinschneider & Brown (2013).

The weather generator takes as input the gridded weather forcing data of precipitation, temperature, and potential evapotranspiration from the 30-year period of 1990 to 2020 from selected forcing dataset. There are several components included in the methodology:

[5] https://github.com/Deltares/weathergenr

1. a wavelet decomposition coupled to an autoregressive model to account for structured, low-frequency climate oscillations,
2. a Markov-chain and k-nearest-neighbor (KNN) resampling scheme to simulate spatially distributed, multivariate weather conditions over a region, and
3. a quantile mapping procedure to enforce long-term distributional shift in weather variables.

The output from the implemented code corresponds to a list of dates from the input data with the length of the desired weather generation, which for our case is a 100-year period. The result is a daily resampling of weather data in which all statistical characteristics (yearly and seasonally) are maintained.

This output is not meant to be used as a linear time series, but for selecting randomly one year out of the 100-year to be used as a resemblance to the forecast input for each timestep. The selected weather data is then used as input for the hydrological model to generate the discharge forecast.

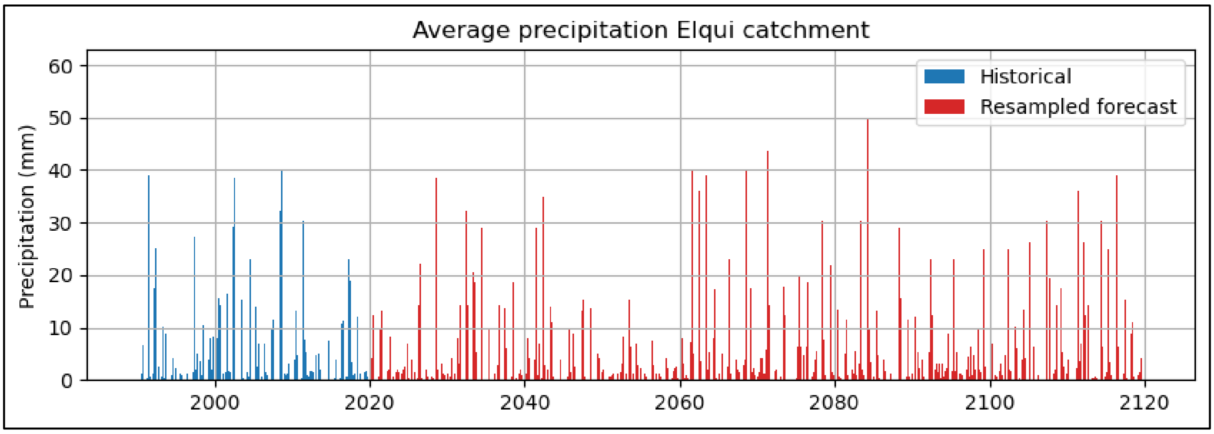

Figure 8: Average daily precipitation over Elqui catchment. Comparison between historical data and resampled forecast data, generated with the weather generator.

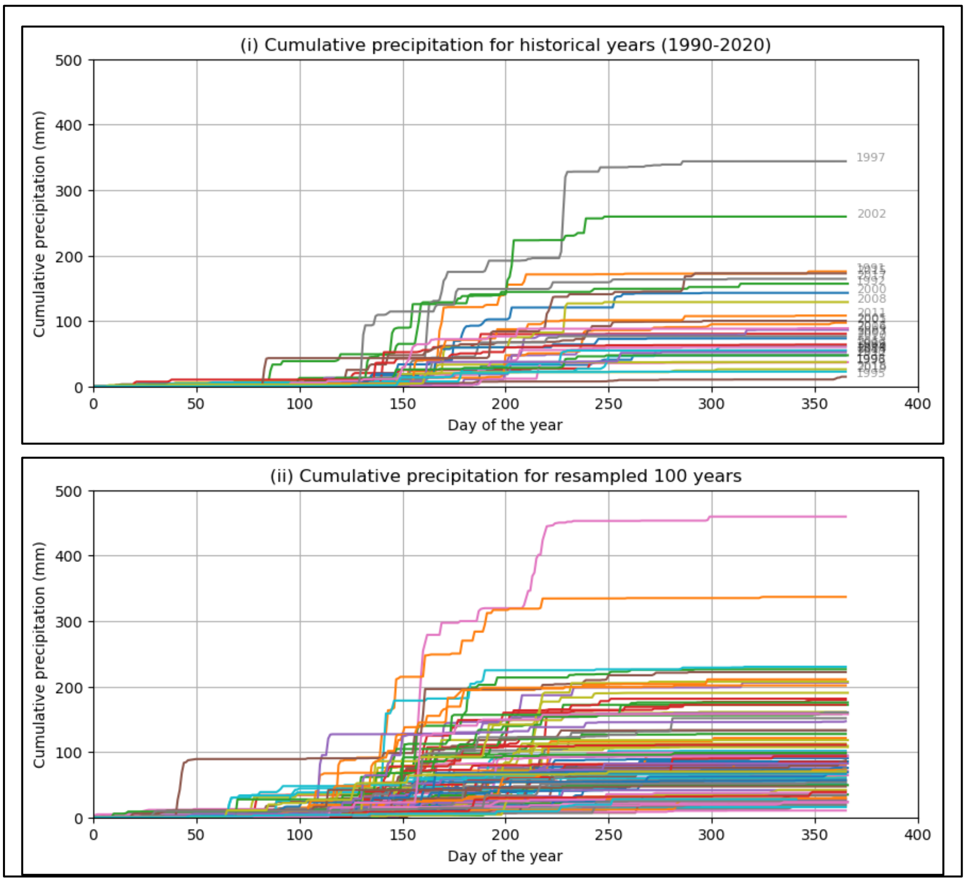

Figure 9: (i) Cumulative precipitation over the historical 30-years period (1990 – 2020). (ii) Cumulative precipitation over the generated, resampled 100-years period.

This methodology is part of the implementation described in Chapter 5.5 and is important for answering Research Question C.

4.5. Materials and sources of information

4.5.1. Giragua project

The unique conditions and situation of the Elqui catchment and its aquifers have drawn the attention of different parties, a situation that led to a joint venture, in which the government of Chile and the government of The Netherlands worked together on a first-stage project ("Giragua" project), where the infiltration capacities of both Elqui Bajo and Pan de Azúcar aquifers were studied and evaluated, with enormous knowledge generation within the basins (Deltares, 2021). A general view of the study area is shown in Figure 10.

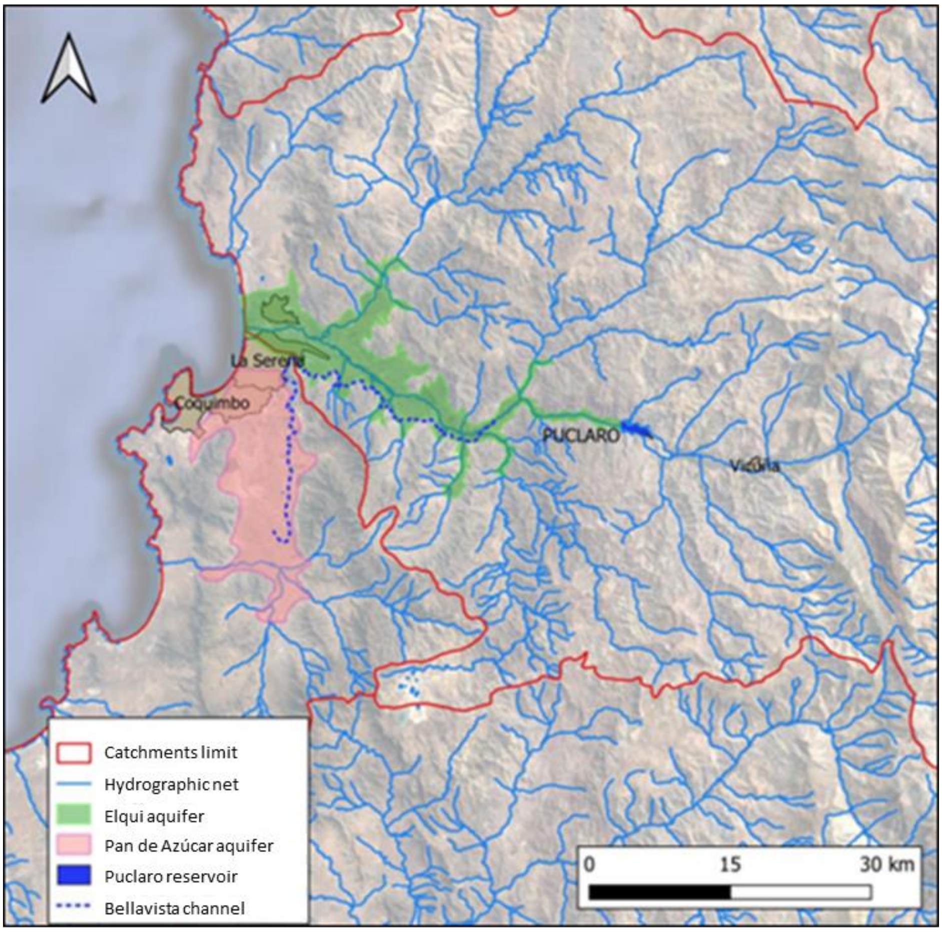

Figure 10: Study area
Source: GIRAGUA report (Oct. 2022)

By the end of the GIRAGUA project, one of the issues that arose was the possibility of recovering and improving the aquifer levels through optimized water resources management of the catchment, a subject that is in part addressed in the present research.

4.5.2. Existing groundwater models (iMOD)

During the GIRAGUA project, two different physical models for the groundwaters of both Elqui and Pan de Azúcar aquifers were developed using the iMOD[6] software. These aquifers are depicted in Figure 10.

The spatial resolution of both groundwater models consists of a 50 m x 50 m grid cell size, with three layers with different characteristics. The Elqui aquifer model was based on a previous model developed by *Geohidrología Consultores* (Geohidrología Consultores, 2011) while the Pan de Azúcar aquifer model was built from scratch. The time step used for both models is monthly.

- *Boundary conditions:*

The boundary conditions considered for both models correspond to:

- Constant head for the interaction with the sea
- The tributary streams that recharge the aquifers were simulated as wells for the Elqui aquifer and as a permeable border for the Pan de Azúcar aquifer
- Impermeable border for the rest of the aquifers' borders
- Surface drains for the Pan de Azúcar aquifer according to the topography

- *Recharge:*

The different recharges considered in both models and their respective sources of data are summarized in Table 3.

Table 3: Groundwater models recharges and their respective sources

Type of recharge	Elqui aquifer	Pan de Azúcar aquifer
Precipitation recharge	From an existing Wflow model[7]	From an existing Wflow model[7]
Agriculture recharge	From an existing WEAP model[8]	From an existing WEAP model[8]
Channels loses recharge	Provided by JVRE	Provided by JVRE

- *Surface water:*

Inside the domain of the Elqui aquifer, the Elqui River plays an important role in the interaction between its surface water and the aquifer. Because there was no hydraulic model for the river when the groundwater models were developed, the river-aquifer interaction is incorporated by discretizing in four discharge flow ranges for the Elqui River at the fluviometric station of "*Rio Elqui en La Serena*" (when reaching the sea) and using a representative water level line along the river for each range. The representative water lines were extracted from (Geohidrología Consultores, 2011). The discharge ranges and representative water levels are detailed in Table 4.

Table 4: Elqui river representative discharge flows

Discharge flow range (m^3/s)	Flow description	Date of the representative water line
> 20	Maximum flows	01-01-2003
5.0 – 20	Average flows	01-09-2006
3.5 – 5.0	Low flows	01-09-2007
0 – 3.5	Very low flows	01-08-2011

[6] https://www.deltares.nl/en/software-and-data/products/imod
[7] (Deltares, 2021)
[8] (RHODOS, 2016)

- *Pumping wells:*

Finally, the pumping wells incorporated in the groundwater models address the human intervention in the aquifers. The information about the pumping wells was obtained from the official DGA cadaster, where the number of wells, location, and pumping rates are stated. Additionally, the later information was complemented with the available information included in the existing groundwater model developed by (Geohidrología Consultores, 2011)

More detail about the groundwater models used can be found in (Deltares, 2021).

4.5.3. Deltares Internship

Between September and November 2022, this author realized an internship at Deltares with the objective of exploring the use of real-time and forecast data to optimize reservoir and aquifer management.

The internship focused on the potential of an optimization tool using historical data for water resources management and concludes that the implementation of an optimization model accompanied by other technical and organizational improvements would be an effective way of stopping the depletion of the aquifer without jeopardizing the irrigation supply.

During the internship, a reference case was established, corresponding to the closest situation to the actual conditions of the basin. Additionally, four different scenarios were established and later analyzed. The description of the analyzed scenarios inputs is presented in Table 5 and the input values for the reference case and each scenario are presented in Table 6.

Table 5: Deltares internship: Analyzed scenarios inputs description

Input	Ref. case	Scenario A	Scenario B	Scenario C	Scenario D
Min_EcoFlow (%)	20 % of the Environmental Reserve	Same as Reference Case	Same as Reference Case	Same as Reference Case	Same as Reference Case
Q_max of Canal Bellavista (m^3/s)	Current capacity based in total number of "acciones"	Same as Reference Case	The discharge capacity is increased with 35%	The discharge capacity is increased with 35%	The discharge capacity is increased with 35%
Q_max_inf. Elqui Medio (m^3/s)	Scenario B of Giragua (0.90 m^3/s)	Same as Reference Case	Same as Reference Case	Infiltration capacity increased 3 times	Infiltration capacity increased 3 times
Q_max_inf. Elqui Bajo (m^3/s)					
Q_max_inf. Pan de Azúcar (m^3/s)	Giragua max infiltration discharge (0.92 m^3/s)	Infiltration capacity equals the discharge capacity of Canal Bellavista	Infiltration capacity equals the discharge capacity of Canal Bellavista	Infiltration capacity equals the discharge capacity of Canal Bellavista	Infiltration capacity equals the discharge capacity of Canal Bellavista

Table 6: Deltares Internship: Analyzed scenarios input values

Input	Ref. case	Scenario A	Scenario B	**Scenario C**	Scenario D
Min_EcoFlow (%)	0.20	0.20	0.20	**0.20**	0.20
Q_max of Canal Bellavista (m^3/s)	3.67	3.67	4.95	**4.95**	4.95
Q_max_inf. Elqui Medio (m^3/s)	0.45	0.45	0.45	**1.35**	1.35
Q_max_inf. Elqui Bajo (m^3/s)	0.45	0.45	0.45	**1.35**	1.35
Q_max_inf. Pan de Azúcar (m^3/s)	0.92	3.67	4.95	**4.95**	4.95

One of the conclusions of the Internship corresponded to the high potential for artificial infiltration of the aquifers without jeopardizing the irrigation water allocation of Scenario C. Because of it, Scenario C is the starting point of the present Thesis research.

The details of this internship can be found in the Internship Report (Garcia Grez, 2022)[9], which is a cornerstone of this thesis research.

4.5.4. Other sources of information

Many different sources of information were used during this thesis research, and some of them date to the internship described in Chapter 4.5.3. This information and respective sources are mentioned in Table 7. For more detail refer to Garcia Grez (2022). The new sources of information used in this research are given in Table 8:

Table 7: Deltares Internship sources of information

Input data required[10]	Source
Water demands	Universidad de La Serena (ULS)
Drinking water supply	
River discharge to the sea or minimum ecological flow	PEGH[11], DGA.
Aquifer recharge	Giragua project, Deltares
Aquifer extractions	

Table 8: Thesis Research sources of information

Input data required	Source
Discharge flow observations on fluviometric stations	DGA
Precipitation measurements on DGA stations	DGA
Historical weather raster data	- ERA5 daily (Pp, T, and PET) - CHIRPS daily[12] (Pp) - CR2MET[13] (Pp and T) - CAMELS-CL[14] (averaged data over Pp, T, and PET)

[9] http://resolver.tudelft.nl/uuid:5679914b-172c-4978-937c-bb7f98e93242
[10] Using the same denomination as in Figure 5.
[11] "Plan Estratégico de Gestión Hídrica en la Cuenca de Elqui" (Nov–2020), realized by UTP Hídrica -ERIDANUS for Dirección General de Aguas (DGA-MOP Chile).
[12] Climate Hazards group InfraRed Precipitation with Station data
[13] https://www.cr2.cl/datos-productos-grillados/
[14] https://camels.cr2.cl/

5. Models and methods implementations

5.1. Hydrological model

The hydrological model used is made with Wflow[15] software, developed by Deltares. This model is used to represent the precipitation-runoff processes inside the Elqui catchment. It was built through the HydromMT-Wflow[16] plugin that facilitates the process "*by automating the workflow to go from raw data to a complete model instance which is ready to run and analyze model results once the simulation has finished*"[16], additionally including the "*Tapado*" glacier on the model.

The hydrological model results were compared with the historical observation data for existing DGA fluviometric stations.

The Wflow model takes as forcing data precipitation, temperature, and potential evapotranspiration (PET) to compute the hydrological processes inside the catchment.

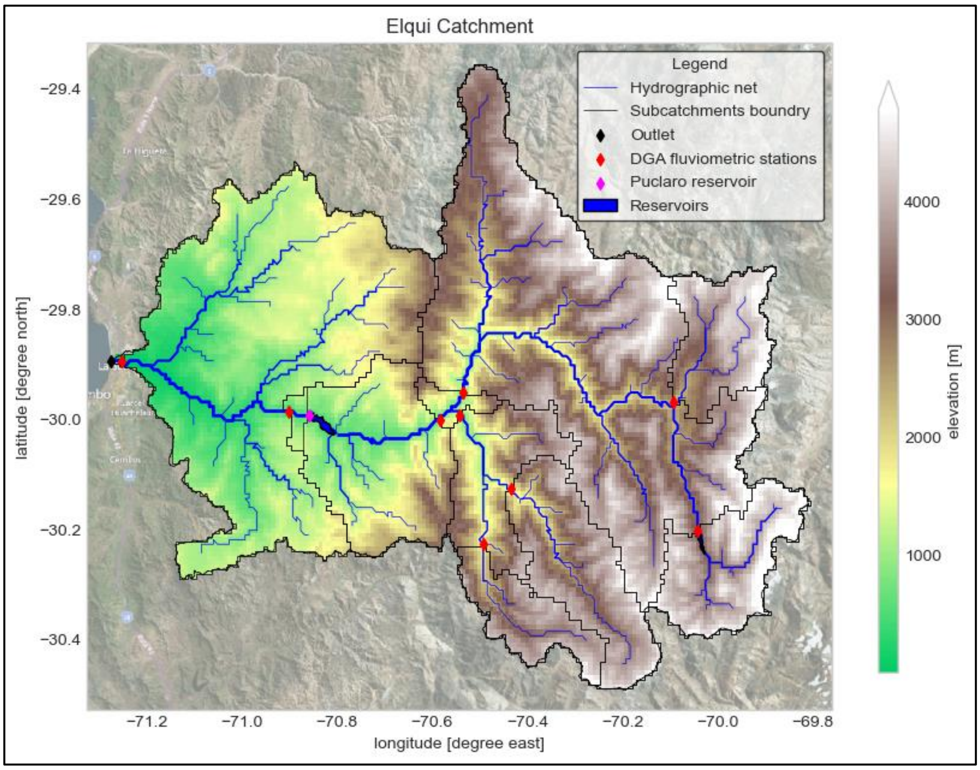

Figure 11: Elqui catchment from the hydrological model

5.1.1. Forcing data

Several meteorological forcing data sources were assessed for use in the hydrological model of the Elqui catchment, as shown in Table 9. Out of these different sources, the most suitable forcing dataset was selected to continue the following steps of this thesis research. This was done by comparing modelled and simulated discharge series for the selected DGA station, as explained in Chapter 5.1.1.2.

[15] https://www.deltares.nl/en/software-and-data/products/wflow
[16] https://deltares.github.io/hydromt_wflow/latest/index.html

Table 9: Different forcing dataset assessed for use in the hydrological model

Forcing Dataset	Data source			Comments
	Precipitation	Temperature	PET	
DGA-PP	DGA stations	ERA5	ERA5	Point data from Pp is interpolated using the Thiessen polygons methodology.
ERA	ERA5	ERA5	ERA5	-
CHIRPS_Global	CHIRPS_global	ERA5	ERA5	-
CR2MET	CR2MET	CR2MET	ERA5	Product developed using ERA5 and point data.
CR2MET_ERA	CR2MET	ERA5	ERA5	CR2MET using ERA5 for temperature
CAMELS average	CR2MET*	CR2MET	ERA5	*Is possible to choose between CR2MET, CHIRPS, MSWEP and TMPA.

5.1.1.1. Snow coverage results

Because of the high altitude of the eastern part of the catchment, snow accumulation plays a key role in the hydrology of the catchment. The discharge flows of the Elqui River during the dry months depend mostly on snow melt. Because of this, an additional check over the snow representation of the model was done by comparing the snow coverage percentage of the model over the catchment with MODIS[17] snow cover data.

The snow coverage percentage is defined as the number of grid cells in the catchment with snow divided by the total number of grid cells in the catchment. This methodology was applied to hydrological model results for all forcing dataset and for the MODIS data available through Google Earth Engine[18] (GEE). The script used in the GEE is shared in Appendix A.

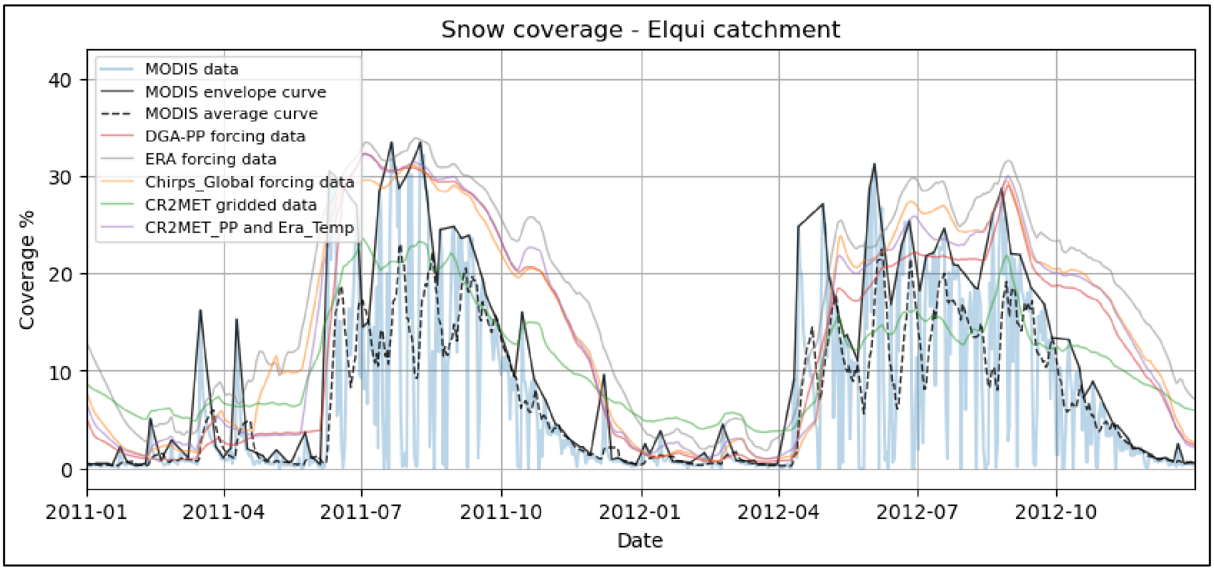

Figure 12: Snow coverage percentage over the Elqui catchment (2011-2012)

When analyzing the complete results (partially shown in Figure 12), the MODIS data (in blue exhibits an extremely high oscillation, ranging from above 30% to 0% of snow coverage within a very short

[17] Moderate Resolution Imaging Spectroradiometer aboard the Terra satellite, NASA.
[18] https://code.earthengine.google.com/

period (e.g., 3 days), followed by a sudden increase. This variation is noteworthy and cannot be entirely disregarded. It may be attributed to significant factors such as wind erosion and melting-refreezing processes, which necessitate specific consideration.

The solid black line in the graph corresponds to the superior envelope curve for the MODIS data, with the assumption that the high variation of the latter corresponds to noise in the observations. To be precautious, the dashed black line in the graph accounts for a moving average of the MODIS data for a 15-day window, assuming that the "noisy" observation is part of the internal catchment processes.

Looking at the results, it is safe to say that the snow representation of the model (at least the surface coverage) is accurate enough for all the sources of forcing data. Both black lines (solid and dashed) in the graph are backed up by some forcing data, which rules out neither forcing dataset until subsequent analysis is done.

5.1.1.2. Discharge flow results

The specific fluviometric stations that were considered for the calibration process are the three with minimal human intervention in their upstream catchment areas (shown in red in Figure 13) and additionally, the closest station upstream of the Puclaro reservoir (*Rio Elqui en Algarrobal*), as is detailed in Table 10.

Table 10: Calibration fluviometric stations

Station ID	Station Name	Location		Altitude	Upstream area
		Lat (°)	Lon (°)	(m.a.s.l)	(km^2)
4302001	Rio Toro antes junta Rio La Laguna	-29.97	-70.09	2,165	467.4
4313001	Rio Cochiguaz en el Peñon	-30.13	-70.44	1,360	675.3
4311001	Estero Derecho en Alcohuaz	-30.22	-70.50	1,645	338.2
4320001	Rio Elqui en Algarrobal	-30.00	-70.59	760	5,669.7

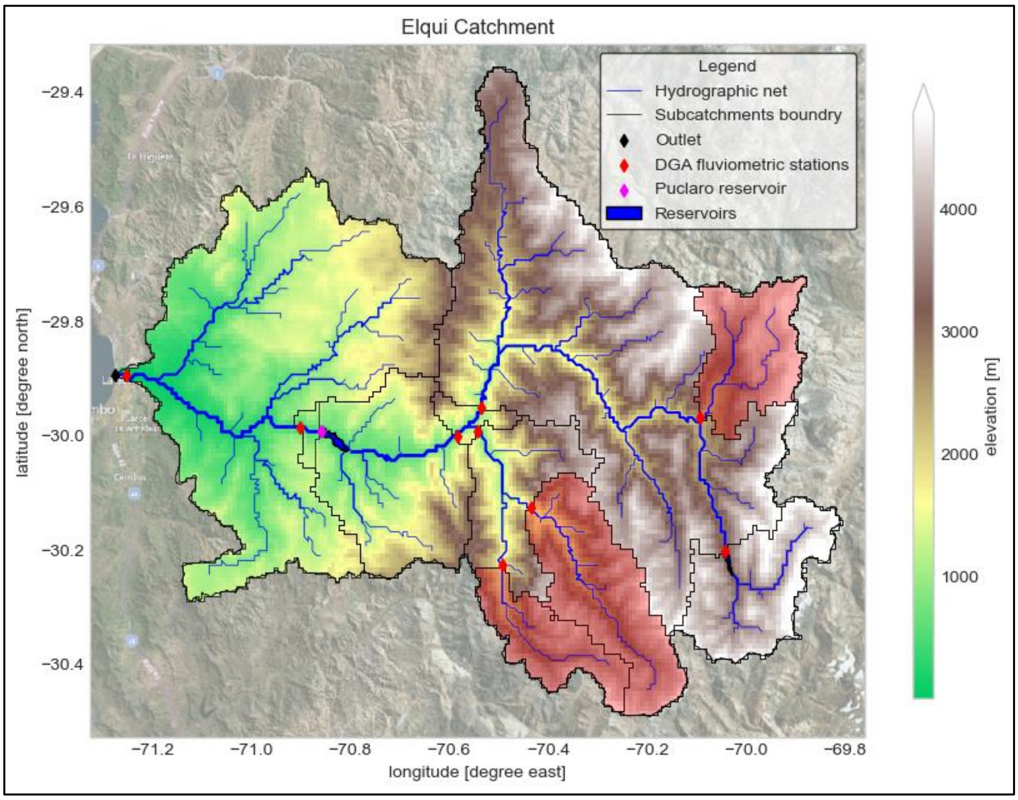

Figure 13: Calibration stations and their respective catchments areas

The results at each calibration station for the different forcing datasets are presented in Appendix B. Regarding these results, the following observations are made:

1. The ERA forcing data is too high at all the calibration stations, so was not used for further analysis.
2. The CHIRPS forcing data also seems to be overrepresenting the discharge flows, not as much as the ERA forcing data, but still in a significant magnitude, so this dataset was not used for further analysis either.
3. The observed discharge flow signal was also hard to represent for the CR2MET and the DGA-PP forcing data, sometimes overestimating and other times underestimating the total generated water volume.

The previous observations are inconclusive about which forcing dataset should be used. But, since the main purpose of the hydrological model is to accurately translate precipitation, temperature and potential evapotranspiration into inflow volume per timestep into the Puclaro reservoir, another approach based on the total volume per year was used.

Based on the results presented in Appendix B, the total water volume per year has been computed for the observed discharge flow and for each forcing dataset, for the “Rio Elqui en Algarrobal” station, the closest fluviometric station upstream of Puclaro reservoir, which is shown in Table 11.

Table 11: Yearly volumes into Puclaro reservoir and percentage from the observed values.

Year	Annual volume (Mm^3)			Percentage of the DGA observed values	
	Observed	DGA-PP	CHIRPS	DGA-PP	CHIRPS
2010	110.7	17.3	150.0	16%	136%
2011	91.9	71.3	228.9	78%	249%
2012	100	115.0	195.3	115%	195%
2013	94.6	120.9	165.4	128%	175%
2014	97.4	89.8	148.9	92%	153%
2015	121.6	238.0	125.4	196%	103%
2016	367.1	391.2	299.7	107%	82%
2017	402.5	474.9	353.0	118%	88%
2018	185.1	171.5	276.1	93%	149%
2019	118.8	18.6	185.3	16%	156%
Average	-	-	-	96%	149%
St. Dev.	-	-	-	50%	48%
Total	1,689.7	1,708.5	2,127.9	101%	126%

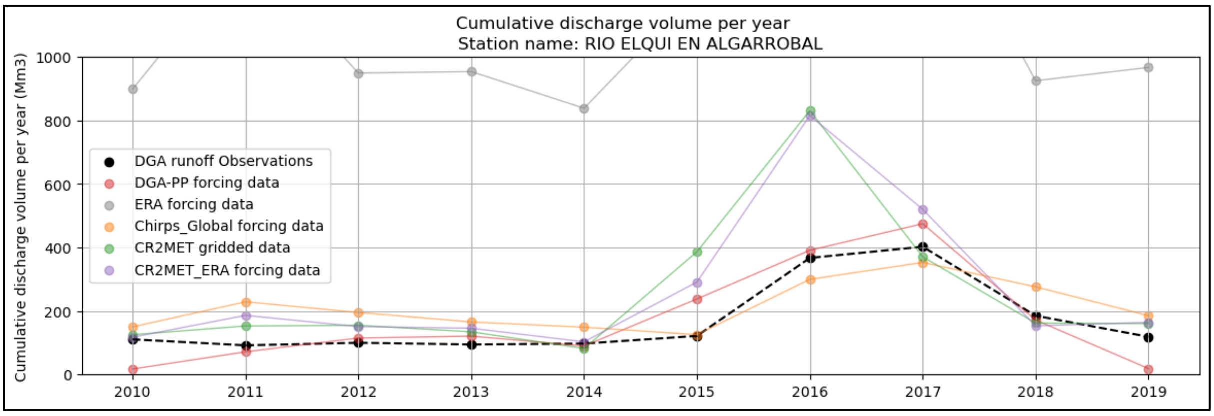

Figure 14: Cumulative inflow volume per year for each forcing dataset

Based on Figure 14, when the model is run with the DGA-PP forcing data, the results are very accurate at computing the annual total volume that flows into the Puclaro reservoir, with an average value of 101% of the values calculated from the observed values from the DGA runoff observations. The CHIRPS forcing data tends to overestimate the annual inflow volume into the reservoir with an average value of 149% of the observed annual inflow volume.

Based on this last analysis, this research will use the DGA-PP forcing dataset for the remaining analysis.

5.1.2. Model calibration

Calibrating the hydrological model is a crucial step in this kind of research. However, the author was only able to dedicate limited time to the calibration process. Firstly, the model's initial setup with HydroMT-Wflow in combination with the DGA-PP precipitation data and ERA5 temperature and potential evapotranspiration data was already quite good, reaching an average volume of 96 % with respect to the observed values, eventhough an enhancement of the first and last year’s is necessary.

Secondly, the lack of reliable and available data on soil parameters and even the observed discharges don't support an extensive calibration process since there is no need for more accuracy when cumulative discharge flow results are good enough. Lastly, time constraints imposed important limitations on this research, needing a balanced allocation of time resources. As a result, this calibration process focused only on the analysis of key parameters and making changes based on an iterative "trial and error" approach to improve the model's performance within the given time frame.

Therefore, a simple sensitivity analysis was done, using the DGA-PP forcing dataset. For four key model parameters, a range around the default[19] parameter value was defined to check the sensitivity of the model to each of these parameters, as is shown in Table 12.

Table 12: Sensibility analysis for four key model parameters

Parameter	Values			Results
	Low	Default	High	
Cfmax (mm/°C/Δt) Degree-day-factor	3.00	3.76	4.50	Minimum effect on hydrological model results. For high values higher discharge peaks are observed.
InfiltCapSoil (mm/day) Infiltration capacity	100	600	1,000	No significant effect on hydrological model results
KsatHorFrac Multiplication factor [-] applied to the horizontal saturated conductivity used for computing lateral subsurface flow.	10	100	300	Large impact on the hydrological model results. Low values increase the base flow and flatten the peaks.
rootdistpar (mm) Rooting depth of the vegetation	-300	-500	-1,000	No significant effect on hydrological model results

Taking the results of the sensitivity analysis into account, the only parameter that was modified for the final model corresponds to the "KsatHorFrac", adopting a fixed value of 20, which achieves results that better suit the observations. The graph of the updated cumulative discharge volume per year is presented in Figure 15.

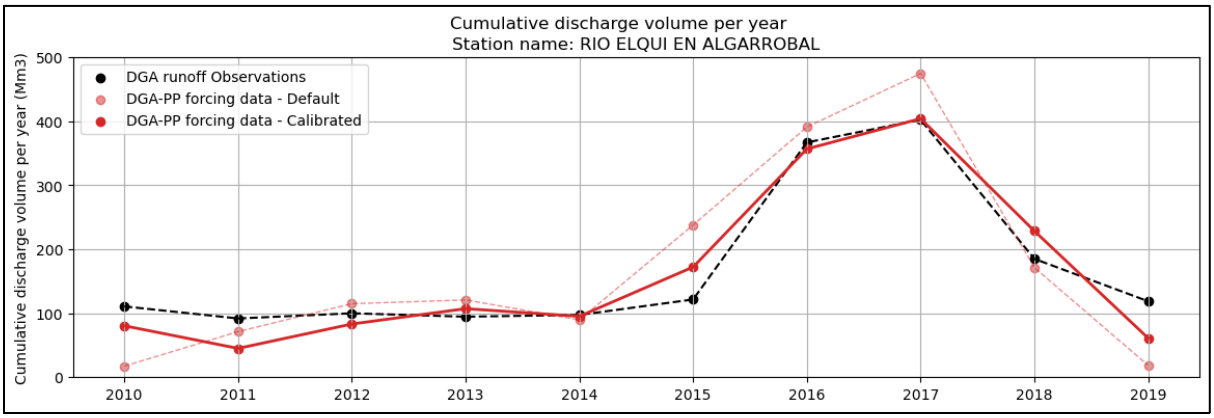

Figure 15: Calibrated model: Cumulative discharge volume per year

[19] Based in global datasets, HydroMT-Wflow assign default values for different parameters.

After the model calibration, the average percentage of the annual volume, compared to the observed volumes into the Puclaro reservoir has a small loss in accuracy (from 96% to 93%), but a high improvement of the standard deviation results (from 50% to 28%) as is shown in Table 13. The trade-off between the average percentage of the annual volume and the standard deviation is welcome since the default model achieves a slightly better average value by greatly oscillating around the observed results. Instead, the calibrated model displays a more stable and less unpredictable behavior. The calibration is lastly checked by a visual inspection of the results as shown in Figure 15.

Table 13: Calibrated model. Yearly volumes into Puclaro reservoir and percentage from the observed values.

Year	Annual volume (Mm³)		Percentage of the DGA observed values
	Observed	DGA-PP	DGA-PP
2010	110,7	80,5	73%
2011	91,9	45,1	49%
2012	100	83,2	83%
2013	94,6	107,2	113%
2014	97,4	95,2	98%
2015	121,6	172,3	142%
2016	367,1	356,9	97%
2017	402,5	404,3	100%
2018	185,1	228,6	124%
2019	118,8	61,2	52%
Average	-	-	93%
St. Dev.	-	-	28%
Total	1689,7	1634,5	97%

Interesting to notice that there is no one special difference on the annual volume accuracy when comparing dry and wet years. Dry years results like 2012, 2013 and 2014 are as reliable as those obtained for wet years like 2016 and 2017. The less accurate results are found at the beginning and at the end of the period of interest, apart from 2015 where results are overestimated.

5.1.3. Water balance on catchments

As one final check, a basic water balance analysis is computed using the calibrated model.

The water balance is an assessment of the inputs and outputs of water over a specific system (in this case, the calibration catchments) and over a specific time period (in this case a 10-year period, from 2010-2020). The input of water is the precipitation, and the output is the sum of the runoff out of the catchments and the evaporation. The difference between the input and output water over a specific time corresponds to a change (positive or negative) in the stored water (reservoir, aquifers, etc.) inside the system. See Figure 16.

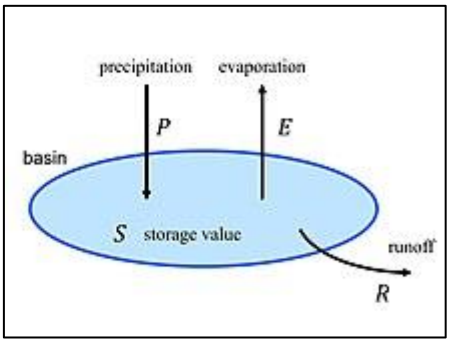

Figure 16: Water balance sketch
Source: Wikipedia (https://en.wikipedia.org/wiki/Water_balance)

Therefore, the water balance check is done by comparing the total water stored in the catchment through two different methods:

1. The sum of the Wflow model results over the storage states for each timestep
2. The manual calculation of the storage, looking at the difference between the input and output of water.

To model for all the storage states, the total storage in Wflow uses the parameters detailed in Table 14.

Table 14: Wflow parameters relevant to the catchment storage

Parameter ID	Parameter detail
satWdepth	Saturated store (mm)
canopystorage	Canopy storage (mm)
glacierstore	Water within the glacier (mm)
ustoredepth	Total amount of available water in the unsaturated zone (mm)
snow	Snow storage (mm)
snowwater	Liquid water content in the snow pack (mm)

To properly compare results, all the storage parameters, the precipitation, and the evaporation results correspond to the mean values over the specific catchment areas (mm/d). The runoff result is divided by the corresponding catchment area, thus also obtaining units of mm/d. The water balance graph for the sub-catchment of "*Rio Elqui en Algarrobal*" station is presented in Figure 17. Table 15 details the water balance errors between the two different methods for each catchment. The rest of the catchment's water balance graphs are included in Appendix C.

The water balance error over each sub-catchment is calculated according to:

$$WB\ error\ (\%) = \frac{Sto_{man} - Sto_{WF}}{Sto_{man}}$$

Where:
Sto_{man}: Storage calculated manually for the last timestep
Sto_{WF}: Storage calculated by Wflow for the last timestep

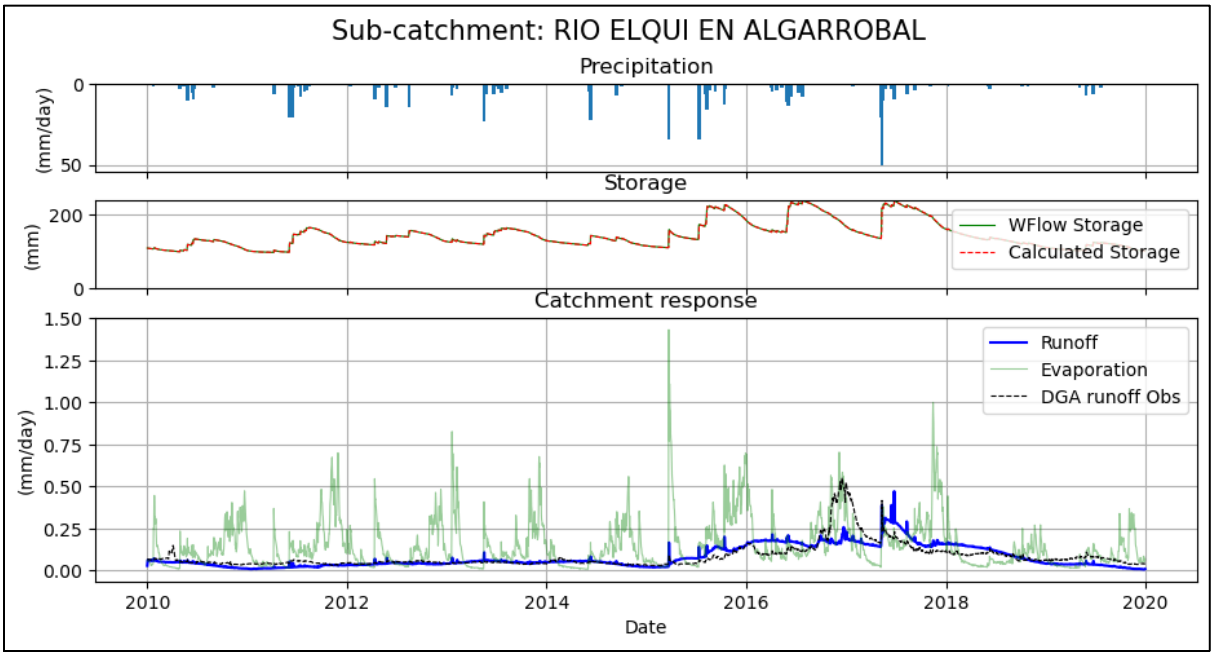

Figure 17: Water balance graph for "Rio Elqui en Algarrobal" station

At Figure 17, on the top graph is showed the average precipitation over the upstream area of the "*Rio Elqui en Algarrobal*" station considering the forcing data used. On the bottom graph, the catchment response is shown, where the computed runoff and evapotranspiration are displayed. The observed discharge flow on that same station is also displayed as reference. Finally, on the middle graph the storage of the catchment is shown computed by the two different ways already described. For this water balance both methods have almost same results.

Table 15: Water balance error

Subcatchment	Water balance error (%)
Rio Toro antes junta Rio La Laguna	3.78
Rio Cochiguaz en el Peñon	2.68
Estero Derecho en Alcohuaz	12.82
Rio Elqui en Algarrobal	-0.01

5.2. Allocation model

The objective of this allocation model is to establish the routing of the water inside the catchment downstream of the Puclaro reservoir, where the optimization model will be applied.

The model was implemented in the OpenModelica[20] software, where all connections and boundary conditions are stated. OpenModelica translates the graphic schematization defined to a writeable version of it so it can be easily exported and used for other software. Figure 18 shows what the model looks like in the OpenModelica software, which was created based on the conceptual model previously shown in Figure 5.

[20] https://openmodelica.org/

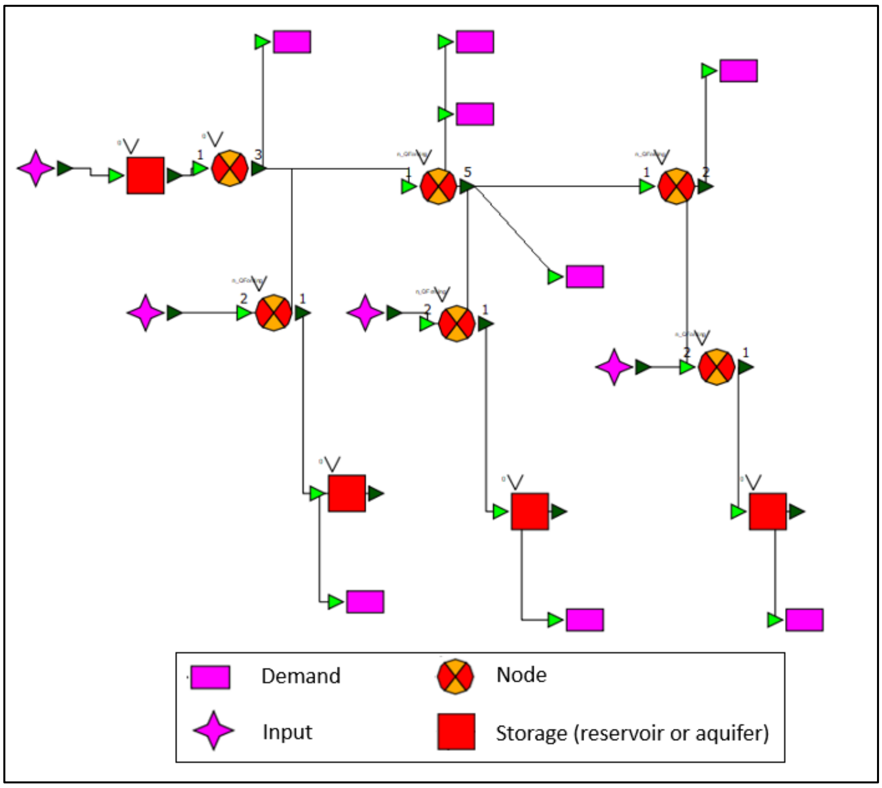

Figure 18: OpenModelica schematization of the Elqui catchment downstream of Puclaro reservoir

There are some restrictions regarding the parameters of the allocation model. The restrictions can be classified into two types: non-negative values and possible value ranges.

The non-negative value criteria apply to the to the reservoir's outflow, the aquifer's recharge flow, and the river discharge flow. These restrictions assure that the routing of the water follows "gravity" criteria.

On the other hand, the *Desmarque* value is limited in the allocation model between 20% and 50%. These values are not randomly selected. The 20% *Desmarque* is the minimum value stated in the Operational Manual of the reservoir (Junta de Vigilancia Rio Elqui y sus Afluentes, 2019), since it corresponds to the amount of water generated by the own catchment with 85% probability, without any water management measures applied. The 50% value is slightly more than what the farmers can effectively use under any circumstances, based on the available information presented by Universidad de la Serena (ULS).

5.3. Optimization model

The optimization model is based on a multi-objective methodology coded inside the RTC-Tools[21] software package, developed by Deltares. The multi-objective methodology allows for seeking the optimal results in a time series for different goals when each goal i has a weight w_i and a priority p_i. In this context, each goal can be defined as the desired outcome of performance metric that is important to the problem being solved simultaneously, and these objectives may conflict with each other.

Goal programming is used to handle an optimization problem with multiple goals of the form:

$$minimise \sum_{i:pi}^{N} w_i \, f_i(x) \, ,$$

$$subject\ to\ g_{ij}\ (x) \leq\ 0\ for\ j = 1, \dots, m_i$$

for $i\ =\ 1, \dots, N$, with N the total number of goals and $j = 1, \dots, m_i$, with m_i the total number of boundary conditions for goal i.

Problems with different priorities are solved from higher to lower priority (first the priority 1, then the priority 2 and so on). The results from first priorities are used as new constraints for the following goals with the next priority to ensure that the minimal values of the previous priorities remain optimal.

The optimization model that has been used is based on the RTC model developed during the Internship in 2022, specifically over Scenario C stated there (Garcia Grez, 2022).

[21] https://www.deltares.nl/en/software-and-data/products/rtc-tools

5.3.1. Goals

For the case study, the goals and priorities used are stated in Table 16.

The prioritization of the goals was analyzed in the Deltares Internship (Garcia Grez, 2022), where Priority 1 and 2 are stated by Chilean laws and Priority 3 is part of the water management policies, allowing no flexibility regarding the priority orders of the top three.

Table 16: Optimization model goals

Priority N°	Goal	Description
1	Drinking water supply demands	The drinking water supply demand is the first need to be met. The cities of La Serena and Coquimbo depend on this.
2	Minimum ecological flow	Environmental criteria have been introduced in the catchment, assuring a minimal discharge flow to reach the sea to maintain the biodiversity of the area.
3	Puclaro operational rules – Minimum volume	The operational manual of the Puclaro reservoir states a minimum volume of 50 Mm^3 needs to be satisfied at the end of each irrigation season (31 of August)
4	Avoid Puclaro depletion (by forcing a fixed final volume)	This goal is built to not empty the reservoir at the end of the run. Furthermore, for a useful comparison between the historical data and the optimization results, this goal also demand that the final volume in the reservoir matches the historical volume for the same date.
5	Irrigation demands	The irrigation demands are met as much as possible. This goal is related to the *Desmarque* value, which is stated as a constraint.
6	Minimize rate of change in aquifer infiltration	The objective is to smooth the aquifer infiltration behavior, avoiding frenzied patterns.
7	Aquifer artificial infiltration	Maximization of the artificial water infiltration in the aquifers.
8	Fairness on the aquifer artificial recharge	This last goal seeks an equilibrium in the infiltration between the two aquifers, aiming for an equal change rate between them.

5.3.2. Constraints / boundaries

The optimization model includes some constraints and boundary values for some of the parameters to assure the feasibility of the solutions. The constraints stated can be due to physical constraints (e.g.: carrying capacity of a canal) or due to methodological criteria (e.g.: one *Desmarque* value per irrigation season).

The constraints included in the optimization model are detailed in Table 17:

Table 17: Optimization model contraints / boundaries

Constraint / boundaries	Detail
Carrying capacity of "Canal Bellavista"	Correspond to the physical capacity of the canal, stated in "*Análisis de la oferta y demanda de recursos hídricos en cuencas criticas Huasco y Elqui*" (Dirección General de Aguas, 1995) Q. max = 4.95 m^3/s
Maximum infiltration capacity in the aquifers	There is always an infrastructure limitation on the aquifer infiltration. In this case, the limiting capacity is that stated in Scenario C. See Table 6. Elqui Medio aquifer = 1.35 m^3/s Elqui Bajo aquifer = 1.35 m^3/s Pan de Azúcar aquifer = 4.95 m^3/s
Equal *Desmarque* values per irrigation season	The irrigation demands are formulated as: $Q\_Demand = Desmarque * Q\_Target$ The constraint applied is that on each irrigation season, the *Desmarque* value is unique. So, to maximize the water allocated for irrigation is needed to indirectly maximize the *Desmarque* value.

5.4. Implementation of the Receding Horizon Control (RHC) methodology

Once the hydrological model, the allocation model, and the optimization model have proven to be working properly, the objective is to implement a receding horizon control methodology over the catchment with different RHC lengths (H) as shown in Figure 19.

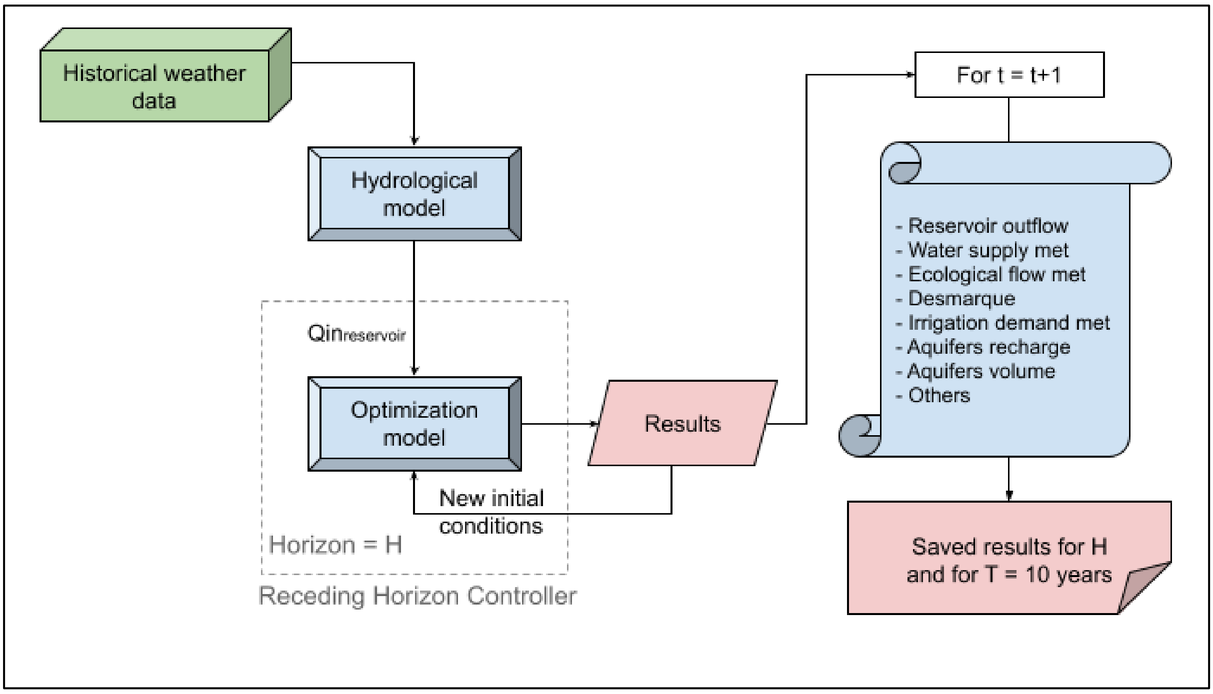

Figure 19: RHC methodology implementation.

The different values used for the RHC length (days) are 30, 45, 60, 120, 150, 180, 240, 360, 420, 480, 540, 600, and 660. The selected range goes from one month until approximately two years, covering the entire time span of interest.

It is expected that for short values of H, the optimization model works on a short-term basis, satisfying all the demands without concern for future requirements. This means that for short values of H, the regulatory role of the reservoir quickly will lose relevance, resulting in a situation where the reservoir outflow matches the reservoir inflow values. This is because in the first timestep the optimization model will allocate almost all the available water, including reservoir storage, ending in a depleted reservoir where all the inflows are immediately used.

The iterative solving of the optimization problem inside the RHC methodology makes it necessary to incorporate a new restriction that ensures that the *Desmarque* value computed for the first day of each irrigation season remains fixed during that season.

The Python script used for this implementation can be found in Appendix D.

5.5. Implementation for new decision-making methodology

Based on the weather generator addressed in Chapter 4.4.2, any year from the generated time series can be randomly selected as input for the hydrological model. The fact that on each timestep a random but probable weather condition is chosen assures that the superimposed results maintain the statistical weather properties of the location, but also take the extremes into account.

Moreover, this new decision-making methodology is run several times and the obtained results are then combined to be presented as average values accompanied by a confidence of interval. This mechanism assures that the average weather conditions used are highly probable since is based on the statistical distribution of 30 years of weather conditions records.

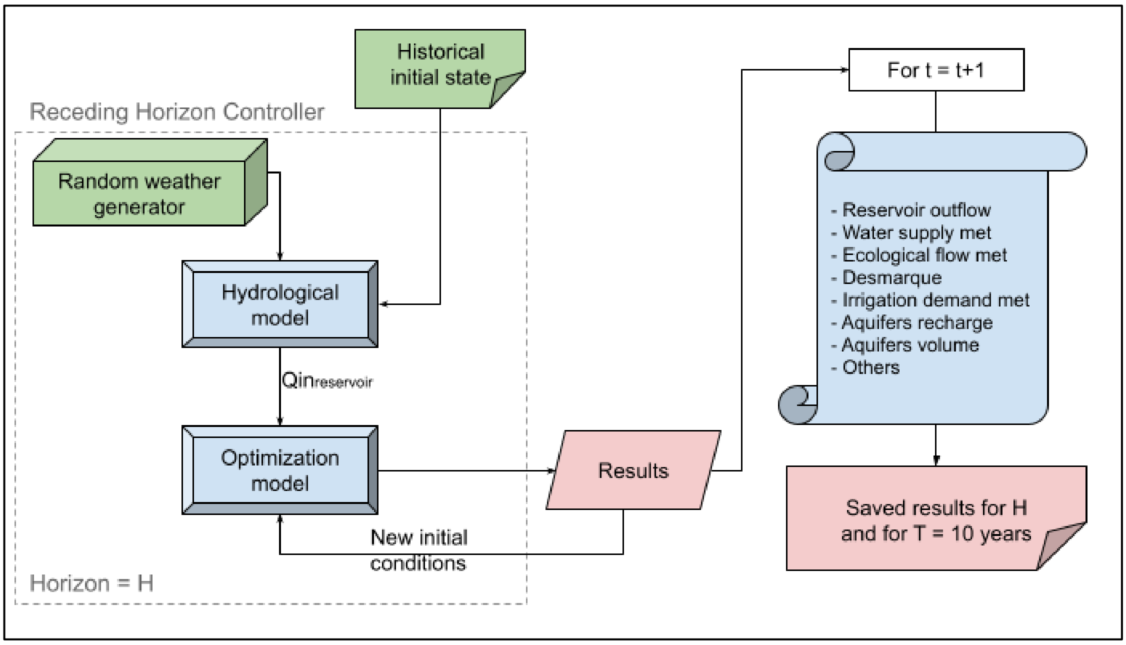

Figure 20: Forecast & decision-making methodology implementation

Due to the extensive computing resources needed for the implementations described in Chapter 5.4 and Chapter 5.5, DelftBlue supercomputer[22] was used to perform the calculations.

The Python script used for this implementation can be found in Appendix E.

[22] Delft High Performance Computing Centre (DHPC), DelftBlue Supercomputer (Phase 1), 2022, https://www.tudelft.nl/dhpc/ark:/44463/DelftBluePhase1

6. Optimization results

6.1. Current situation vs incorporation groundwater infiltration

The first objective of this thesis research was to be able to develop a new methodology for water management in the catchment. This involves that the new methodology can successfully establish an optimum *Desmarque* value under the same conditions as the existing methodology.

To validate the optimization model, it was first run without considering aquifer infiltration as it is done currently by the management authority of the catchment. These results were afterward compared with the historical values and with the optimization results that do include the aquifers' infiltration. In Figure 21 the results are presented. The *Desmarque* values computed for the current situation (without aquifer infiltration) are in the expected range compared with the historical values as is detailed in Table 18, where the average for the historical *Desmarque* value corresponds to 36.5 % while the average *Desmarque* value computed by the optimization model for the current situation is slightly higher with a value of 39.9 %.

Especially interesting is the fact that when the aquifer infiltration is included in the optimization model, it has no effect on the *Desmarque* value, but it does on the aquifer stored volume as it is presented in Figure 22. *Desmarque* values have no impact since it corresponds to a higher priority on the optimization model, and the aquifer infiltration is only allowed when Desmarque goal is not degrade.

Finally, the maximum aquifer infiltration flows considered in the optimization model correspond to those presented as Scenario C of the internship detailed in Chapter 4.5.3. The magnitude of the eventual infiltration that could be implemented in both aquifers might recover in only two years the accumulated deficit on the aquifers over the 10-year period.

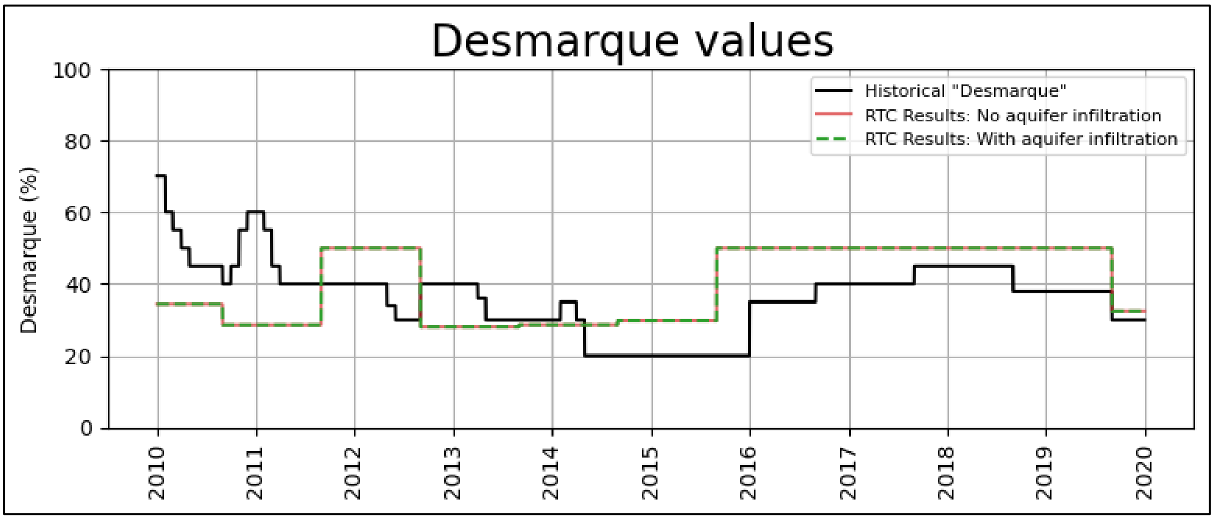

Figure 21: Compared results when including aquifer infiltration and not including aquifer infiltration for the Desmarque value

Table 18: *Desmarque values. With and without groundwater criteria, using DGA inflow input.*

Results	*Desmarque* value (%)		
	Average	Max	Min
Historical observed data	36.5	70.0	20.0
No aquifer infiltration	39.9	50.0	28.0
With aquifer infiltration	39.9	50.0	28.0

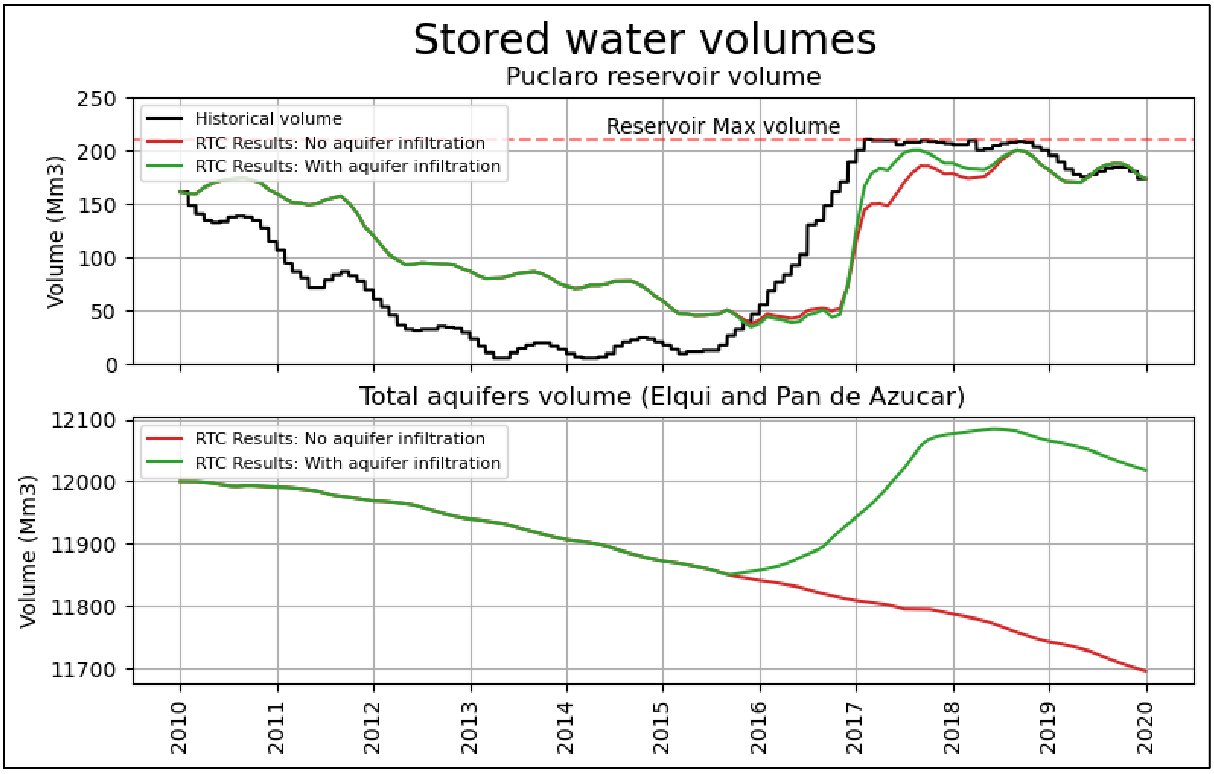

Figure 22: Compared results when including aquifer infiltration and not including aquifer infiltration for the stored water volumes in the catchment.

6.2. Coupling with the hydrological model (Wflow)

Now that the optimization model has been validated, the inflow discharges to the reservoir can be extracted from the hydrological model, detailed in Chapter 5.1. The results are going to be compared with the results using the DGA inflow discharge inputs to the reservoir. Two different scenarios for different inflow timeseries into the reservoir are analyzed:

1. Using the monthly observations at the DGA fluviometric station immediately upstream of the Puclaro reservoir ("*Elqui en Algarrobal*").
2. Using the DGA-PP forcing data as an input for the hydrological model (Wflow) and from there extracting the discharge flow to the reservoir.

Both optimization results correspond to historical simulations where the whole data for the 10 years simulated was available for the optimization model (perfect information). In Figure 23 a general view of the optimization results is shown.

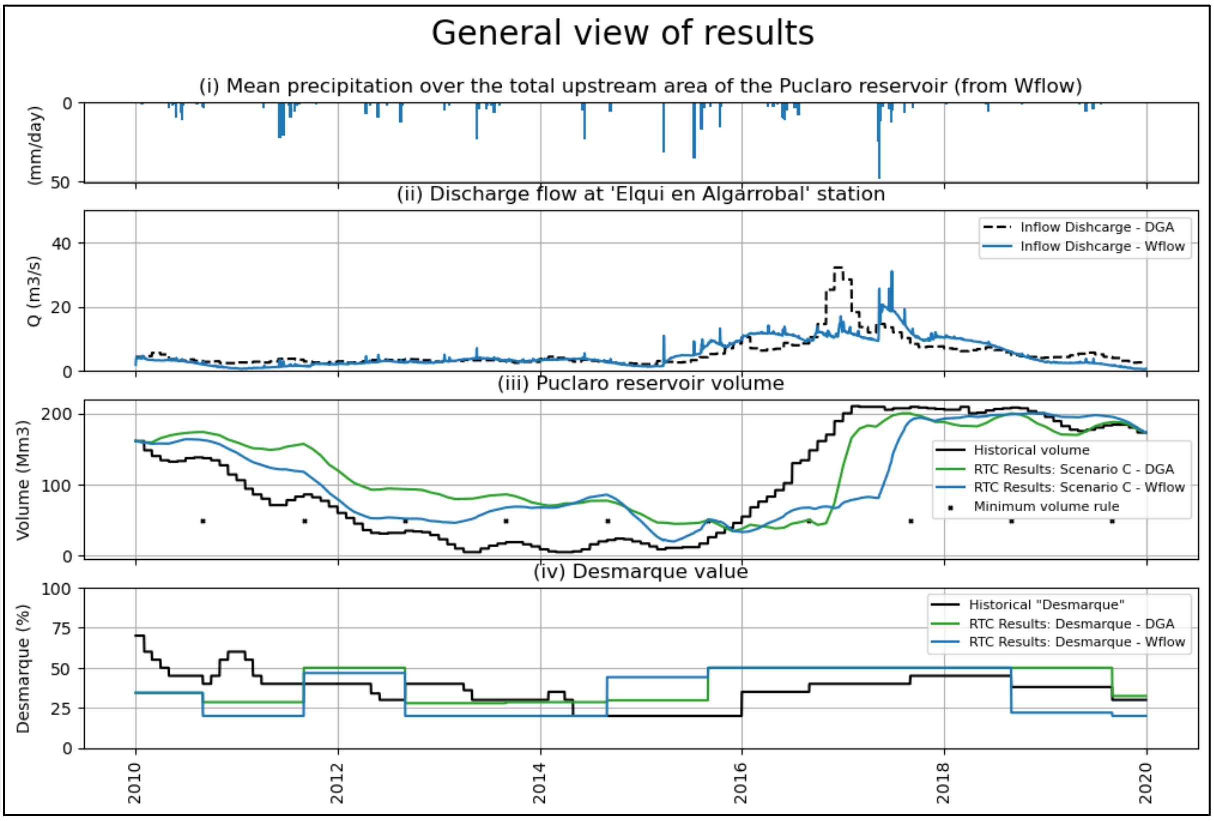

Figure 23: Optimization results. General view.

The precipitation shown in (i) corresponds to the mean value over the whole area upstream of the Puclaro reservoir, which was computed based on the DGA-PP forcing data.

In (ii) is possible to compare, for the fluviometric station upstream the Puclaro reservoir de DGA observed discharges and the ones calculated by the Wflow model. The calculated discharge has a high accuracy and reliability for the dry periods (e.g.: 2010 to 2016). This skill decreases for the wet period observed between 2016 to 2018, but still maintained a reasonable accuracy on the annual volumes, as was detailed in Chapter 5.1.1.2.

In (iii), the comparison of the Puclaro reservoir volume is of great interest. There are two considerations needed to properly compare the historical volume with the two volumes calculated with the optimization model. Firstly, the operational manual of the reservoir clearly stated a minimum volume of at least 50 Mm^3 at the end of each irrigation season (August 31th). This goal of course was included in the optimization model but was not considered during the historical management as we can observe. That means that the historical *Desmarque* values for the period between 2010 to 2016 should have been lower. Secondly, for the optimization results using the DGA input, the observed discharge flow at the "*Elqui en Algarrobal*" station was used as the discharge inflow to the reservoir, since no better data was available. It means that the discharge inflow could be somehow underestimated in this model. Besides these two considerations, the volume results are remarkable compared with the historical observations due to the close resemblance.

Finally, in (iv) the historical *Desmarque* values are compared with the computed *Desmarque* values. To properly compare these results, the average, maximum, and minimum *Desmarque* values over the

10-year period were calculated and presented in Table 19. There is a decrease in the average *Desmarque* value once the hydrological model is coupled, and this can be explained based on the difference between the discharge flows into the reservoir between the DGA observations and the one extracted from the hydrological model, which was slightly inferior as was concluded in Chapter 5.1.1.2.

Table 19: Average, maximum, and minimum Desmarque values incorporating groundwater criteria, for both DGA and Wflow inflow input.

Results	***Desmarque* value (%)**		
	Average	Max.	Min.
Historical observed data	36.5	70.0	20.0
DGA input	39.9	50.0	28.0
Wflow input	35.3	50.0	20.0

On the other hand, when analyzing what happened with the aquifer's infiltration and total volume, surprisingly the infiltrated volume for the optimization model with the Wflow input is considerably larger compared with the infiltrated volume when using the DGA input, as shown in Figure 24. The most captivating thing about the last results is that would be straightforward to attribute the higher infiltrated volumes to the Wflow input results because of the more spread distribution on the high discharge flows observed between 2015 to 2019, but in both optimization results the aquifer infiltration starts exactly at the same time.

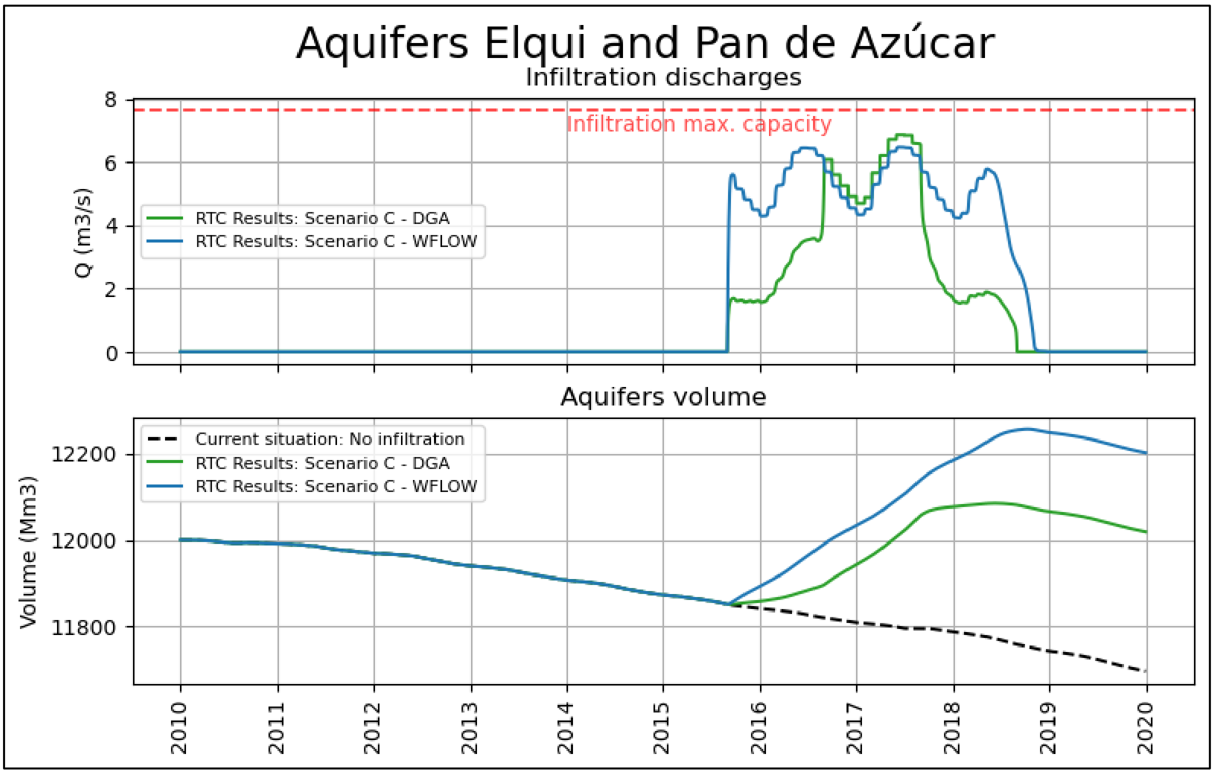

Figure 24: Infiltrated volume to the aquifers with the two different input data (DGA and Wflow model)

6.3. Answering Research Question A

How suitable is an optimization model for defining the yearly Desmarque value in a reservoir-aquifer catchment?

- *How well does the historical simulation model reproduce the historical Desmarque data?*
- *What are the contributions of incorporating the groundwater component (criteria) in the simulation to a change in the historical Desmarque?*

One of the main concerns during the thesis research was the feasibility of reproducing the *Desmarque* values through the optimization model. No one can deny that this achievement would already be a game changer for the catchment being able to replace or at least be comparable with the actual methodology.

Looking at the previous results of Chapter 6.1, is exciting to realize that the computed *Desmarque* values are in the same order of magnitude as the historical *Desmarque* data. Moreover, independently of the input data source that is used for the inflow at the Puclaro reservoir, DGA, or Wflow, the obtained results are always reasonable under the constraints stated.

Even though the results do not exactly match the historical *Desmarque* values, this can be easily explained by the fact that the historical optimization model can anticipate the upcoming weather conditions due to the perfect information knowledge, whereas the water authorities could not during the normal functioning of the water allocation process.

However, the most important finding at this stage corresponds to the fact that the incorporation of the aquifer infiltration in the water optimization process only comes with benefits. The recommended aquifer infiltration has no adverse impact on the computed *Desmarque* values (as indicated in Table 18) and remarkably, it can lead under the made assumptions to the restoration of the groundwater volumes during the period of interest, regardless of the input data used (See Figure 24). This is an especially positive finding for the integrated water management stakeholder of the catchment, as it addresses the concern of the farmers who can perceive aquifer infiltration as competition for limited water resources.

7. Receding Horizon Control (RHC) results

7.1. RHC results analysis

The previous optimization results were computed forcing the model to end with the exact same final volume in the Puclaro reservoir as the historical volume for the same date, having then the same starting and ending point, as is explained in Goal 4 of Table 16.

The receding horizon methodology is not suitable anymore to maintain that goal on the iterative optimization problem. To address this difference, three steps are taken before the RHC implementation:

a) Two different optimization models were established. The first includes the final volume goal (*Wflow input – Fixed final vol.)*, and the second without considering the final volume goal (*Wflow input – No Fixed final vol.)*.
b) Finding the date (timestep) where both different results deviate from each other, happening to be on 31.08.2018.
c) Implement the RHC methodology using the date found in b) to select which optimization model should be implemented for each specific timestep.

By following the previous steps approach, it is possible to compare the receding horizon results within the complete historic simulation 2010-2020 period, corresponding to the blue line shown in Figure 25 (*Wflow input – Fixed final vol.)*.

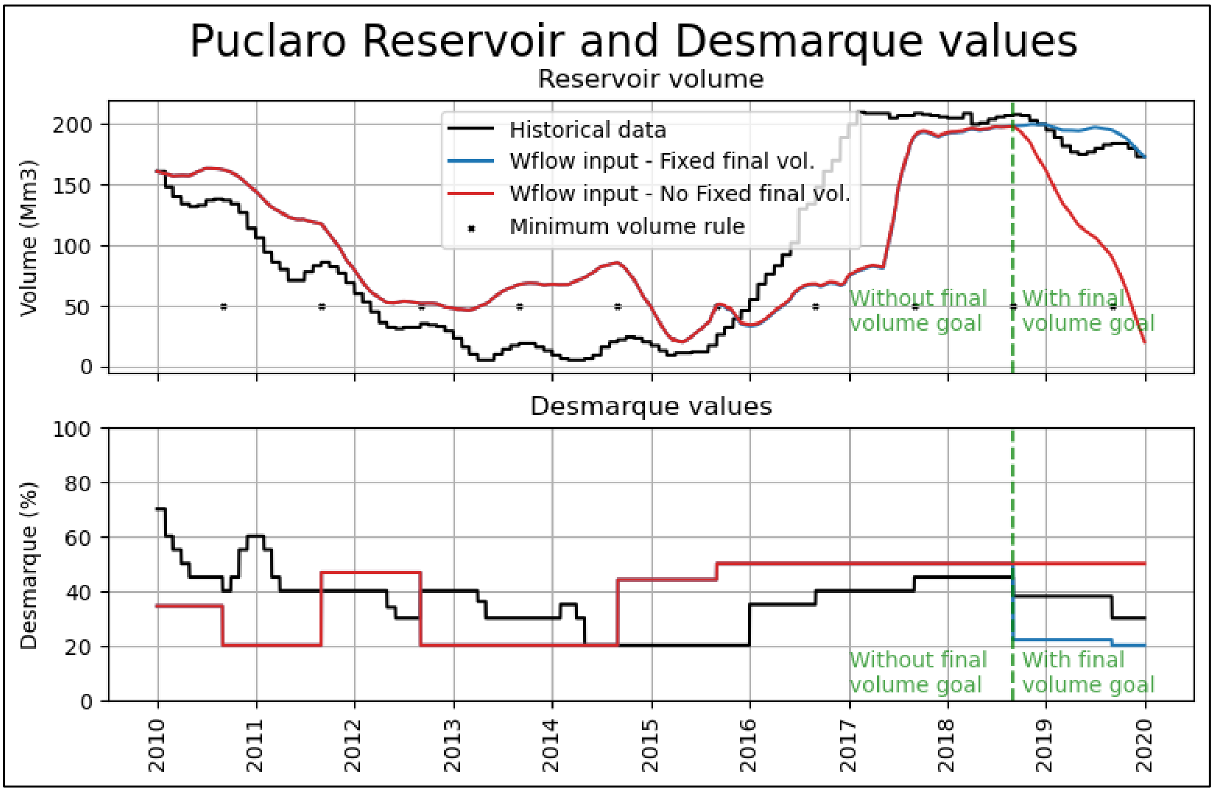

Figure 25: Methodology for the optimization problem to compare with the observed data.
Source: Own elaboration

Figure 26 shows the obtained results with the different receding horizon lengths for the Puclaro reservoir and for the *Desmarque* values. The legend of the receding horizon results has not been included since the objective of the graphs below is just to display the differences between the different receding horizon lengths.

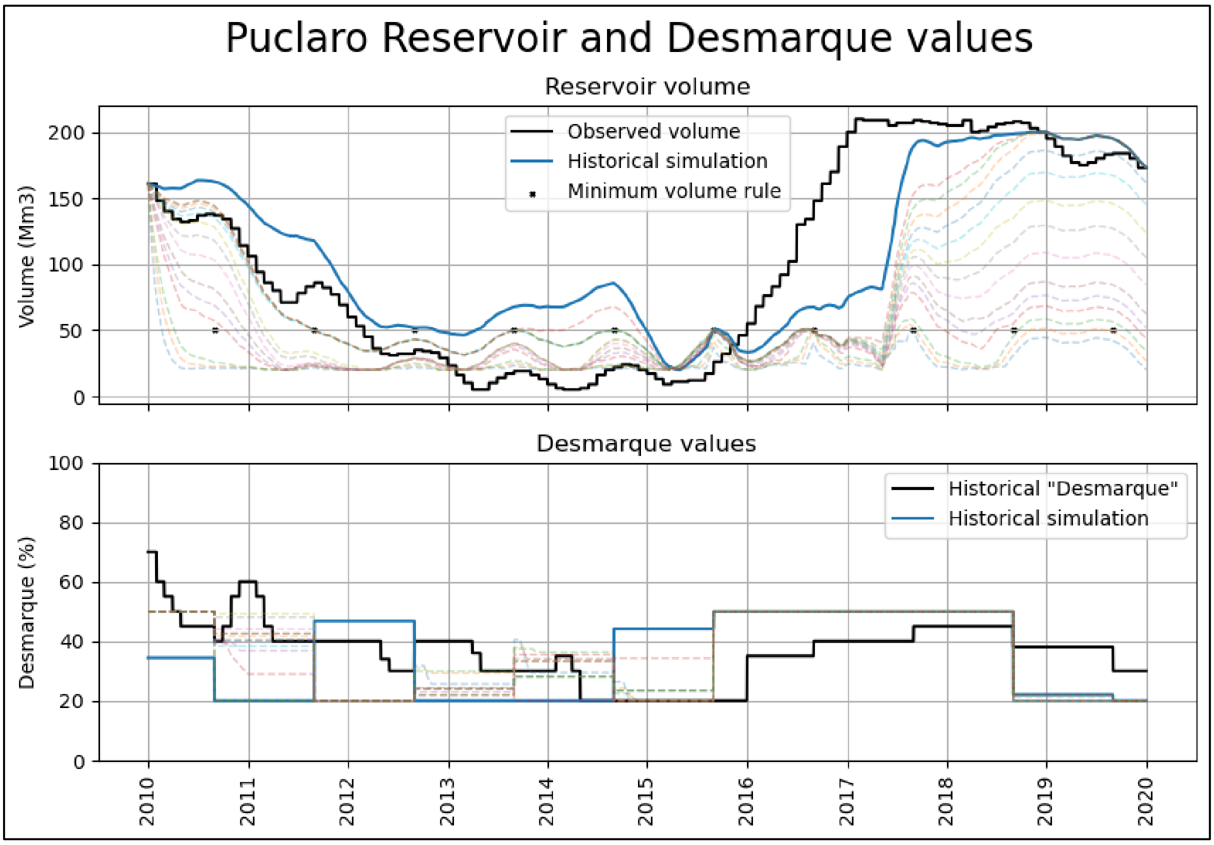

Figure 26: Receding horizon results over the Puclaro reservoir volume and Desmarque values.

To compare the feasibility of the different receding horizon (RH) results, a natural step corresponds to looking at the performance over the most relevant optimization goals, such as the drinking water supply, ecological flow, *Desmarque* values, and the total aquifer infiltration, as is shown in Figure 27 and Figure 28.

The aquifer infiltration goal is expressed as:

$$Aquifer\ infiltration\ goal\ (\%) = \frac{(Total\ volume\ injected\ to\ aquifer)_{RH=i}}{(Total\ volume\ injected\ to\ aquifer)_{Hist.\ simulation}} * 100$$

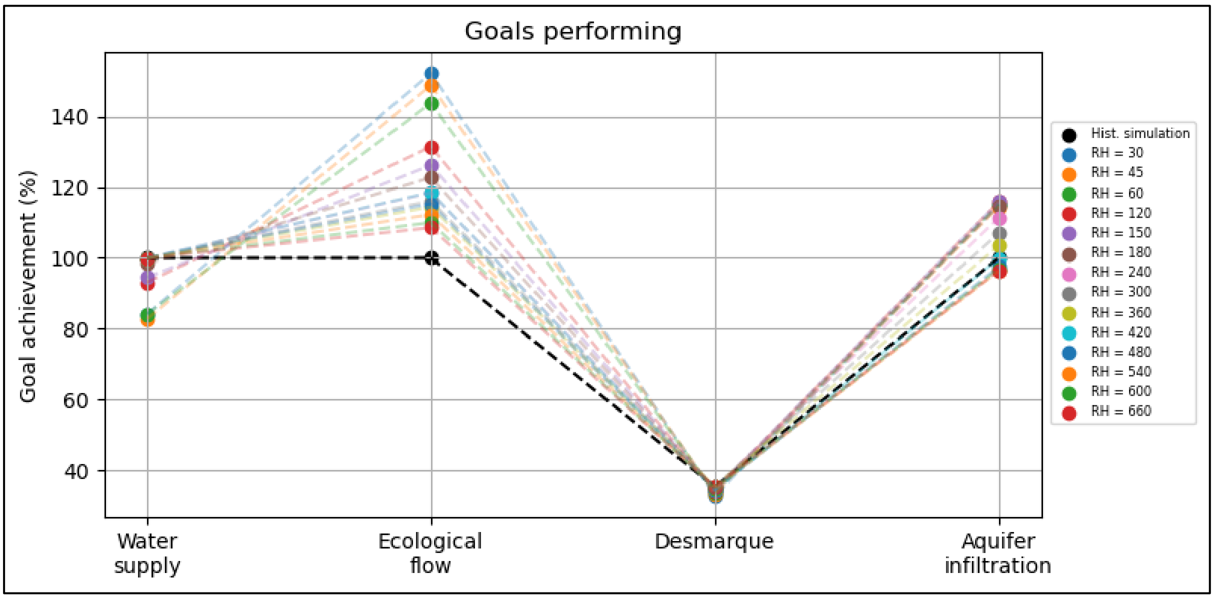

Figure 27: Goals achievement for different receding horizon length

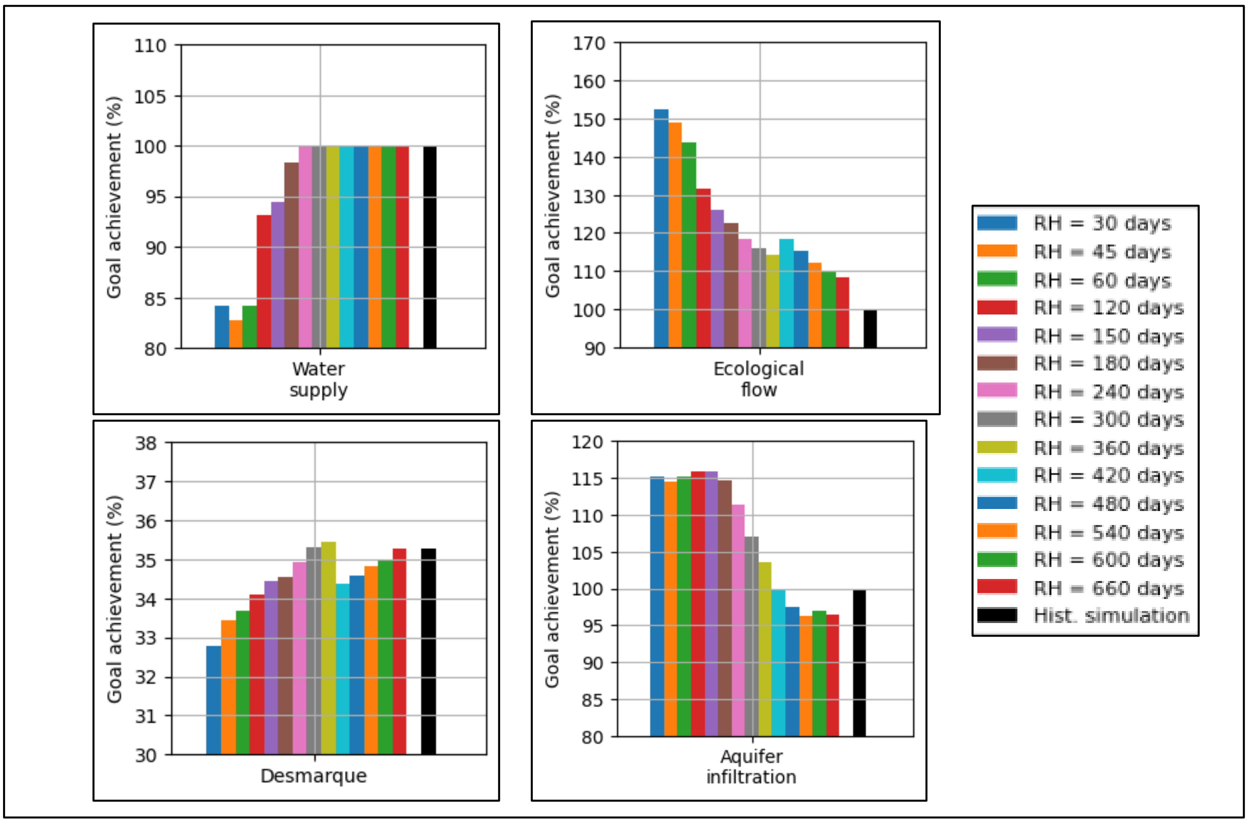

Figure 28: Zoom in. Goals achievement for different receding horizon length

After analyzing the performance of the RH lengths in achieving the different goals, some interesting observations can be made. To begin with, it is important to highlight that for RH lengths shorter than 240 days, it is not always possible to achieve the goal of ensuring a sufficient drinking water supply.

As a result, these options can be disregarded. Additionally, the ecological flow goal shows a very consistent and linear trend, approaching from above to 100% goal as the RH length increases. This indicates that less water is being wasted into the sea.

Regarding the average *Desmarque* value, it follows a saw-tooth shape curve. The performance rapidly increases when increasing the RH length from 30 days until reaching the max value at a RH length of 360 days. Afterwards the performance drops to start increasing again, aligning with the historical simulation values at around an RH length of 660 days.

For the aquifer goal, the results indicate that for shorter RH lengths, the aquifer infiltration is higher compared to the historical simulation. It continues to increase until an RH length of 150 days when it reaches its peak infiltration volume. However, beyond that point, the aquifer infiltration goal quickly declines, dropping below the levels of the historical simulation.

What's remarkable about these findings is that for shorter RH lengths, the focus is on the importance of aquifer infiltration rather than maximizing the *Desmarque* value. However, as the RH lengths increase, the optimization process leads to better solutions, shifting the focus towards maximizing the *Desmarque* value over the aquifer infiltration. This fact can be easily observed in Figure 29 thanks to the color grading used.

RH length (days)	Goals achievement			
	Watter supply	Ecological flow	Desmarque	Aquifer infiltration
30	84%	152%	32,78%	115%
45	83%	149%	33,44%	114%
60	84%	144%	33,69%	115%
120	93%	131%	34,09%	116%
150	94%	126%	34,44%	116%
180	98%	123%	34,54%	115%
240	100%	118%	34,92%	111%
300	100%	116%	35,32%	107%
360	100%	114%	35,43%	104%
420	100%	119%	34,38%	100%
480	100%	115%	34,58%	98%
540	100%	112%	34,82%	96%
600	100%	110%	35,01%	97%
660	100%	109%	35,28%	96%

Figure 29: Goals achievement for the different RH length

Considering the previous results and their respective analysis, the recommended RH length should balance both the *Desmarque* values and aquifer infiltration goals performance. A 360 RH length can be then recommended. As an additional check for this assumption, the Root Mean Squared Error (RMSE) and the determination coefficient (R^2) were computed for each RH with respect to the historic simulation 2010-2020 for the key results, shown in Figure 30.

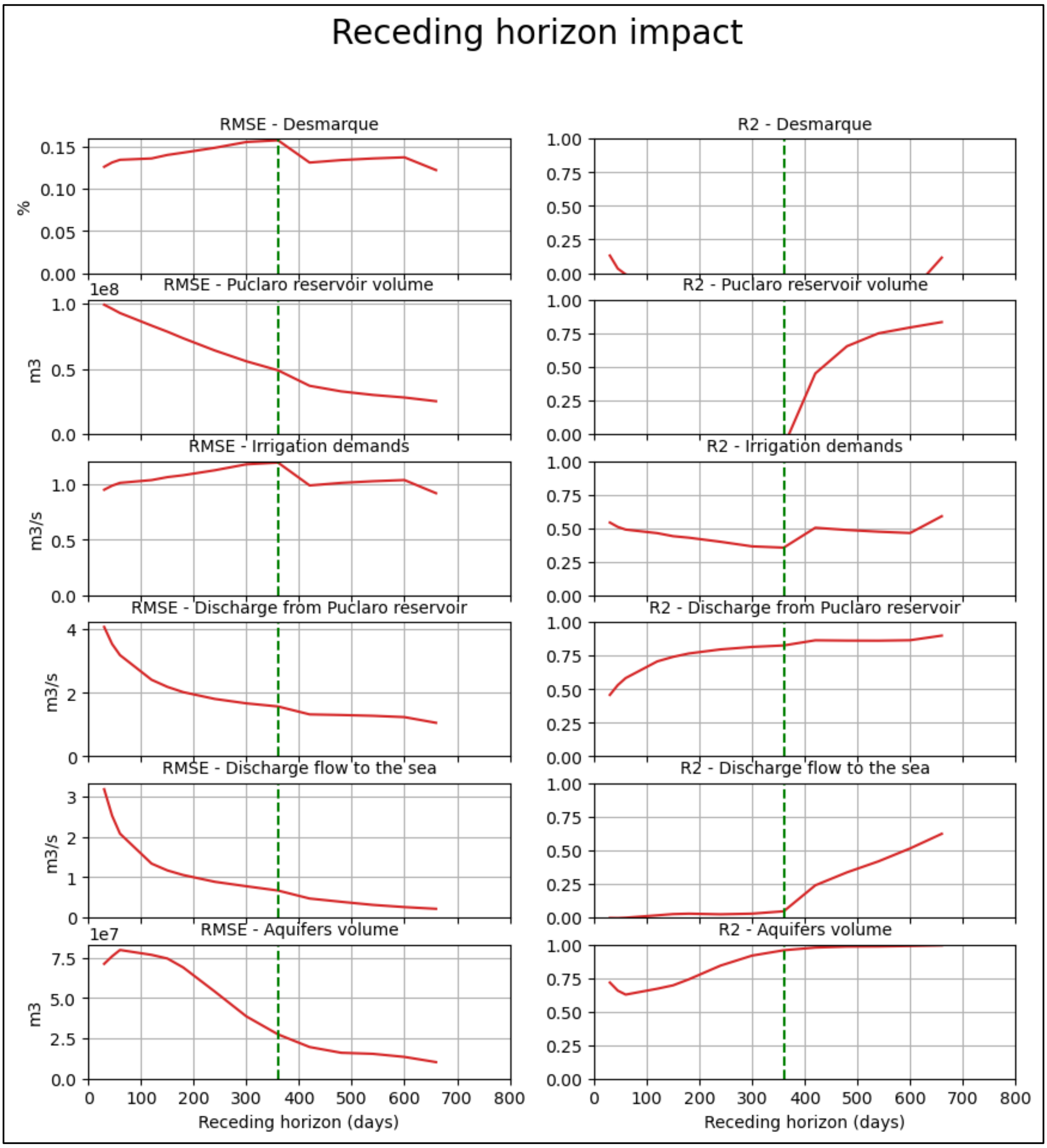

Figure 30: Root Mean Squared Error and Determination Coefficient analysis for the key model parameters over the different receding horizon lengths. The recommended RH length (360 days) is shown in green.

7.2. Answering Research Question B

What is the impact of the different receding horizon lengths on the optimized water management parameters in basins where there is an interaction between reservoirs and aquifers?

- How close is each receding horizon optimization results when comparing them with the historical simulation results?

The impact of RH length on the results cannot be underestimated, and it's clear that larger RH lengths bring the solution closer to the optimum. However, what is less obvious is the subtle trade-off between aquifer infiltration and irrigation goals when considering different RH lengths.

When aquifers are included as part of the optimization model, they offer a tireless water receptor always available to receive infiltration as part of their maximization goal. On the contrary, the irrigation needs, represented through the *Desmarque* value have a well-defined water demand pattern over time. For short RH length, where the focus is on short-term objectives, it occurs a huge aquifer infiltration on the first season, eliminating the storage capacity of the system. This leads to a decline on the *Desmarque* values along the following irrigation seasons, thus an overestimation of aquifer infiltration. As a results, at shorter RH lengths, there is a higher aquifer infiltration at the expense of the *Desmarque* value.

Nevertheless, longer RH lengths come with significant computational requirements, causing delays in decision-making. Therefore, a balanced alternative is necessary.

It is unfortunate that the analysis for a longer receding horizon was not feasible due to time-computing constraints. Besides that, when comparing the obtained results with the historical simulation, the irrigation parameter of the *Desmarque* value reaches the historical simulation values when using an RH length of 660 days, the maximum length considered. However, even at 660 days, improvements can be made by allocating more water into the aquifers instead of letting it flow to the sea, as the goals of aquifer infiltration and ecological flow show.

Another interesting fact to consider is that for the recommended RH length of 360 days, the goal's performing exceeds the obtained with the historical simulation, regarding de *Desmarque* value and the aquifer infiltration in exchange of depleting the Puclaro reservoir at the end of the period and so not achieving the goal of matching the historical observed volume at the end of the analysis period.

To fully understand the relation between the different RH length results with the historical simulation, Figure 30 provides valuable insights. It is evident that the aquifers' volumes along with the discharge flow out from the reservoir and the discharge flow at the river reaching the sea have reached RMSE and R^2 acceptable levels from the recommended RH length and onwards. Regarding the reservoir volume case, the tendency is similar to the previous parameters but has not yet achieve a reasonably good RMSE and R^2 level at the recommended RH length. Finally, for the *Desmarque* value and the corresponding irrigation demands, the RMSE and R^2 are far from what an acceptable result would be but still do not improve much inside the analyzed range of RH lengths.

8. New decision-making methodology results

8.1. Results analysis

The new decision-making methodology (proposed methodology) corresponds to the integration of the RHC methodology, the weather generator methodology and the hydrological model developed. This integration is described in Chapter 5.5.

Due to the randomize component of the proposed methodology, several runs are needed to visualize the complete potential of the model results. However, because of the extensive computing time of each run and the limited computing resources, a limited number of runs were executed. Additionally, period of interest (2010-2020) needed to be split in two, 2010-2015 and 2015-2020. Coincidentally it happens that the first period can be classified as "dry years" and part of the second to "wet years".

The comparison shown in Figure 31 and Figure 32 is helpful to understand the degradation of the results when going from a historical simulation (blue), then to an RH (360 days) historical simulation (green), and finally the results for the proposed methodology (red) which includes the 95% confidence interval when considering the standard deviation for the different runs.

The confidence interval (CI) was calculated for each timestep using the expression:

$$CI = \bar{x} \pm z * \frac{s}{\sqrt{n}},$$

Where:
$\bar{x}$ = mean value
z = z-value for the confidence level. Corresponds to 1.96 for a 95 % of confidence
s = standard deviation
$\sqrt{n}$ = sample size[23]

The situation, in general, shows that for "dry years", the proposed methodology has slightly better result compared with the RH simulation with the actual weather conditions. The only exception corresponds to the 2010-2011 irrigation season. Differences in the Puclaro reservoir volume and the aquifers infiltration discharges during that period led to an overestimation of the *Desmarque* value for that specific irrigation season, that could not be kept along the complete irrigation season. This could be explained due to the low precipitation that occurred in 2011 and 2012, where both years have a cumulative precipitation of about 50 mm when the average corresponds to almost 100 mm. This is translated on the historical simulation in maintaining the reservoir levels by avoiding aquifers' infiltration, contrary to what was implemented by the proposed methodology.

Additionally, the precipitation during the dry years seems to be so low that even the minimum volume at the end of each irrigation season is not achieved. This is also the situation for the observed historical volume. This could be explained by the fact that when each Desmarque value is set, the minimum volume constrain is 5 days away from the optimization window of 360 days.

For the last 5 years the situation is different. This period had higher discharge flows into the Puclaro reservoir, allowing the historical simulation (with and without the receding horizon window) to

[23] Each period (dry & wet) has a sample size of 10 runs.

infiltrate large amounts of water volumes into the aquifers. Surprisingly, the proposed methodology could well adjust their parameters to have also large amounts of aquifer infiltration even though the only real weather data available corresponds to the initial state included in the hydrological model.

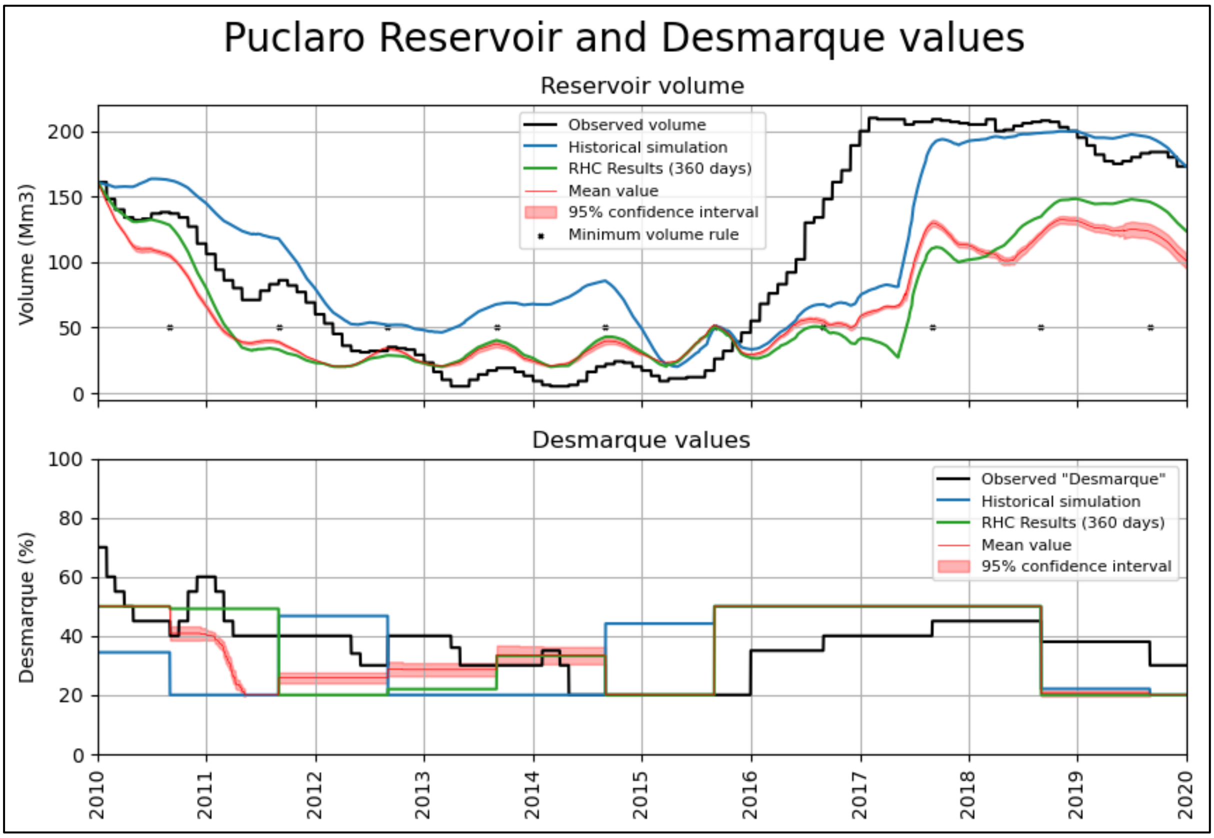

Figure 31: Proposed methodology results. Puclaro reservoir volume and average Desmarque values.

About the *Desmarque* values obtained with the proposed methodology, there is a similarity between them and the RH results, but what is more significant is that in terms of the *Desmarque* value, the obtained results are almost always between the RH and the Historical simulation results.

The widest confidence interval, as expected, can be observed in the aquifer's infiltration discharges, due to the instant reaction of the optimization model under the changing behavior of the "future" generated weather conditions. The high variability of it doesn't have a great impact on the aquifers' volume which tends to have a very stable behavior.

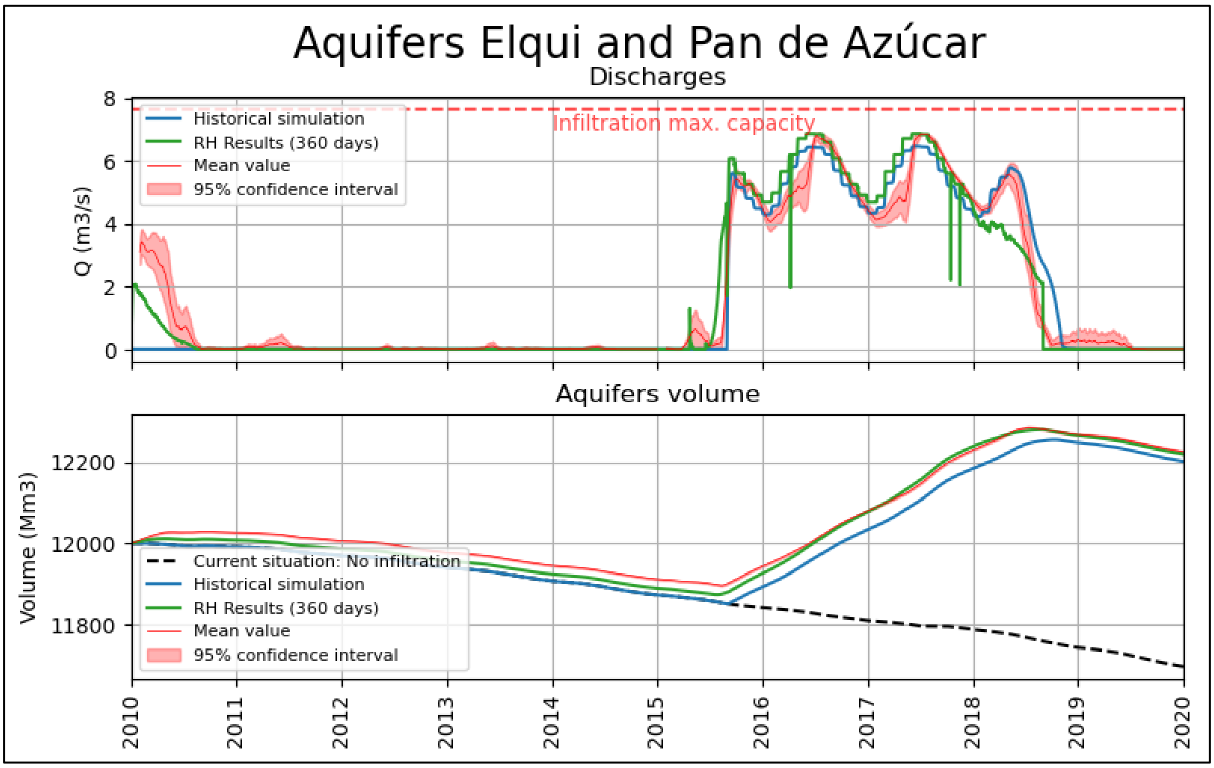

Figure 32: Proposed methodology results. Aquifer total infiltration and aquifers total volume

When evaluating the proposed methodology under the different optimization goals, the results are surprising due to the high performance on each goal compared with those simulations with the historical observed information available. The comparison is presented in Table 20 and Figure 33. Since the weather patterns observed for the first 5 years differ from the pattern of the last 5 years that were analyzed, the goal performance has also been calculated independently for both periods, in order to have more insights into the proposed methodology performance.

Table 20: Proposed methodology goals performing. Comparison with the historical optimizations.

Results	**Water supply goal (%)**	**Ecological flow goal (%)**	**Average *Desmarque* value (%)**	**Aquifer infiltration goal (%)**
Historical observed data	-	-	36.5	0.0
Historical simulation	100.0	100.0	35.3	100.0
RH simulation (360 days)	100.0	114.4	35.4	103.5
Proposed methodology	98.4	124.4	35.0	104.7

The confidence interval (CI) values range, as the spread from the mean value in a specific timestep, is also an important value to consider. For the case of Puclaro reservoir volume, the 95% CI values range corresponds to an average of 3,4 Mm^3, equivalent to the 2% of the total reservoir volume. For the *Desmarque* value, the 95% CI values range have an average of 3.41% for the first 5 years and 0.37% for the last 5 years. Lastly, for the total aquifer volume, the 95% CI values range ascend to 2 Mm^3, which corresponds to an insignificant percentage of the total aquifers volume, meaning that the improvement on the aquifer is highly certain. This ranges are summarized in Table 21.

Table 21: Confidence interval range

Parameter	**95% confidence interval range**		
	First 5 years (2010-2015)	Last 5 years (2015-2020)	Full period (2010-2020)
Puclaro reservoir volume (Mm^3)	2.3	4.6	3.4
Desmarque (%)	3.41	0.37	1.89
Aquifer infiltration (m^3/s)	0.22	0.46	0.34
Aquifer volume (Mm^3)	1.8	2.2	1.99

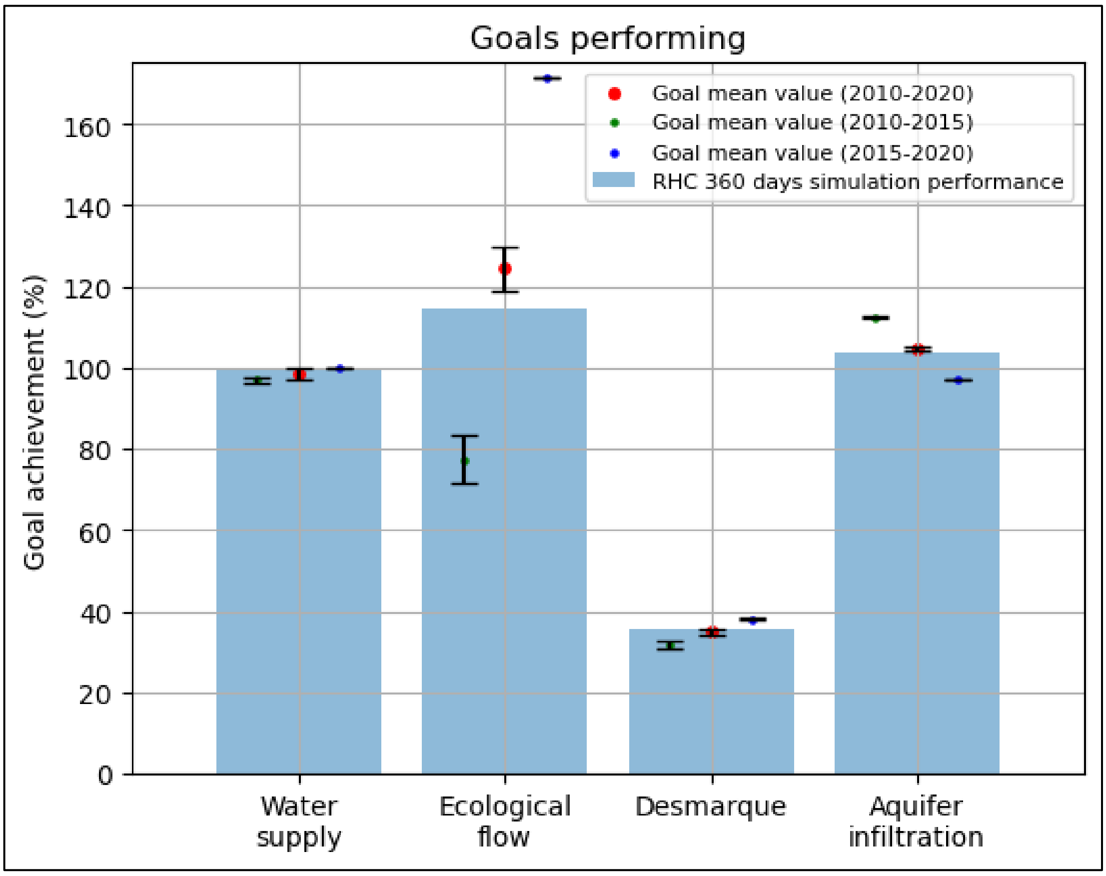

Figure 33: Proposed methodology goals performing

The evaluated goals demonstrate different performance between the complete period of interest and when analyzing independently the two (dry and & wet) analyzed periods. For the water supply goal, is observed that for the dry period, the 100% is not always achieved. This is because of how the unique *Desmarque* value was implemented in the optimization model. Instead of using the previous state of the *Desmarque* value as a constraint for the following timestep, it should be implemented as another goal. This way the prioritization of the goal would not be harmed.

Regarding the Ecological flow goal, the results from the dry period (2010-2015) show a closer approximation to 100%, while during the wet period (2015-2020), the river discharge flows exceed the minimum required by a considerable margin. This observation suggests that the proposed methodology lacks the ability to effectively respond to conditions of water abundance when using the weather generator, resulting in less efficient outcomes.

On the other hand, when examining the aquifer infiltration goal during the dry period, the proposed methodology slightly overestimates future discharges, leading to increased infiltration into the aquifers. Consequently, during the wet period, the aquifer infiltration goal is lower than the results obtained from the RH methodology due to the lower discharge flows generated by the weather generator compared to the discharges obtained from observed weather conditions. One of the inconvenient of the proposed methodology is that over implement the aquifers 'infiltration at the end of the simulated period, reallocating part of the water volumes from the Puclaro reservoir to the aquifers as is seen in results from 2018 onwards.

Finally, the performance of the *Desmarque* goal tends to be lower during the dry period compared with the wet period. The *Desmarque* value depends on both the upcoming/forecast discharge flows and the snow accumulation, reflected on the hydrological model. In this case the explanation comes directly from the 2010-2011 irrigation season where the *Desmarque* value with the proposed methodology was much lower than those calculated with the RH methodology due to the increase aquifer infiltration during the previous period (Jan-2010 to Aug-2010), for the reasons explained in previous paragraphs.

8.2. Answering Research Question C

How well does the stochastic approach of the weather generator work when replacing the unpredictable and low skill forecast data with these highly probable weather conditions in the RHC optimization model?

The performance of the proposed methodology, which incorporates the weather generator input data, is surprisingly good. The results obtained are comparable to those achieved using real future weather conditions, indicating that using highly probable weather conditions instead of actual forecast weather data has minimal impact on the model's performance.

The hydrological processes within the catchment play a significant role in achieving these high-quality results. While precipitation is typically considered the primary driver of catchment processes and discharge flow, it is found that temperature also plays a crucial role in this catchment. The future temperature conditions, along with the accumulated snowpack, are more important than future precipitation, because they determine snowmelt. The hydrological model takes into account the historical hydrological model's weather data, including snow accumulation, as the initial state, providing sufficient information for effective future water planning. This can be somehow related with the obtained results in (Van der Heijden, Palensky, van de Giesen, & Abraham, 2022), “where the value of a good” precipitation (in this case) “forecast becomes smaller as”, snow accumulation becomes larger (again, in this case).

Finally, the proposed methodology provides valuable insights by estimating the confidence interval for different parameters. This allows decision-makers to understand the variability of these parameters and make well-informed decisions based on this knowledge. Nonetheless, as mentioned before, there are some considerations for the decision-makers that need also to be taken into account, like the different performance of the proposed methodology under dry & wet weather conditions, along with the overestimation of aquifer infiltration in some specific situations.

9. Conclusions

The research conducted on optimizing water management in reservoir-aquifer catchments has yielded several noteworthy findings. The study investigated the feasibility and effectiveness of incorporating an optimization model, different receding horizon (RH) lengths, and a stochastic weather generator into the decision-making process. The following conclusions can be drawn:

a) The optimization model for defining the yearly *Desmarque* values in the catchment has shown promising results. The computed *Desmarque* values align closely with historical data, demonstrating its potential as a viable alternative to the heuristic conventional methodology.

b) The incorporation of aquifer infiltration in the water optimization process brings significant benefits. It is evident that the aquifer infiltration has zero impact on the computed *Desmarque* values, and stopping depletion and following restoration of the aquifers can be achieved. This finding addresses the concerns of stakeholders regarding competition for scarce water resources and supports integrated water management strategies.

c) The impact of receding horizon (RH) lengths on optimized water management parameters is crucial. Larger RH lengths bring the solution closer to the optimal, but a balance must be struck to avoid excessive computational requirements and decision-making delays. Shorter RH lengths tend to overestimate aquifer infiltration at the expense of the *Desmarque* value. The recommended RH length of 360 days achieves a close alignment with historical simulation values for the *Desmarque* value but still offers room for improvement.

d) The stochastic weather generator proves to be a valuable tool for replacing unpredictable and low skill forecast data in the optimization model. The highly probable weather conditions generated provide comparable results compared with using real future weather data. This is because the model's performance is driven not only by precipitation but also by temperature and accumulated snowpack, which are crucial factors in the catchment's hydrological processes.

e) Finally, on a broader view, the proposed methodology enables a “fairness” redistribution of the water resources by allocating surface water (that could potentially be used by the surface water users) to be infiltrated and then be used by the groundwater users. This redistribution needs to be understood not as a “benefit for some, harm to the others”, but as an integrated and sustainable water resources management for the benefit of the environment and all water users.

10. Discussions

Even though the results are already promising regarding the implementation of this methodology, there are still aspects of it that could be improved. During the thesis research process, three main topics were found that might be interesting for future research:

a. Hydrological model calibration
b. Enhancing the selection mode for the generated synthetic weather time series.
c. Coupling the existing groundwater model with the hydrological model

a. The hydrological model serves as the mechanism that connects weather data with inflow discharges and, consequently, the volumes entering the Puclaro reservoir in this case. The calibration process employed in this research focused on matching the computed annual volumes entering the reservoir with the observed data, with only a few key parameters being adjusted due to time constraints. Despite the calibrated model being satisfactory for the purpose that it has been used, there is much that can be done for improving the hydrological model to better replicate the observed data within the catchment, especially for the discharge flow signal in the different fluviometric stations. An interesting and very innovative way of calibrating the hydrological model in the future could be by using a Markov-Chain Monte Carlo (MCMC) methodology, so after a very large number of runs, being able to find the parameters' values that are the most probable due to the observed data.

   Additionally, if more time can be dedicated to model calibration, it would be worth trying to use the CHIRPS-global forcing data instead of the DGA-PP forcing data. The advantage of the first one is that it completely depends on satellite remote sensing data, not depending on DGA as an intermediary to get the stations' precipitation data. This fact, combined with an MCMC methodology for the calibration could produce a reliable and accurate hydrological model.

b. Despite that incorporating the weather generator, as part of the forecasting and following RHC methodology for the water management decision-making, should be a randomize process as it is implemented in this thesis research, there is an autoregression component of the weather (in general) that is not being used. For instance, if the first three or four months of a year have been consistent with a "wet year", it is more probable that the following months also fall in that classification. In fact, the effect of El Niño – La Niña, that it is considered in the weather generator resampling, could be somehow included over the observed previous weather conditions so the methodology could choose a random year over similar weather conditions years, and not randomly over the 100 different weather conditions that were generated. This improvement could reduce the uncertainty gap for the decision-makers and with no doubt can improve the results of this methodology. Worth to mention that could be interesting on future research to use the weather generator resampling as a continues time series instead of randomly selecting years from it, comparing the obtained results with those from this thesis research.

c. Lastly, even though the results from the existing groundwater model plays an important role in this new methodology, there are many aspects of the existing model that could be improved. For instance, the assumption used for modeling the interaction between the surface waters (Elqui River) with the aquifer is a discrete range of 4 river discharges where each associated with a specific water level along the river length, as it is explained in the groundwater model description in Chapter 4.5.2. Additionally, the water levels are part of third-party model results, while the hydraulic model is not available.

The latter raises three issues. Firstly, the discrete river discharge water levels eliminate the sensitivity of the river-aquifer interaction in the model, rendering any effort to raise the river water level ineffective in increasing infiltration, for instance. Furthermore, if the river discharge value fluctuates near one of the range boundaries, the water level used by the model would abruptly switch between two significantly different scenarios at each timestep. Secondly, it might happen that the most common discharge flow in the river (the mode) does not match the specific discharge flow corresponding to the water level used over the river, leading to inaccurate modeling of the river-aquifer interaction. And finally, the fact that the hydraulic model is not available makes it impossible to evaluate different scenarios to improve the natural aquifer's infiltration as could be the implementation of a stepped riverbed or similar.

To sum up on this last topic, would be very convenient to develop our own hydraulic model to well represent the water levels on the Elqui River downstream of the Puclaro reservoir. Even more, these three models (hydrological, groundwater, and hydraulic models) could be run in a coupled way at some point, containing then the complete physical representation of the catchment.

Besides the technical discussions about the improvements that can be done over this new methodology, the social discussion about its implementation feasibility is also extremely important. The first step would be to share this new methodology with the catchment water authorities and stakeholders along with the results so far. The following steps would depend on this, but this is now out of the scope of this thesis research.

11. References

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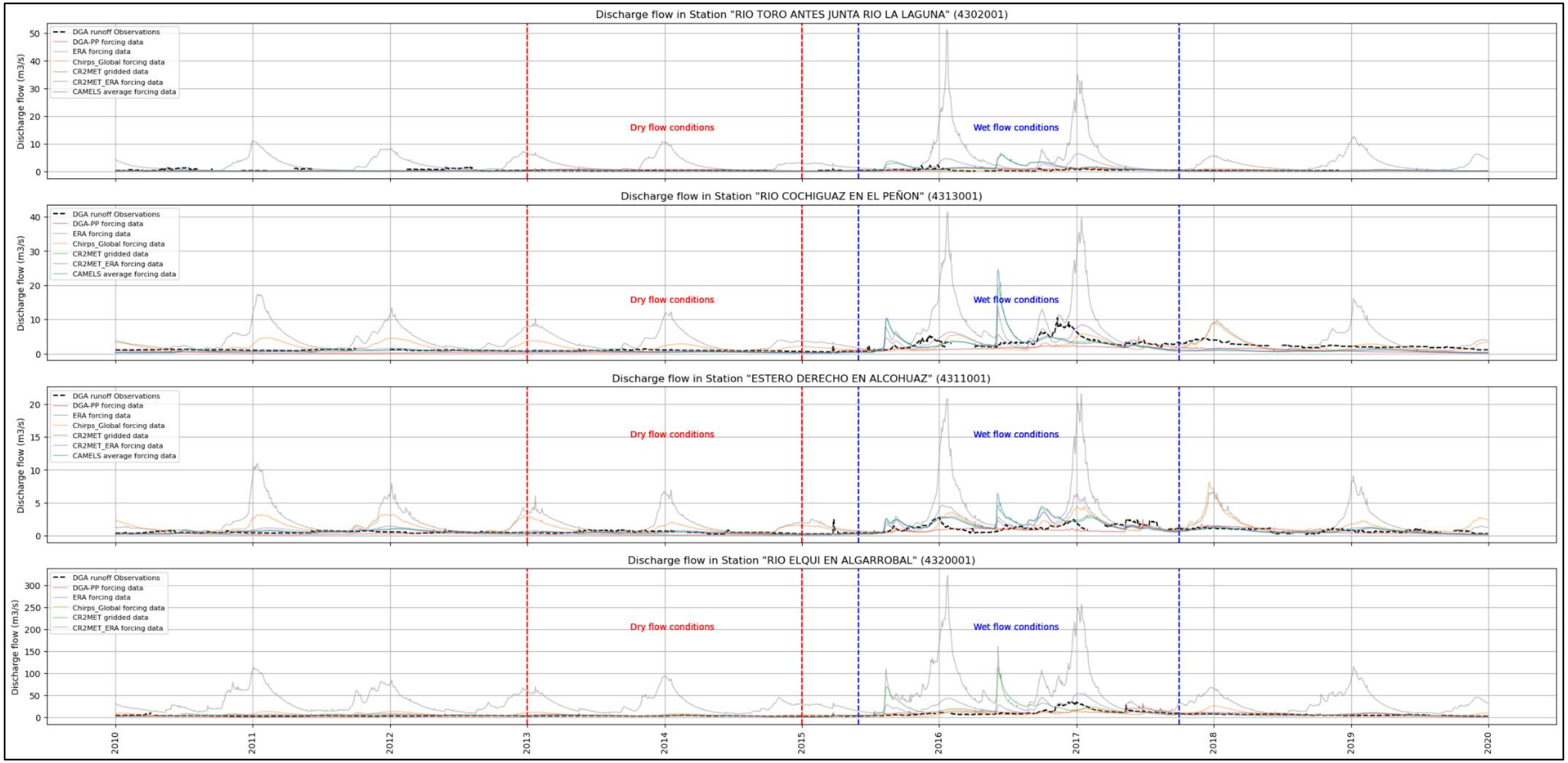
Appendix A: GEE script

SnowCovPercentage * | Get Link | Save | Run | Reset | Apps

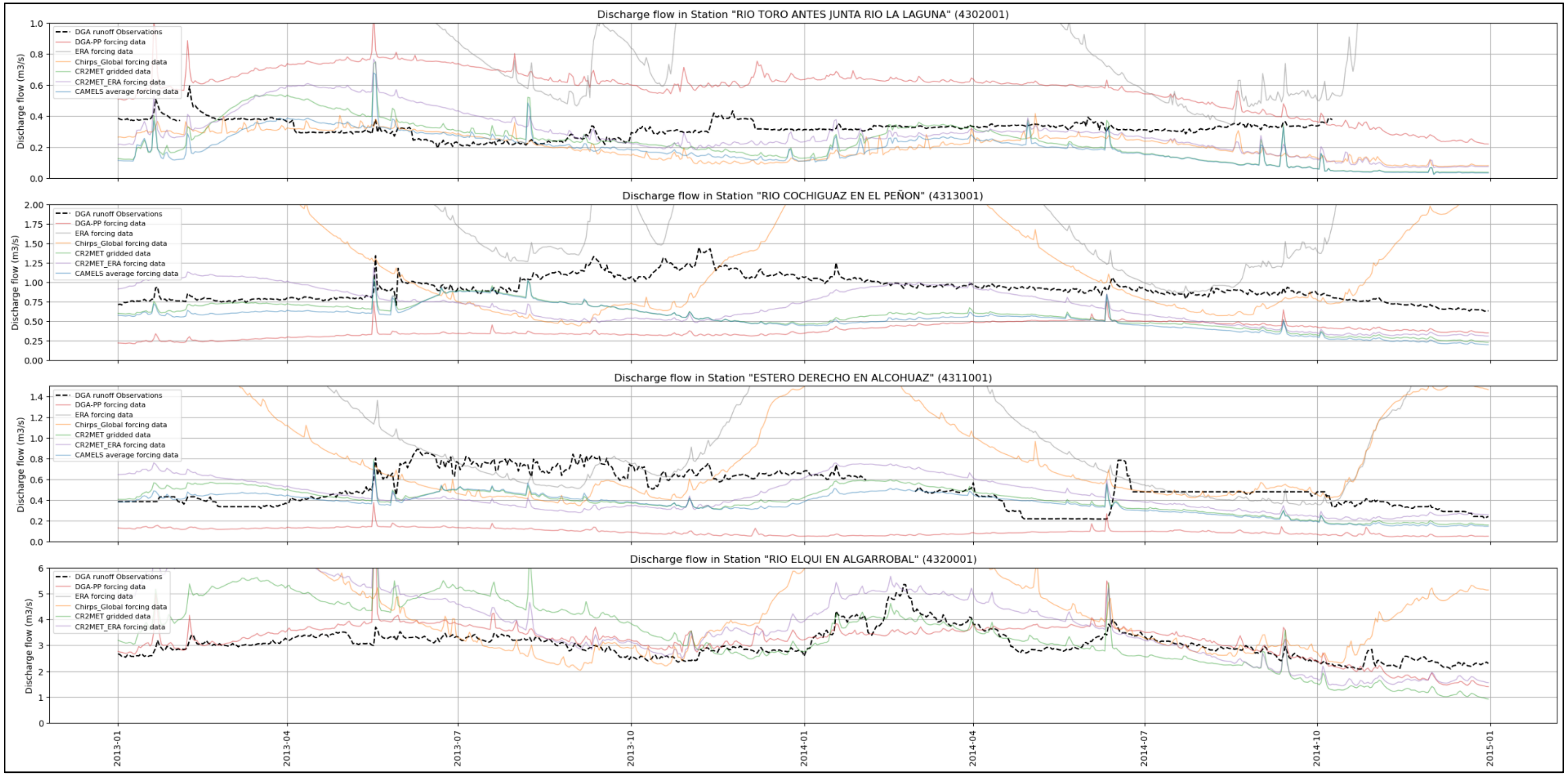
```
Imports (1 entry)
 var bbox: Polygon, 4 vertices
// Define the bbox of the region of interest

// Load the MODIS Snow Cover daily data collection
var modisSnowCover = ee.ImageCollection('MODIS/006/MOD10A1')
                      .select('NDSI_Snow_Cover')
                      .filter(ee.Filter.calendarRange(1, 12, 'month'));

// Define the start and end dates of the time period
var startDate = '2010-01-01';
var endDate = '2019-12-31';

//--------------------------------------------------
print(bbox.area())
// Get the first image in the collection
var modisImage = ee.Image(modisSnowCover.first());

// Get the pixel area image
var pixelArea = ee.Image.pixelArea();

// Mask the pixel area image based on the bounding box
var bboxMask = pixelArea.clip(bbox);

// Reduce the masked pixel area image to get the total area in square meters
var totalArea = bboxMask.reduceRegion({
  reducer: ee.Reducer.sum(),
  geometry: bbox,
  scale: modisImage.projection().nominalScale(),
});

// Calculate the total number of pixels
var pixelCount = ee.Number(totalArea.get('area')).divide(modisImage.projection().nominalScale()).divide(modisImage.projection().nominalScale());

print('Total number of pixels in the bounding box:', pixelCount);

//--------------------------------------------------

// Filter the MODIS Snow Cover daily data collection by date and region
var modisSnowCoverFiltered = modisSnowCover.filterDate(startDate, endDate)
                                           .filterBounds(bbox);

// Define a function to compute the snow cover percentage for a given image
function computeSnowCoverPercentage(image) {
  var snowCoverCount = ee.Number(image.gt(0).reduceRegion({
    reducer: ee.Reducer.sum(),
    geometry: bbox,
    scale: 500,
    maxPixels: 1e9
  }).get('NDSI_Snow_Cover'));
  var snowCoverPercentage = snowCoverCount.divide(pixelCount);
  return image.set('snow_cover_percentage', snowCoverPercentage);
}

// Map the computeSnowCoverPercentage function over the MODIS Snow Cover daily data collection
var modisSnowCoverProcessed = modisSnowCoverFiltered.map(computeSnowCoverPercentage);

// Create a feature collection with snow cover percentage data
var features = modisSnowCoverProcessed.map(function(image) {
  var date = ee.Date(image.get('system:time_start'));
  return ee.Feature(null, {
    date: date,
    snow_cover_percentage: image.get('snow_cover_percentage')
  });
});

// Create a chart of the snow cover percentage over time
var chart = ui.Chart.feature.byFeature(features, 'date', 'snow_cover_percentage')
  .setChartType('LineChart')
  .setOptions({
    title: 'Daily Snow Cover Percentage',
    vAxis: {title: 'Snow Cover Percentage'},
    hAxis: {title: 'Date'},
    lineWidth: 1,
    pointSize: 2,
  });

// Print the chart
print(chart);
```

Appendix B: Hydrological model results for the different forcing data used

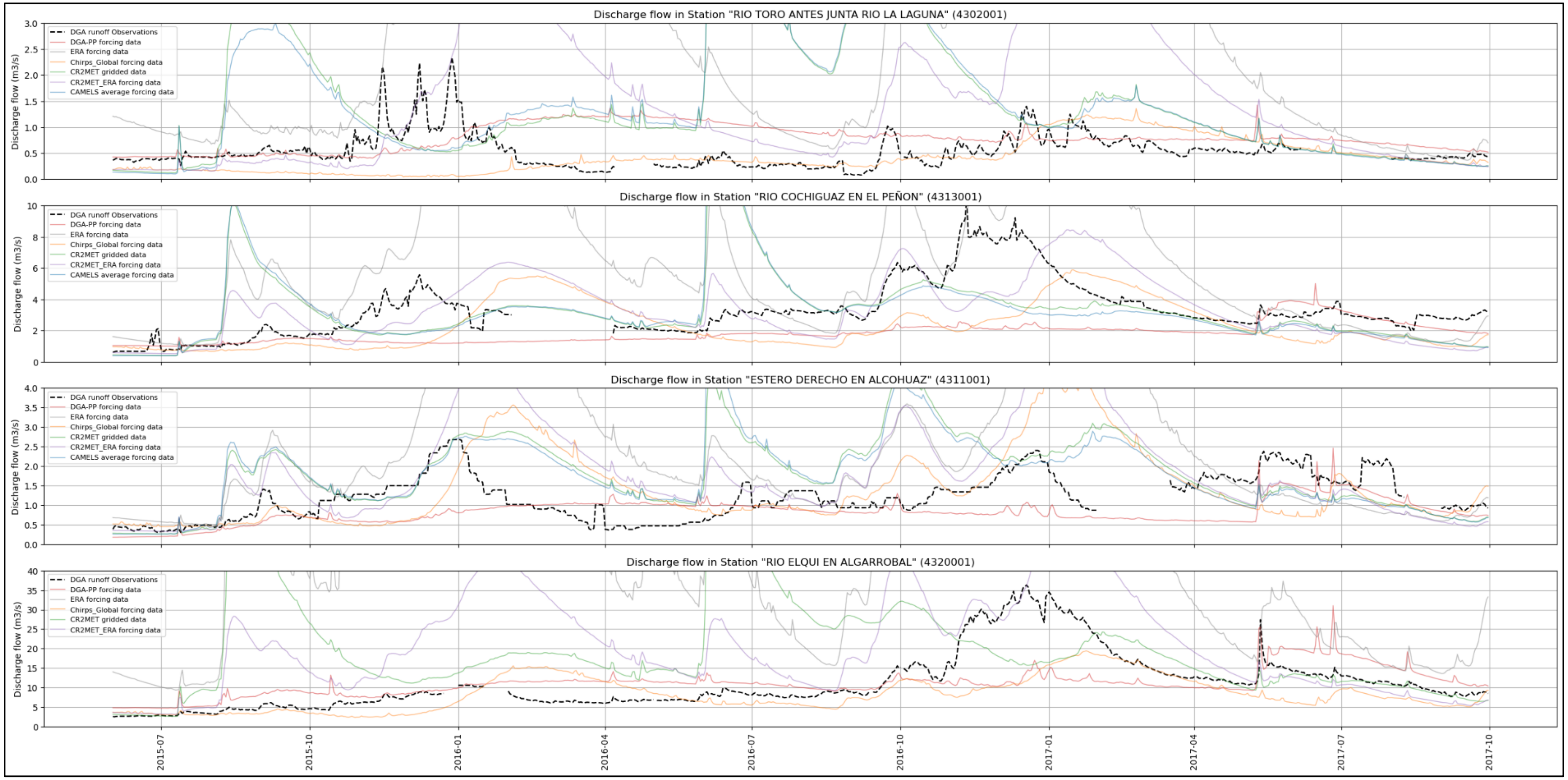
Complete results for each calibration station



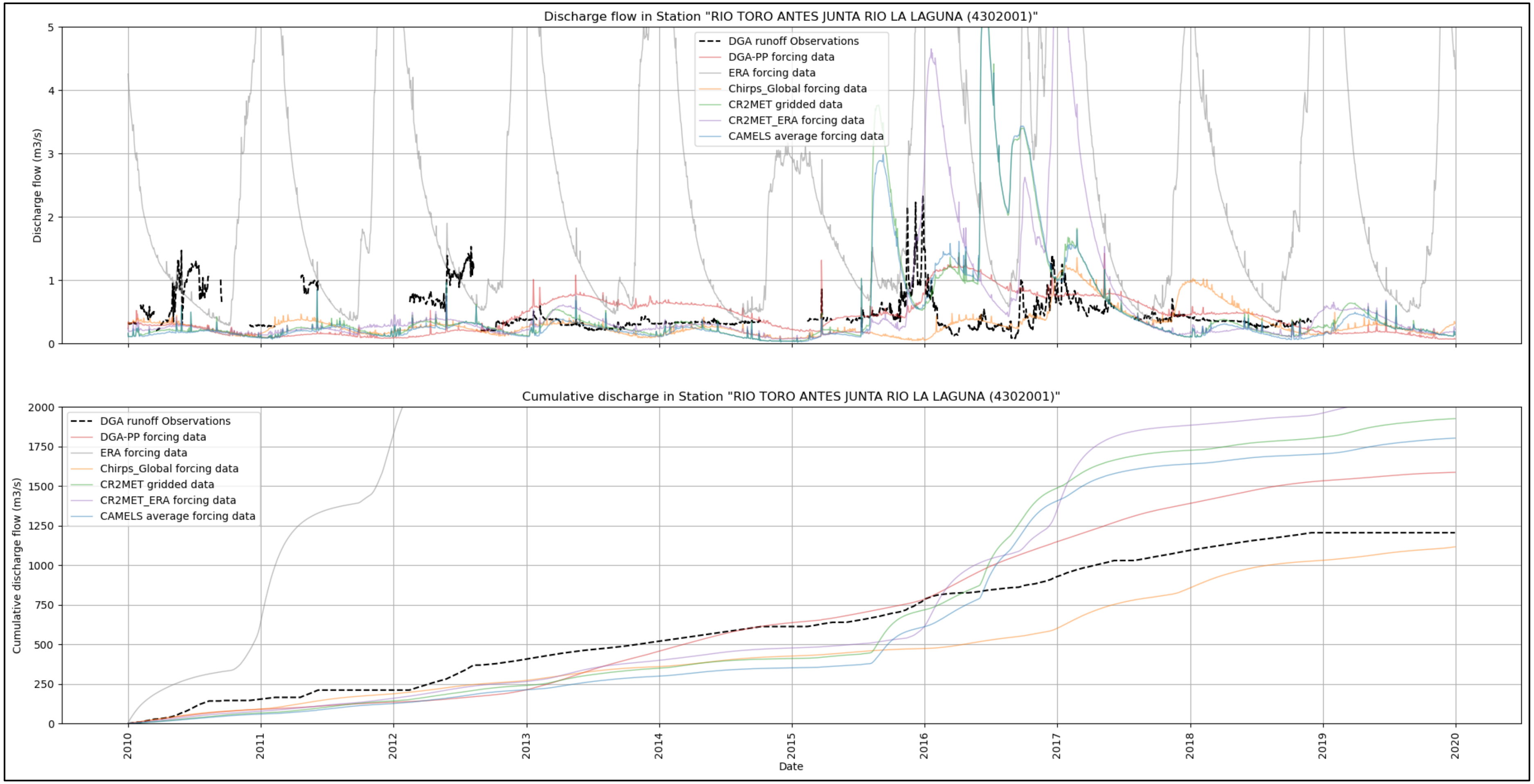
Dry flow conditions results for each calibration station



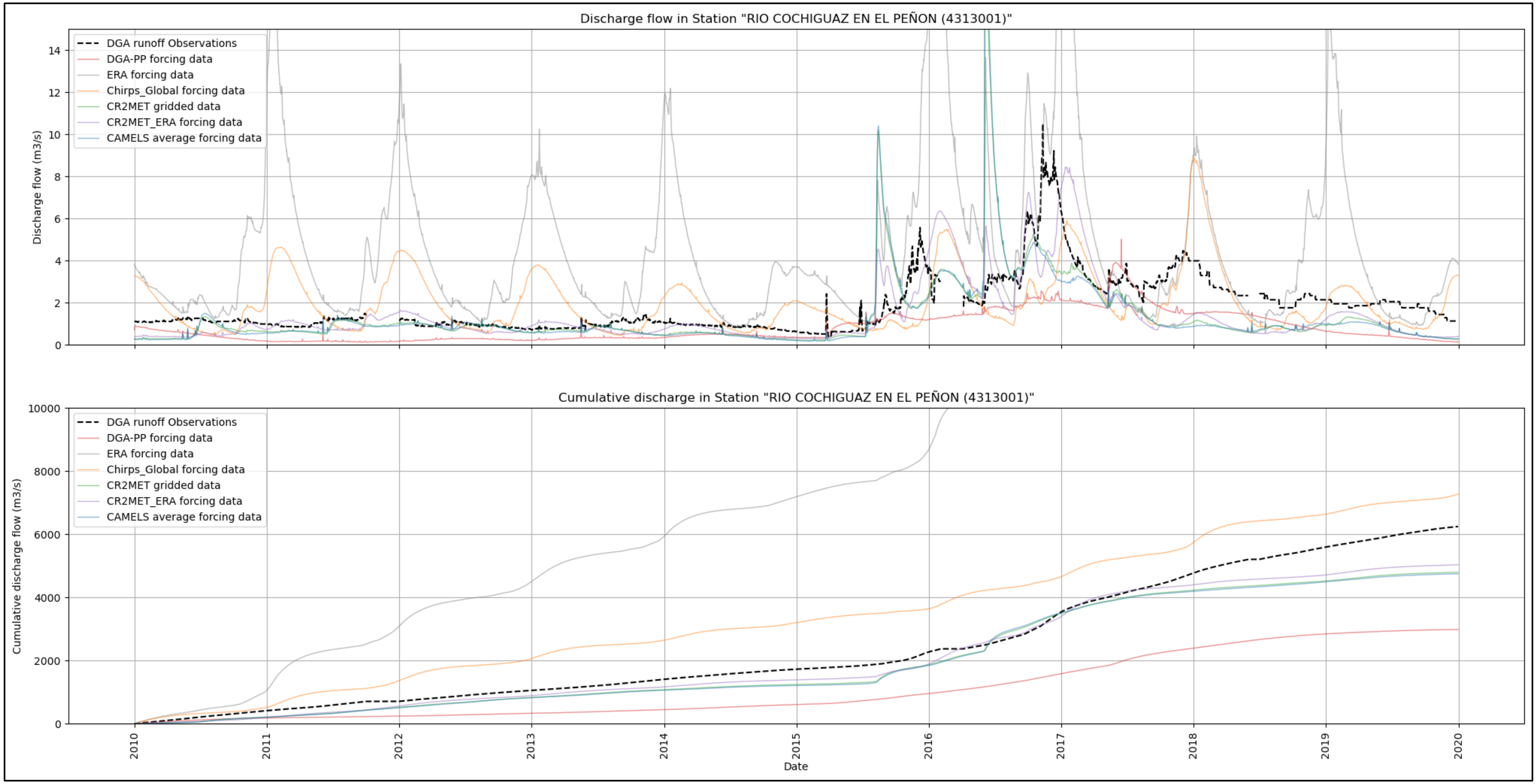
Wet flow conditions results for each calibration station



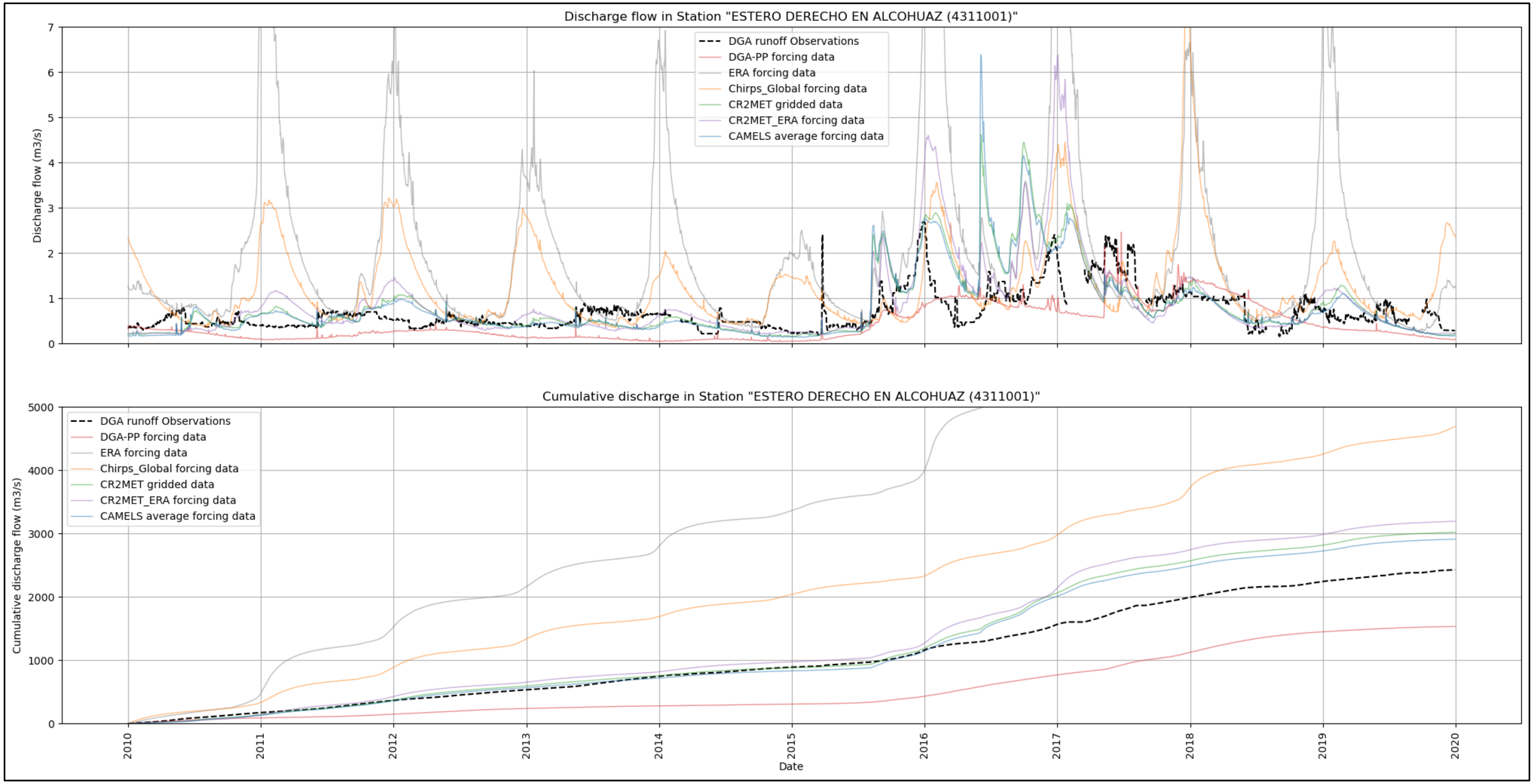
Results at "RIO TORO ANTES JUNTA RIO LA LAGUNA" station



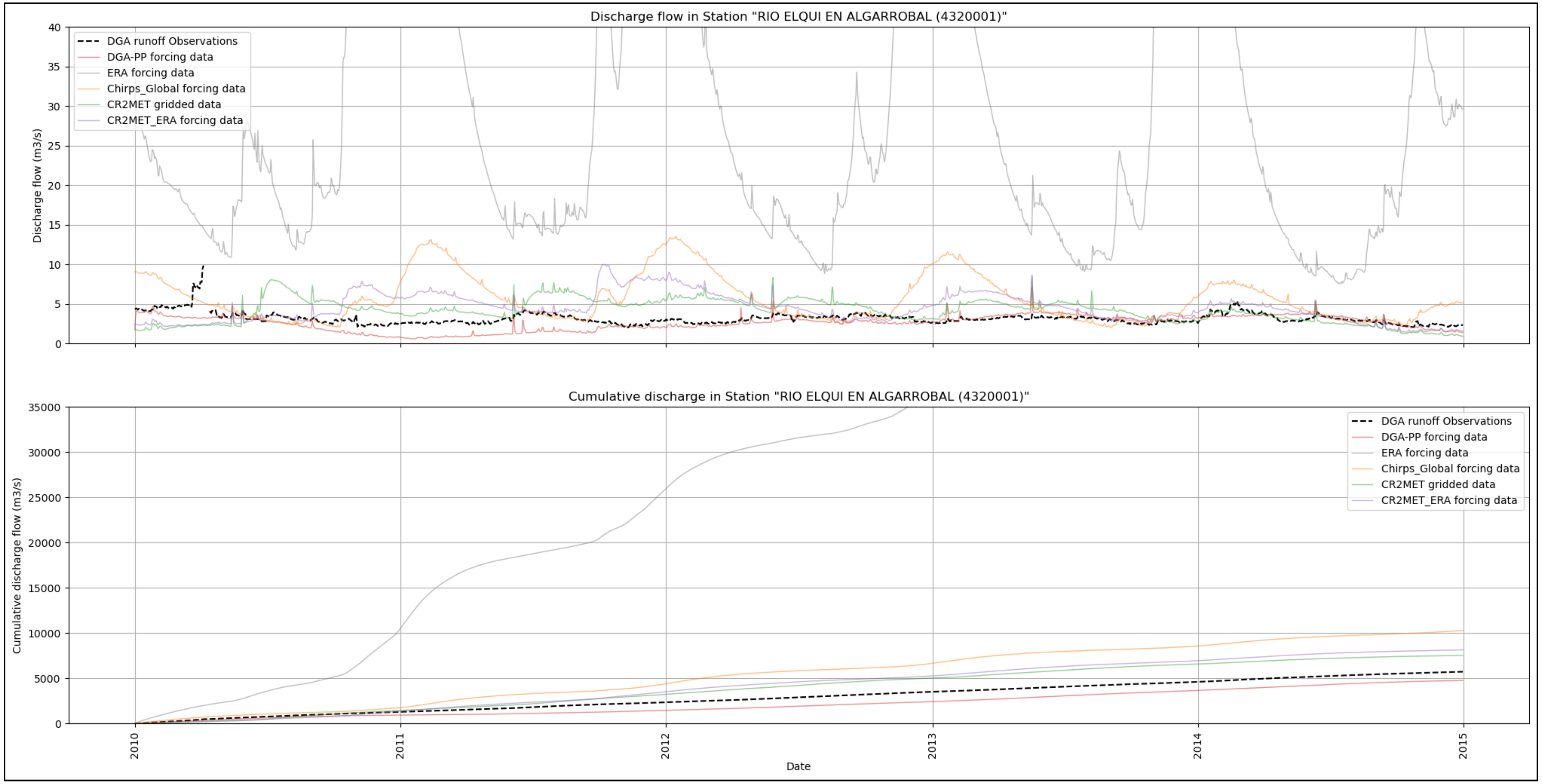
Results at "RIO COCHIGUAZ EN EL PEÑON" station



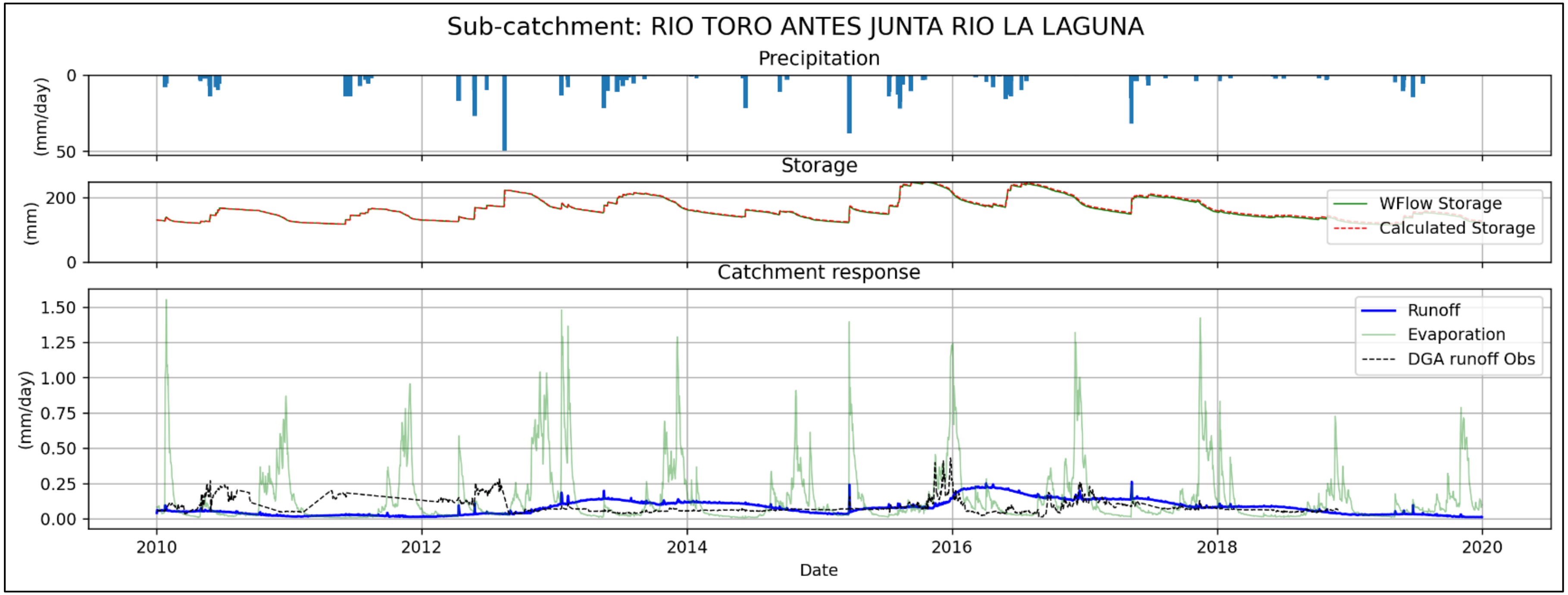
Results at “ESTERO DERECHO EN ALCOHUAZ” station



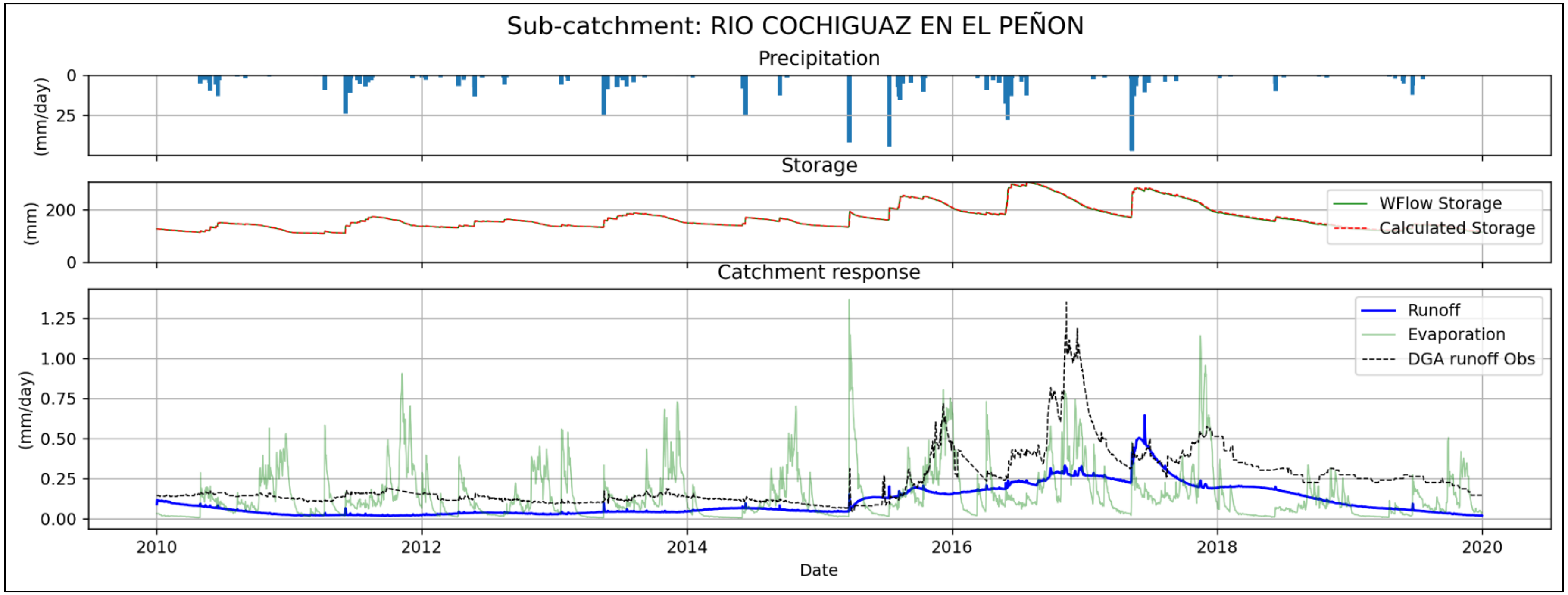
Results at “RIO ELQUI EN ALGARROBAL” station



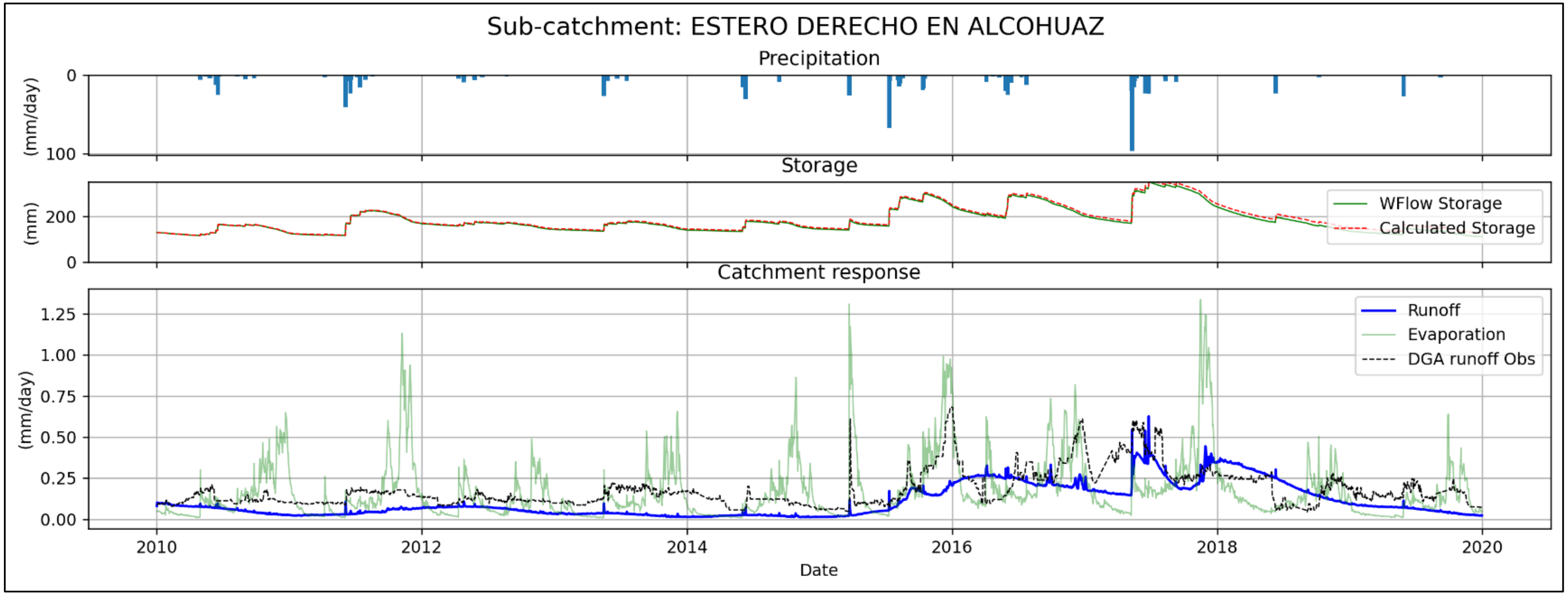
Appendix C: Water balance results



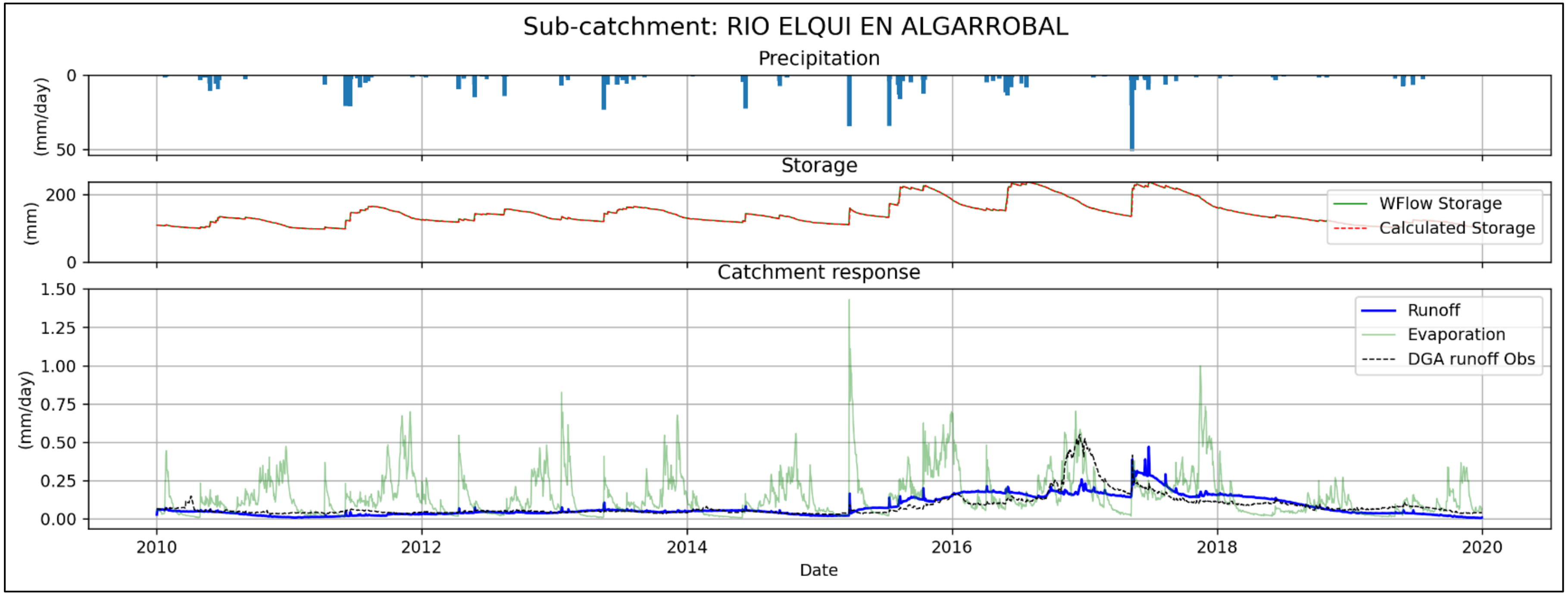
	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Q_in (mm)	71.60	51.68	115.00	113.75	40.65	170.21	105.07	77.60	30.84	48.08
Q_evap (mm)	57.61	40.40	61.96	74.49	40.23	54.79	77.95	53.08	36.93	37.86
Q_runoff (mm)	16.53	8.27	14.44	44.86	33.34	27.16	67.09	44.47	26.46	9.94
Q_out (mm)	74.14	48.68	76.41	119.35	73.56	81.95	145.04	97.54	63.39	47.80
Q_in - Q_out (mm)	-2.54	3.00	38.59	-5.60	-32.91	88.26	-39.97	-19.94	-32.55	0.28
End_Storage (mm)	127.94	130.94	169.53	163.94	131.03	219.29	179.32	159.38	126.83	127.11



	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Q_in (mm)	53,46	83,88	54,55	84,94	49,70	186,39	170,59	159,89	28,49	35,66
Q_evap (mm)	42,02	55,81	42,10	57,01	39,58	71,40	83,45	78,74	31,48	31,24
Q_runoff (mm)	23,06	7,51	11,74	14,61	20,93	44,94	81,15	103,69	58,04	17,96
Q_out (mm)	65,08	63,32	53,84	71,62	60,51	116,33	164,60	182,43	89,52	49,20
Q_in - Q_out (mm)	-11,62	20,56	0,71	13,32	-10,81	70,05	6,00	-22,54	-61,02	-13,54
End_Storage (mm)	114,98	135,54	136,25	149,57	138,76	208,81	214,81	192,27	131,24	117,70



	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Q_in (mm)	74,36	122,88	40,21	55,92	56,36	221,11	143,73	232,79	33,30	34,62
Q_evap (mm)	53,90	65,09	41,76	46,45	44,73	88,99	97,07	98,99	54,36	35,60
Q_runoff (mm)	22,54	14,57	23,23	10,47	7,00	31,22	86,46	89,97	82,89	21,51
Q_out (mm)	76,45	79,66	64,99	56,92	51,73	120,22	183,53	188,96	137,26	57,11
Q_in - Q_out (mm)	-2,08	43,22	-24,79	-0,99	4,63	100,90	-39,80	43,84	-103,95	-22,49
End_Storage (mm)	126,96	170,18	145,39	144,39	149,02	249,92	210,12	253,96	150,01	127,52



	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Q_in (mm)	55,29	85,60	62,69	77,49	42,61	178,47	122,01	145,28	22,51	32,20
Q_evap (mm)	47,36	56,13	45,75	56,18	40,06	78,16	76,24	81,53	32,31	30,57
Q_runoff (mm)	14,15	7,93	14,63	18,85	16,74	30,30	62,76	71,09	40,20	10,76
Q_out (mm)	61,51	64,06	60,38	75,03	56,80	108,45	139,00	152,62	72,51	41,33
Q_in - Q_out (mm)	-6,21	21,54	2,31	2,46	-14,19	70,01	-16,99	-7,34	-50,00	-9,13
End_Storage (mm)	103,01	124,55	126,86	129,31	115,12	185,13	168,14	160,80	110,80	101,68

Appendix D: RHC methodology implementation. Python script.

```
import numpy as np
import pandas as pd
import datetime
from datetime import timedelta
#Generate the Historical Simulation input CSV
# import Generate_InputData_daily
import os
import warnings
warnings.filterwarnings("ignore")

exec(open('Generate_InputData_daily.py').read())
inp_folder = os.path.join(os.path.dirname(os.getcwd()), 'input')
aux_folder = os.path.join(os.path.dirname(os.getcwd()), 'Auxiliar')
results_folder = os.path.join(os.path.dirname(os.getcwd()), 'output')
output_path = os.path.join(os.path.dirname(os.path.dirname(os.getcwd())),
'Results')

Input_original = pd.read_csv(os.path.join(inp_folder, 'timeseries_import.csv'),
parse_dates=[0], index_col=0)
IniState_original = pd.read_csv(os.path.join(inp_folder, 'initial_state.csv'),
parse_dates=[0], index_col=0)


Horizontes = [30, 45, 60, 120, 150, 180, 240, 300, 360, 420, 480, 540, 600, 660,
720, 780, 840, 900, 960, 1020, 1080]

for n, hor in enumerate(Horizontes):
    #Restart input data and initial state
    exec(open('Generate_InputData_daily.py').read())

    Horizon_results = pd.DataFrame()
    for i in range(Input_original.shape[0]-1):
        if i>(Input_original.shape[0]-hor):
            Input_aux = Input_original[i:]
        else:
            Input_aux = Input_original[i:i+hor]

        #Reemplace the original input_data for the respective Receding horizon
input_data
        Input_aux.to_csv(os.path.join(inp_folder, 'timeseries_import.csv'),
index=True, date_format='%Y-%m-%d %H:%M:%S')

        #Run the simulation
        if i < 3164:
            exec(open('FORMA2.py').read())

        else:
            exec(open('FORMA.py').read())
        Run_results = pd.read_csv(os.path.join(results_folder,
'timeseries_export.csv'), parse_dates=[0])

        #Saving results for last run
        if i==0:
            Horizon_results = Horizon_results.append(Run_results.iloc[0],
ignore_index=False)
        Horizon_results = Horizon_results.append(Run_results.iloc[1],
ignore_index=False)
```

```
        # if i==(Input_original.shape[0]-1):
        #     Horizon_results = Horizon_results.append(Run_results.iloc[2],
ignore_index=False)

        #Create the new initial_state values for next timestep.
        if i!=(Input_original.shape[0]-2):
            Puclaro_Init_Volume = [Run_results.V_storage[1]] # m3
            Puclaro_Init_Qrelease = [Run_results.Q_release_reservoir[1]] # m3/s
            Aquifer1_Vol = [Run_results.V_aquifer1[1]] # m3
            Aquifer2_Vol = [Run_results.V_aquifer2[1]] # m3
            Aquifer3_Vol = [Run_results.V_aquifer3[1]] # m3
            Desmarque = [Run_results.Desmarque[1]] # m3

            ini_state = pd.DataFrame({'storage.V': Puclaro_Init_Volume,
                                      'Q_release_reservoir': Puclaro_Init_Qrelease,
                                      'Aquifer1.V': Aquifer1_Vol,
                                      'Aquifer2.V': Aquifer2_Vol,
                                      'Aquifer3.V': Aquifer3_Vol,
                                        'Desmarque': Desmarque})
            ini_state.to_csv(os.path.join(inp_folder, 'initial_state.csv'),
index=False)
        print('')
        print(f'Iteracion N_{i+1} del con Horizonte {hor} terminada')
        print('')

    file_name = f'{n}_Results_H'+str(hor)+'.csv'
    Horizon_results = Horizon_results.set_index('time')
    Horizon_results.to_csv(os.path.join(output_path, file_name))
```

Appendix E: New decision-making methodology implementation. Python script.

```python
# Import all needed packages
import os
import xarray as xr
import numpy as np
import sys
import pandas as pd
import warnings
warnings.filterwarnings("ignore")
import datetime
import subprocess
from datetime import timedelta, date

inp_folder = os.path.join(os.path.dirname(os.getcwd()), 'input')
Wflow_folder =
os.path.join(os.path.dirname(os.path.dirname(os.path.dirname(os.getcwd()))), 'WFlow
models')
WFlow_model = 'wflow_elqui_reservoirs'

RH_lenght = 360

rng = pd.date_range('2010-01-01', '2019-12-31', freq='D')
Final_results = pd.DataFrame()

os.chdir(os.getcwd())
subprocess.run(['python', 'Generate_InputData_daily.py'])
Input_original = pd.read_csv(os.path.join(inp_folder, 'timeseries_import.csv'),
parse_dates=[0], index_col=0)

#inside the loop the init_date and end_date change on each iteration
init_date = datetime.datetime(rng[0].year, rng[0].month, rng[0].day, 0, 0, 0)
end_date = (init_date + datetime.timedelta(RH_lenght)) # timedelta corresponds to
the Receding Horizon time

Forecast_folder = os.path.dirname(os.path.dirname(os.getcwd()))
print(Forecast_folder)

# LOAD Historical model NC-File
output_NC = xr.open_dataset(os.path.join(os.path.join(Wflow_folder,
WFlow_model),'run_default//output.nc')) # Historical simulation
output_NC.isel(time=[0]).to_netcdf(os.path.join(Forecast_folder, 'wflow_elqui_DGA-
PP//instate//outstates.nc')) # Outstate for time-period 0 is used as initial state

# LOAD Forecast NC-File
Forecast_NC = xr.open_dataset(os.path.join(Forecast_folder, 'Forecast_NC.nc'))

def NCfileGen(date1, date2):
    print(date1, date2)
    check = False
    first_years = np.arange(2020, 2100, 4)
    addit_years = [2104, 2108, 2112, 2116]
    leap_years = np.append(first_years, addit_years)

    while check==False:
        if (date1.month==2) and (date1.day==29):
            rnd_year1 = leap_years[np.random.random_integers(0, len(leap_years)-1)]
        else:
            rnd_year1 = np.random.random_integers(2020, 2119)
```

```
        # date1 = datetime.datetime.strptime(date1, '%Y-%m-%d')
        # date1 = datetime.datetime.strptime(date1, '%Y-%m-%d')
        new_init_date = datetime.datetime(rnd_year1, date1.month, date1.day)
        days = datetime.datetime(date2.year, date2.month, date2.day) -
datetime.datetime(date1.year, date1.month, date1.day)
        new_end_date = new_init_date + timedelta(days=(days).days)

        if new_end_date < datetime.datetime(2119, 12, 7):
            check = True

    new_range = pd.date_range(new_init_date.strftime('%Y-%m-%d'),
new_end_date.strftime('%Y-%m-%d'), freq='D')
    New_NCfile = Forecast_NC.sel(time=new_range)
    New_NCfile['time'] = pd.date_range(init_date.strftime('%Y-%m-%d'),
end_date.strftime('%Y-%m-%d'), freq='D')
    New_NCfile.to_netcdf(os.path.join(Forecast_folder, 'wflow_elqui_DGA-
PP//IterationData.nc'))
    # return(new_init_date.strftime('%Y-%m-%d'), end_date.strftime('%Y-%m-%d'))


for t in range(len(rng)-1):
    print(t, rng[t])

    #-----------------------------------------------------
    # WEATHER GENERATOR
    # Generate the weather forcing data starting from rng[t] with a length of
RH_length.
    # The .nc file should replace the .nc file at the WFlow Folder.
    # NCfileGen(datetime.datetime.strftime(rng[t], '%Y-%m-%d'), RH_lenght)

    NCfileGen(init_date, end_date)

    #-----------------------------------------------------
    # WFLOW MODEL

    # Then, the TOML.file dates are edited
    txt1 = 'starttime'
    txt2 = 'endtime'
    with open(os.path.join(Forecast_folder, 'wflow_elqui_DGA-PP//wflow_sbm.toml'),
mode="r") as file:
        lines = file.readlines()
    for i in range(len(lines)):
        if lines[i][:len(txt1)] == txt1:
            lines[i] = txt1 + " = " + init_date.isoformat('T') + 'n'
        if lines[i][:len(txt2)] == txt2:
            lines[i] = txt2 + " = " + end_date.isoformat('T') + 'n'
    with open(os.path.join(Forecast_folder, 'wflow_elqui_DGA-PP//wflow_sbm.toml'),
"w") as file:
        file.writelines(lines)

    # Initial conditions for WFLOW model are updated based on the historical data.
    output_NC.isel(time=[t]).to_netcdf(os.path.join(Forecast_folder,
'wflow_elqui_DGA-PP//instate//outstates.nc')) # Outstate for time-period t is used
as initial state

    # Run the WFLOW model with the generated forcing data
```

```
    julia_command = f"julia -e 'using Wflow; Wflow.run()'
{os.path.join(Forecast_folder, 'wflow_elqui_DGA-PP//wflow_sbm.toml')}"
    subprocess.run(julia_command, shell=True, check=True)

    #-----------------------------------------------------

    # RTC-TOOLS MODEL
    indx_aux = Input_original.index.get_loc(init_date)
    indx_aux2 = Input_original.index.get_loc(end_date)

    # Truncate the original input file and update the Q_in input_data
    if t>(Input_original.shape[0]-RH_lenght):
        Input_aux = Input_original[indx_aux:indx_aux2]
    else:
        Input_aux = Input_original[indx_aux:indx_aux+RH_lenght]

    # print(len(Input_original[t:t+RH_lenght+1]))
    # print(len(pd.read_csv(r"P:11209032-forma4-Forecast_Planingwflow_elqui_DGA-
PPrun_defaultoutput.csv", index_col=0, parse_dates=[0])['Q_2000']))

    Input_aux['Q_in_reservoir'] = pd.read_csv(os.path.join(Forecast_folder,
'wflow_elqui_DGA-PP//run_default//output.csv'), index_col=0,
parse_dates=[0])['Q_2000']

    # Reemplace the original input_data for the respective Receding horizon
input_data
    Input_aux.to_csv(os.path.join(inp_folder, 'timeseries_import.csv'), index=True,
date_format='%Y-%m-%d %H:%M:%S')

    # Run the simulation
    if init_date < pd.to_datetime('2018-08-31'):
        subprocess.run(['python', 'FORMA.py'])
    else:
        subprocess.run(['python', 'FORMA2.py'])

    Run_results = pd.read_csv(os.path.join(Forecast_folder,
'forma_daily//output//timeseries_export.csv'), parse_dates=[0])

    #Saving results for last run
    if t==0:
        Final_results = Final_results.append(Run_results.iloc[0],
ignore_index=False)
    Final_results = Final_results.append(Run_results.iloc[1], ignore_index=False)

    #Create the new initial_state values for next timestep.
    if i!=(Input_original.shape[0]-2):
        Puclaro_Init_Volume = [Run_results.V_storage[1]] # m3
        Puclaro_Init_Qrelease = [Run_results.Q_release_reservoir[1]] # m3/s
        Aquifer1_Vol = [Run_results.V_aquifer1[1]] # m3
        Aquifer2_Vol = [Run_results.V_aquifer2[1]] # m3
        Aquifer3_Vol = [Run_results.V_aquifer3[1]] # m3
        Desmarque = [Run_results.Desmarque[1]] # m3

        ini_state = pd.DataFrame({'storage.V': Puclaro_Init_Volume,
                                  'Q_release_reservoir': Puclaro_Init_Qrelease,
                                  'Aquifer1.V': Aquifer1_Vol,
                                  'Aquifer2.V': Aquifer2_Vol,
```

```
                                  'Aquifer3.V': Aquifer3_Vol,
                                    'Desmarque': Desmarque})
        ini_state.to_csv(os.path.join(inp_folder, 'initial_state.csv'),
index=False)

    init_date = (init_date + datetime.timedelta(1))
    end_date = (init_date + datetime.timedelta(RH_lenght))
    end_date = (init_date + datetime.timedelta(RH_lenght))
    if end_date > rng[-1]:
        end_date = rng[-1]

    #Save results for each timestep
    Final_results.to_csv(os.path.join(Forecast_folder, 'RESULTS_inProgress.csv'))


Final_results = Final_results.set_index('time')
Final_results.to_csv(os.path.join(Forecast_folder, 'RESULTS.csv'))
```