Integrated hydrological and economic modelling of a mining region

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Integrated hydrological and economic modelling of a mining region

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Sustainable Minerals Institute

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Abstract

Hydro-economic modelling is an established field of research that takes a multi-disciplinary approach to analysing water resources. This approach can be used to analyse water policies, assess impacts of changing climate conditions and explore synergies between water users, amongst other applications. Hydro-economic models have been applied mainly to agricultural and urban water uses. The mining industry, despite being a relevant user in several catchments worldwide, has rarely been included and the modelling challenges that arise in mining applications have not been investigated. The aim of this project was to develop a hydro-economic model in the upper Aconcagua River in central Chile, in order to understand how this approach may support catchment-scale water decision making in regions where mining is an important user.

A literature review on the hydro-economics of mining highlighted several features that make the mining sector a special case. One of the most important was the large differences in both CAPEX and OPEX between this sector and alternative users of water. This means that the set of metrics used to compare the economic value of water between sectors is of particular importance, in order to avoid being biased toward the mining user. The literature review also highlighted the issues of developing water resources models with limited climate observations, as in the case of the many remote regions where mine projects are located.

To address the problem of climate data, the project compared methods for interpolating point observations of precipitation and temperature in the upper Aconcagua River Basin, where precipitation and temperature spatial gradients are high and there is a lack of high elevation measurements. It was found that a relatively simple method that merges the WorldClim datasets (which are available worldwide) with available point observations worked well for the case study, and may support the development of similar models in comparable regions, even when there are few or no climate gauges available.

A conceptual semi-distributed model in the WEAP software, was used as the water resources component of the upper Aconcagua River hydro-economic model (HEM). The calibration involved the comparison of flows, snow water equivalents and hydro-power energy generation, so as to minimise error compensation as much as possible. The economic analysis included four water users: mining, agriculture, hydro-power and urban users. The coupling was done using Python scripts that connected WEAP with the economic functions allowing automatic, constant feedback between components, without sacrificing a detailed representation of both components.

Three metrics were used to analyse water users in the HEM: total value of water (with and without mining), shadow value of water and water scarcity cost. These three metrics provide different viewpoints from the water users in the catchment, and thus all of them are important to take into account in decision making processes.

Three sets of scenarios of potential applications of the HEM were analysed using the HEM. The first explored how changes in climate conditions may affect hydrology, coverage of user's demand for water, and the economic metrics. This scenario helped understanding the added value of a detailed representation of hydrological processes in the catchment, as it showed how small increases in temperature would generate changes in snow melting periods that may not be harmful, and even beneficial in some cases, to all water users.

The second scenario analysed the impacts of including minimum flow requirements in the catchment to improve the ecological condition of the river. Results showed that defining the magnitude of the restrictions and defining their location are equally important. It was highlighted that in this case study, the restrictions in the upper parts of the catchment had the largest economic impact, as they affected mining and hydro-power users mostly.

Finally, the HEM was used to analyse the shared benefits of a mine tailings water recycling project in the catchment. It was found that the economic value of the project for agriculture, urban and hydro-power users may not be very large, because of the allocation rules for the additional water. However, the exercise illustrated how HEMs can be used to valuate the economic contributions that the mining industry can provide to other users by taking a catchment scale approach. This is of particular importance, as this sector tries to improve relations with communities and to demonstrate its contribution to sustainable development of regions.

It is concluded that HEM can provide useful insight into water resources management in mining regions, although the set of metrics used have to be carefully selected as to properly take a catchment scale approach. It was also found that it is important to do a detailed representation of the water resources component, particularly when analysing areas where snow melt is a relevant hydrological process and when exploring the impacts of changing climate conditions. Finally, it was also shown that this tool may be used in the broader context of improving the mining water performance, an enhancing the relations with other water stakeholders in the catchment.

Declaration by author

This thesis is composed of my original work, and contains no material previously published or written by another person except where due reference has been made in the text. I have clearly stated the contribution by others to jointly-authored works that I have included in my thesis.

I have clearly stated the contribution of others to my thesis as a whole, including statistical assistance, survey design, data analysis, significant technical procedures, professional editorial advice, financial support and any other original research work used or reported in my thesis. The content of my thesis is the result of work I have carried out since the commencement of my higher degree by research candidature and does not include a substantial part of work that has been submitted to qualify for the award of any other degree or diploma in any university or other tertiary institution. I have clearly stated which parts of my thesis, if any, have been submitted to qualify for another award.

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Publications included in this thesis

Peer-reviewed papers:

Ossa-Moreno, J., McIntyre, N., Ali, S., Smart, J.C., Rivera, D., Lall, U. and Keir, G., 2018. The Hydro-economics of Mining. *Ecological Economics*, *145*, pp.368-379. – Incorporated as Chapter 2.

Submitted manuscripts included in this thesis

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Other publications during candidature

Peer-reviewed papers

Ossa-Moreno, J., McIntyre, N., Ali, S., Smart, J.C., Rivera, D., Lall, U. and Keir, G., 2018. The Hydro-economics of Mining. *Ecological Economics*, *145*, pp.368-379. – Incorporated as Chapter 2.

McIntyre, N., Angarita, M., Fernandez, N., Camacho, L., Pearse, J., Huguet, C., Restrepo, O., Ossa-Moreno, J. (2018) A framework for assessing the impacts of mining development on regional water resources in Colombia. *Water* 10 (3), 268.

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Conference papers:

- Ossa-Moreno, J., Keir, G. and McIntyre, N., 2016, April. *Bayesian spatiotemporal interpolation of rainfall in the Central Chilean Andes*. In EGU General Assembly Conference Abstracts (Vol. 18, p. 10533).
- Ossa-Moreno, J., Keir, G. and McIntyre, N., 2017, September. *Hydro-economic modelling in mining regions: A case study in the Aconcagua Catchment*. In 4th Water Research Conference Abstracts.
- Ossa-Moreno, J., Keir, G. and McIntyre, N., 2017, September. *Hydro-economic modelling in mining regions: A case study in the Aconcagua Catchment*. In International River Symposium Proceedings, Brisbane, Australia.
- Ossa Moreno, J.S., McIntyre, N., Rivera, D. and Smart, J.C.R., 2017, December. *Hydro-economic modelling in mining catchments*. In AGU Fall Meeting Abstracts.
- Ossa Moreno, J.S., McIntyre, N., Rivera, D. and Smart, J.C.R., 2018, May. *A hydro-economic model of the Aconcagua basin: sensitivity of economic outcomes to climate and other uncertainties*. *Gecamin Water Congress 2018, Santiago, Chile.*
- Ossa Moreno, J.S., McIntyre, N., Rivera, D. and Smart, J.C.R., 2018, September. *Sensitivity of a hydro-economic model in a mining region to changes in hydrological and economic inputs*. In Life of Mine Conference, Brisbane, Australia.

Contributions by others to the thesis

Dr Neil McIntyre (Principal PhD Supervisor) contributed to the design of the PhD, advised on the hydrological modelling methods used and provided advice on the content of all chapters of the PhD document.

Dr Greg Keir contributed by suggesting the methods for the interpolation of climate variables and their implementation as scripts in R.

Dr James Smart (Associate PhD Supervisor) provided guidance on economic analysis during the project and reviewed the document sections related to this field.

Dr Josue Medellin-Azuara (Associated PhD Supervisor) provided support with the development of the Positive Mathematical Programming model for the analysis of the agricultural users in the case study.

Dr Diego Rivera provided feedback on the local context of water resources management in Chile.

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Roger Higgins provided editorial support and editing of the document, and a mining perspective.

Statement of parts of the thesis submitted to qualify for the award of another degree

No works submitted towards another degree have been included in this thesis.

Research Involving Human or Animal Subjects

No animal or human subjects were involved in this research.

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List of Abbreviations used in this thesis

ACC	Annualised Capital Costs
API	Application Programming Interface
CUA	Canal User Associations
CAPEX	Capital Expenditure
CR2	Chilean Centre for Climate Science and Resilience
CLP	Chilean Peso
CHIRPS	Climate Hazards Group InfraRed Precipitation with Station Data
CGE	Computable General Equilibrium
CES	Constant Elasticity of Subsitution
CPI	Consumer Price Indices
CEN	Coordinador Electrico Nacional, Chilean Natioal Energy Coordinator
DEM	Digital Elevation Model
DGA	Direccion General de Aguas, Chilean General Water Directorate
DMC	Direccion Meteorologica de Chile, Chilean Bureau of Meteorology
ENSO	El Nino-Southern Oscillation
EFR	Environmental Flow Requirement
GAMS	General Algebraic Modelling System
GLMM	Generalised Linear Mixed Model
GLMM	Generalised Linear Model
HPC	High Peroformance Computing
HEM	Hydro-economic Model
INE	Instituto Nacional de Estadisticas, Chilean Bureau of Statistics
INIA	Instituto Nacional de Investigaciones Agroupecuarias, Chilean Agricultural Research Institute
INLA-SPDE	Integrated Nested Laplace Approximation - Stochastic Partial Differential Equation
IDW	Inverse Distance Weighting

LR	Lapse Rates
LOOCV	Leave-one-out cross validation
MARE	Mean Absolute Relative Error
MERRA	Modern Era Retrospective Analysis for Research Applications
ML	Megalitres
NSE	Nash-Sutcliffe Efficiency
ODEPA	Oficina de Estudios y Politicas Agrarias, Chilean Bureau of Agricultural Policy and Research
OPEX	Operational Expenditure
PMP	Positive Mathematical Programming
PET	Potential Evapotranspiration
PDF	Probability Distribution Function
QCIF	Queensland Cyber Infrastruction Foundation
PeCAPEX	Ratio of CAPEX to Total Costs
RH	Relative Humidity
RUC	River User Committee
SRTM	Shuttle Radar Topography Mission
SWE	Snow Water Equivalent
SMM	Soil Moisture Model
SWAP	State Wide Economic Agricultural Production Model
TSF	Tailings Storage Facility
TW	Tailings Water
WEAP	Water Evaluation and Planning
WR	Water Right
WC	WorldClim
WCA	WorldClim Adjusting

1. Introduction

Conflicts for access to water resources between different users (e.g. mining and agriculture), are an issue in many parts of the world (Young and Loomis, 2014, Morgan and Orr, 2015, Grafton et al., 2011). These conflicts tend to arise when the demand for water exceeds the available supply, when different users require water at different times (Rivera et al., 2016), and when discharges of poor quality water affect other users (Baresel et al., 2006, Younger and Wolkersdorfer, 2004).

The mining industry, a significant consumer and potential polluter of water, is often at the centre of conflicts. Some of the triggers of these conflicts, including water scarcity and surplus (Northey et al., 2014, Barrett et al., 2014), and the negative impacts of mining on water quality (Kuipers et al., 2006, Lovingood et al., 2004, Amezaga et al., 2010, Dold, 2014), have received attention from researchers. However, water resources management with a catchment scale approach in mining regions has received less attention (ICMM, 2012, Kunz and Moran, 2014).

A regional scale approach should include water resources supply and demand modelling, in order to provide detailed information that facilitates planning and operational decision-making by users and government agencies. An economic assessment of the latter is desirable in order to better simulate users behaviour when facing drought, and to facilitate the comparison of the benefits and costs of strategies to improve water resources management. This PhD project integrates mining water uses into a regional hydro-economic model to achieve this goal.

The term ‘hydro-economics’ may be defined as the discipline of understanding current and potential economic value of water, using hydrologic, economic and social variables, and their interaction with water allocations catchment-wide. This field of research has increasing prominence (Harou et al., 2009, Brouwer and Hofkes, 2008, Cai, 2008), partly due to the emphasis placed on water as an economic good (United Nations, 1992), and partly due to the increasing need for improving water management and promoting transparent and accountable water decision making (Morgan and Orr, 2015).

Hydro-Economic Models (HEMs) are made of two components and a coupling methodology (see Figure 1.1). The first component addresses the physical processes in the hydrological cycle, demand for water, and operation of water infrastructure, amongst others. This includes modelling the temporal and spatial dynamics of precipitation, and the way it turns into runoff or groundwater, to become available for users. It may also include uncertainty analysis and potential future changes in climate conditions.

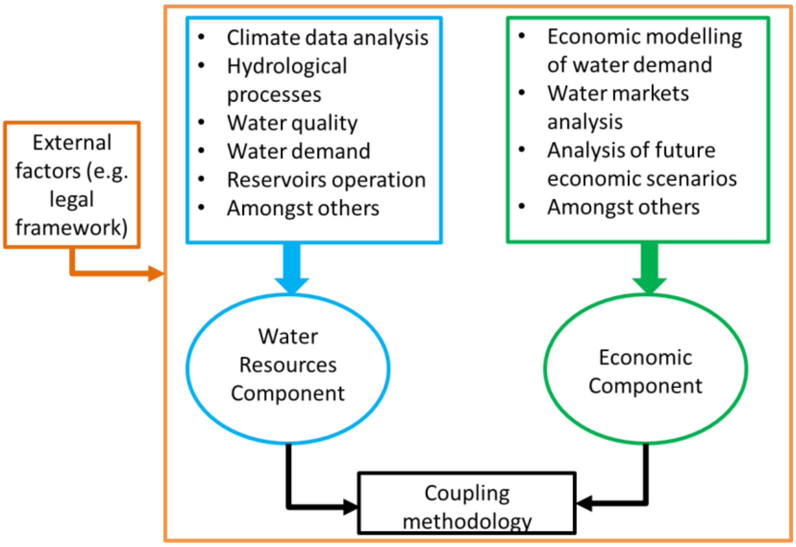

Figure 1.1 – Schematic of the components of a Hydro-Economic model (Adapted from (Ossa-Moreno et al., 2018)).

The second component addresses the economic values that users obtain from water. This may go beyond market prices (WBCSD, 2013), as water abstractions can be free, subsidised, or rated below the real derived value. This analysis allows the exploration of the trade-offs between using water for mining or other purposes, including environmental flows (Kunz and Moran, 2014). The economic values can also be calculated for current and future scenarios, and they may include direct and indirect economic effects.

The coupling methodology merging the two components involves the definition of spatial and time scales, the type of links between components, and other model design decisions (Cai et al., 2006). Furthermore, the links between components may be constrained by legal frameworks that restrict the allocation, trade and use of water, and other external conditions. Depending on the modelling requirements there may be trade-offs between components (Bekchanov et al., 2015). For instance, detailed water availability estimates may only be possible with high spatial resolution hydrological models. Such spatial detail, however, may be cumbersome for the economic analysis, which is often undertaken in a more aggregated scale. This highlights the existing challenge of defining an optimal combination of components.

Common outputs of HEMs include economic metrics such as the total value of water for users in the catchment, water scarcity cost (i.e. the value of the volume required not to make water the constraining resource for users) and shadow values[1] (Harou et al., 2009, Medellín-Azuara, 2006, Cai et al., 2006). These values may be useful for comparing degrees of water conflict between users, as they can contribute to assessing the potential level of satisfaction with determined allocations of water under different scenarios.

Although similar models have been explored by researchers to analyse agriculture, urban water supply, flood management and hydro-power (Harou et al., 2009, Bekchanov et al., 2015), relatively little has been done for mining. Bearing in mind the special characteristics of mining such as large revenues, potentially large environmental impacts, high social scrutiny, presence in remote areas with poor climate monitoring, etc., relevant and material challenges still exist when including mine water use in HEMs.

This project will address some of these challenges by developing a HEM that includes mine water use. To achieve this, concepts and features from HEMs will be first discussed in the literature review, outlining what should and should not be applied for mining taking into account the characteristics of this industry. Then, some of the challenges highlighted in that section will be addressed in the model, including issues with the lack of input climate data in remote mining regions, simulation of complex hydrological process and economic modelling of water users.

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[1] Shadow value or Shadow price or Accounting price, as defined in YOUNG, R. A. & LOOMIS, J. B. 2014. *Determining the economic value of water: concepts and methods*, RFF Press Routledge., is *"The value used in social or public economic analysis when the market price is unknown or judged not to be an appropriate measure of economic value".* This is usually estimated as the price users are willing to pay or give up, in order to obtain an additional unit of the good being valued.

1.1. Research question and hypothesis

The overall research question of this PhD project is: Can hydro-economic models help with the analysis of water conflicts and to support effective water resources management, in catchments with mining projects?

The hypothesis in turn is that despite the differences between mining and other users, and the lack of previous case studies, HEMs can be applied to the regions where this industry operates, and they can provide valuable insight to facilitate more informed water decision making.

This research could be approached from a purely planning stance to analyse greenfields, or from a planning and operating point of view for brownfields. Although both alternatives are relevant, it was decided to analyse the latter through a case study with an existing mining project in full operation. The former option represents an opportunity for future research.

1.2. Specific research questions and objectives

The research question was broken down into specific questions that will be answered in the chapters of this document.

- How applicable are established hydro-economic modelling concepts for analysing regions with mining projects, and what type of metrics should be used? (Chapter 2)
- How can climate data in remote regions, where mining is often located, be complemented with alternative datasets to facilitate the development of HEMs? (Chapter 4)
- What is the added value of a detailed representation of the water resources component in a HEM, compared to more simple approaches? (Chapter 5)
- How can both components of the HEM be merged without oversimplifying or over aggregating any of them? (Chapter 6)
- What type of insights could HEMs provide to water decision makers in mining regions, and could them help calculating the shared benefits of water resources between users in these regions? (Chapter7)

A set of objectives associated to each chapter is also included.

- Identifying the key challenges in applying hydro-economic models to mining regions and defining a set of metrics suitable for catchment scale approaches (Chapter 2).
- Facilitating the development of HEMs in remote mining regions by analysing alternatives to point measurements as climate data inputs (Chapter 4).
- Developing a HEM for a region with mining presence without oversimplifying the water resources component (Chapter 5 and 6).
- Using the HEM to understand the sensitivity of the catchment and its water users to changes in:
    - Climate conditions (Chapter 7).
    - Environmental flow requirements (Chapter 7).
- Using the HEM to analyse the catchment-wide benefits of infrastructure alternatives to reduce water scarcity in the region (Chapter 7).

1.3. Limitations in the scope of this research

It is acknowledged that water resources decision-making is not only influenced by the outputs of models like the one in this project, but also by other factors such as those shown in Figure 1.2. Some of these, like the macro-economic variables, are more often analysed through Computable General Equilibrium (CGE) type of HEMs (van Heerden et al., 2008). However, CGEs tend to be undertaken at coarser spatial scales and tend to simplify the water resources component, thus, shifting the focus of the analysis to the economic realm. In addition, other factors in Figure 1.2 like water quality analysis could be included in future versions of the HEM.

Furthermore, although methods for the appraisal of ecosystem services are being refined (Cardoso, 2015, Li et al., 2011), many outputs of these analyses still have considerable ranges of uncertainty. In addition, other dimensions of anthropocentric value delivered by water systems (e.g. spiritual values) are still difficult to monetise. Thus, the non-market values associated with water, although they should still be part of water decision making in mining regions, are outside the scope of the HEM.

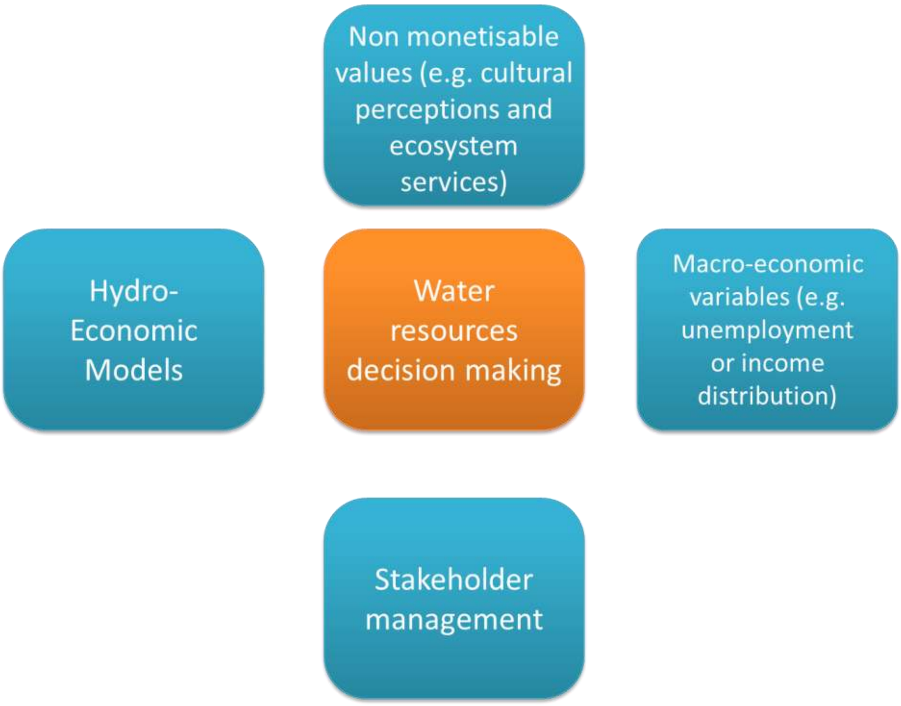

Figure 1.2 – Example of components inside water resources decision making frameworks.

This means that the aim of the HEM developed in this project is not to encompass all possible aspects of the water decision making process. The key innovation here is to provide multi-disciplinary insights that support water resources management, and facilitate more informed decision making in mining catchments.

The target audience for this thesis comprises hydrological modellers, water resources modellers and economic modellers, and the greatest value from it may be delivered to professionals with all three backgrounds. Similarly, the outputs of the model are expected to support the work of mining water professionals who seek to better understand the users surrounding their projects, and the effects of their regional water stewardship[2] on those users.

However, this work also aims to help independent observers (e.g. governments or NGOs) better analysing the relationship between mining and other users, and how water conflicts can be mitigated or exacerbated by external factors and different water

[2] Water stewardship is understood as going beyond an efficient use of water, as it also includes collaborating with governments, other water users and communities to take a catchment scale approach in water decision making, in order to protect water resources.

management strategies. Finally, they results may also be used by other users to understand how synergies can be built with their counterparts in other sectors.

1.4. Clarification on Jargon

The concept of **“Water Demand”** has a double meaning in the water economics and water resources management literature. In the former, it represents a function of price that describes the volume of water that users are willing and able to buy at a particular price through a **water demand curve**. On the other hand, in water resources management it is used more loosely, to describe the volume of water that a user (or user group) considers to be sufficient in a specific context. The latter is different from water consumption, which is the volume of water that users receive.

In order to avoid confusion, in this document it was decided to use “***Water Demand***” in the water economics sense only, and use alternative concepts like “***Volume of Water Demanded***” or “***Demand for Water***” for the water resources management meaning.

Statement of contribution to the paper published in Chapter 2

Contributor	Statement of Contribution
Author Juan Ossa-Moreno	Conception and Design (90%) Analysis and Interpretation (80%) Drafting and Production (75%)
Author Neil McIntyre	Conception and Design (5%) Analysis and Interpretation (10%) Drafting and Production (5%)
Author James Smart	Analysis and Interpretation (5%) Drafting and Production (5%)
Author Saleem Ali	Analysis and Interpretation (5%) Drafting and Production (5%)
Author Diego Rivera	Drafting and Production (5%)
Author Upmanu Lall	Drafting and Production (5%)
Author Greg Keir	Conception and Design (5%)

2. Literature Review

This chapter summarises the main findings of the literature review and is presented as a publication in an academic journal. A full version of this paper is included in the appendix and the details of the reference are as follows:

Ossa-Moreno, J., McIntyre, N., Ali, S., Smart, J., Rivera, D., Lall, U. and Keir, G. (2018) The Hydro-economics of Mining. *Ecological Economics*, 145, 368-379.

It was not the scope of this review to do an exhaustive listing of available hydro-economic models, as this can be found in Harou et al. (2009) and Bekchanov et al. (2015), but to analyse literature on the applicability of hydro-economic models in mining catchments. Specifically the following were covered:

- The features of mining regions that make them challenging for hydro-economic modelling.
- The applicability of current hydro-economic concepts to mining.
- The potential opportunities from analysing mining through hydro-economic models.

The key findings of the review are as follows:

1. Mining has several differences (e.g. capital intensity, longevity of projects, social scrutiny) compared to other uses of water, and this calls for carefully analysing the metrics and methods used in HEMs, before using them in mining.
2. It is difficult to find one only metric that is useful to analyse all aspects of the value of water within a catchment scale approach, thus the use of a group of them may be the best alternative. This is particularly important for mining regions, as the sums of money involved in this industry may bias some metrics towards benefitting the mining user only.
3. Total revenues and revenues per volume of water consumed are relatively easy to calculate for mining users, but it is often more difficult to define net revenues as costs are difficult to calculate due to the confidentiality in the industry. Coarse estimations or industry-wide averages are sometimes the only alternatives.

4. Applying marginality concepts to define the economic value of water for mining is still to be tested academically, but these tools can be applied for alternative users, which is helpful for catchment scale approaches.
5. Willingness to pay and opportunity cost analyses are useful tools to assess the environmental impacts of mining. However, while the former may be more accurate, the latter are often easier to apply.
6. The current lack of HEM applications for analysing mining hinders critical assessment of the metrics and methods used to analyse mining demand for water, and the opportunities for catchments with mining projects to better manage their water resources. This is the key justification of this project, and based on this, it will be developed a case study to provide evidence to develop insights in this topic.
7. Climate and hydrological input data are key to develop HEMs that do not oversimplify the water resources component, and this can be an obstacle for analysing several mining regions remotely located, within poorly monitored catchments. This calls for the development of improved methods and the use of alternative datasets.
8. Before developing a HEM in a mining region, several considerations should be taken into account to tailor the design of the model to the scope of the analysis.
9. Mining has very often been a source of water conflicts between alternative water users, either because mining has not fully recognised the importance of water for other users, they have not accurately forecasted how their decision making will affect others, or because they have rarely tried to take a catchment-wide vision to manage their water infrastructure. HEMs in mining regions may represent an opportunity to address this, as they take a catchment scale approach that involves all the main economic users, allowing to quantify trade-offs of different water allocations and identify strategies to improve water resources management.

This review has defined the roadmap for this PhD project, as the model that will be explained in future Chapters addresses many, although not all, of the points discussed. In some cases, a trade-off between a broader analysis covering more features had to be balanced with the desire of producing a quantitative and not overly complex model. Many features not included in the model are discussed throughout the published paper referenced at the beginning of this chapter, and it is mentioned how future works could address them. The literature review of the methods to analyse climate variables and the hydrological model is presented in other sections. A full version of the academic publication related to this chapter can be found in Appendix A.

3. The Case Study – the Aconcagua River

This chapter provides an overview of the catchment while further details on hydrology, volumes of water demanded, and other features are provided in future chapters.

The Aconcagua River is located in Central Chile in the Valparaiso region (see Figure 3.1 and Figure 3.2). As most rivers on the western slopes of the Andes, this one is relatively short (compared to those on the eastern slopes), and starts in the mountains in the border between Chile and Argentina. Then, it flows west to discharge into the Pacific Ocean near the city of Concón.

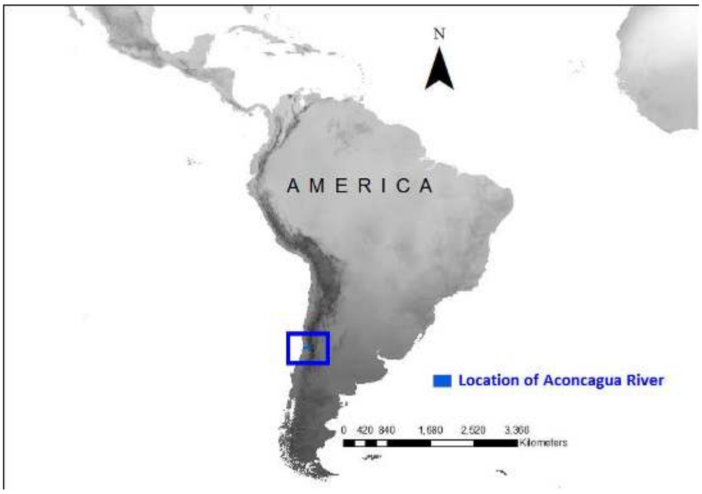

Figure 3.1 – Global location of the case study.

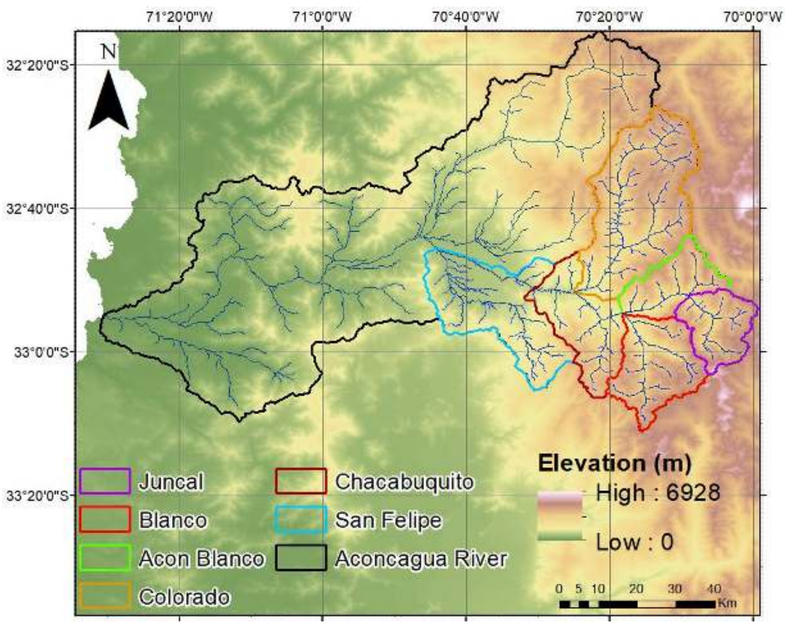

Figure 3.2 – Detailed view of the Aconcagua River and the upper section, which is the main focus of this project.

3.1. Overview of Climate and Hydrology

Central Chile is a semiarid region with a yearly average precipitation of around 350 mm, most of which falls between April and September as frontal rainstorms. The South Pacific Anticyclone hinders the occurrence of precipitation in the region in the austral summer, but it retreats during the winter (Falvey and Garreaud, 2007). There is also inter-annual variability in the region related to El Niño and La Niña phases, with the former usually generating above-average precipitation during winter, and the latter the opposite effect (Montecinos and Aceituno, 2003).

Topography in the catchment oscillates from coastal areas to mountains up to around 6000 m above sea level in the Andes, with coastal ranges in between. The whole area of the catchment is approximately 7300 km^2, and it is divided in five sections as shown in Figure 3.3. The upper section of the River (1st Section) will be used as the case study of this project, although the water resources component will be run up to the DGA[3] flow gauge ***Rio Aconcagua en Chacabuquito*** (see *Chacabuquito* area in Figure 3.2).

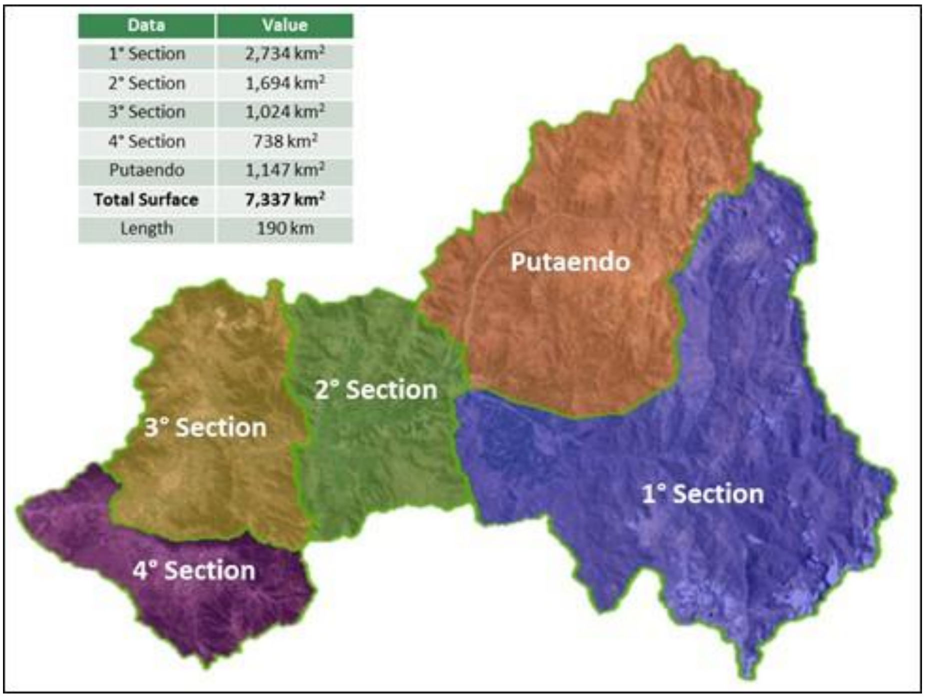

Figure 3.3 – Sections in the Aconcagua River. Taken from (Figueroa San Martin, 2016).

[3] Dirección General de Aguas (General Water Directorate) the most relevant government institution in charge of water issues in Chile.

The main tributaries of the river are the Blanco, Juncal and Colorado Rivers (see Figure 3.3), and it is after the first two merge than most people start referring to the river as the Aconcagua.

3.2. Overview of Land Use and Demand for Water

This upper section of the Aconcagua River was chosen as the case study as it contains mining, urban, agricultural and hydro-power users, thus allows an analysis of several users through the HEM. Although water conflicts exist in all sections, it was decided not to analyse the whole river as it was desired to focus the model on the relationships between mining and other users. If the whole catchment was analysed, urban, mining and hydro-power demand could have been diluted by the much larger agricultural consumption in the five sections downstream, which would have shifted the focus of the analysis towards the latter only.

The upper section, and the catchment in general, is of particular importance to Chile due to the high number of economic activities that are developed within it, many of which have a relevant participation in the national economy. This contrasts with the arising issues of decreasing availability of water resources and the complexity to predict flows (Pellicciotti et al., 2007), both of which hinder managing water resources in the catchment.

3.3. The Chilean Water Policy Context

The water legislation in Chile is mainly based on the 1981 Water Code and the 2005 Water Reform (Hearne and Donoso, 2014, Donoso, 2015, Grafton et al., 2011, Thobanl, 1997), although further amendments have been undertaken in other years, the most recent being in 2018. Briefly, despite being considered a public good, water management is based on a system of Water Rights (WR - see Chapter 2), in which abstraction and consumption are regulated by the conditions of the WRs (Donoso, 2015, Grafton et al., 2011).

These rights can be traded as any other private good through a market system where users can buy and sell different types of WR. These includes consumptive, non-consumptive, permanent, temporal, continuous and sporadic rights.

River User Committees (RUCs) are responsible for maintaining infrastructure, managing WRs and settling disputes between users as a first instance, although, the DGA and the judicial system may intervene in special cases. There is one RUC for every section in the Aconcagua River, but there are also Canal User Associations (CUAs) and Water Communities that group users in the same irrigation channel or nearby areas.

Currently, the volumes of water demanded in the catchment (i.e. existing WRs) often exceeds the supply, and some sections were declared legally depleted (no further WRs can be emitted) as water has been over allocated (Hidrometria-Chile, 2012). During some dry periods the RUC of the first section has placed legal restrictions on users in the case study, in order to face the lack of water supply. In addition, during particularly dry periods, the DGA has intervened to settle disputes between RUCs, which involves defining strategies to redistribute the limited water resources available (Hidrometria-Chile, 2012). Furthermore, should users wanted to increase their production, this may further exacerbate conflicts for access to water resources (Rivera et al., 2016).

These issues summarise the challenges to manage water resources in the area, and highlight the desirability of improved tools to better understand water from hydrological and economic points of view. This is particularly important in the context of an ongoing discussion of further reform to the water code in the last years in Chile, which amongst others, expects to address the challenge of restoring environmentally affected streams through minimum flow requirements.

3.4. Mining Demand for Water in the Case Study

The mining presence in the upper Aconcagua comprises one large-scale copper mine (Codelco Division Andina in the Blanco River). Another mine (Anglo-American Los Bronces) in a nearby catchment has water rights (WR) inside the upper Aconcagua as well (both mines are amongst the 10 largest in Chile by production). This is not a region with multiple mine projects (e.g. Hunter Valley in Australia or Antofagasta region in northern Chile), nor a region with intensive artisanal or small-scale mining, but it is a region with water conflicts between mining and other users.

As detailed in Chapter 5, the water consumption of the Andina Mine is around one quarter of the whole consumption from the agricultural sector. This means that although mining is not the largest user of water in the catchment (this mine may be the largest single user though), it is a very important one, thus deserves special attention from a hydro-economic point of view.

A mine water balance of the Andina project is shown in Figure 3.4. It can be seen that the largest consumption occurs in the concentrator plant (2000 l/s), although most of the water used in this process comes from recycled water after the tailings are thickened. Water is also used in the open pit and in the copper filtration processes.

On the other hand, there are two main outputs from the mine. The first is a 67 l/s discharge after the copper filtration process, which is treated before being released. In addition, water also ends up in the Tailings Storage Facility (TSF), as the thickening does not remove all the water from the tailings. The latter is the largest loss in the system, and this water is stored in a TSF outside of the Aconcagua in the Maipo catchment, where it evaporates.

This mine site has plans to increase its production capacity, and this would involve increasing the supply of water. Currently, recycling of tailings water is seen as one of the most likely options to address this, however, most feasibility analyses have been focused on calculating the benefits that this project would bring to the mine only, and not how this could benefit the whole catchment. This and other challenges in water resources management in the region will be explored in Chapter 7.

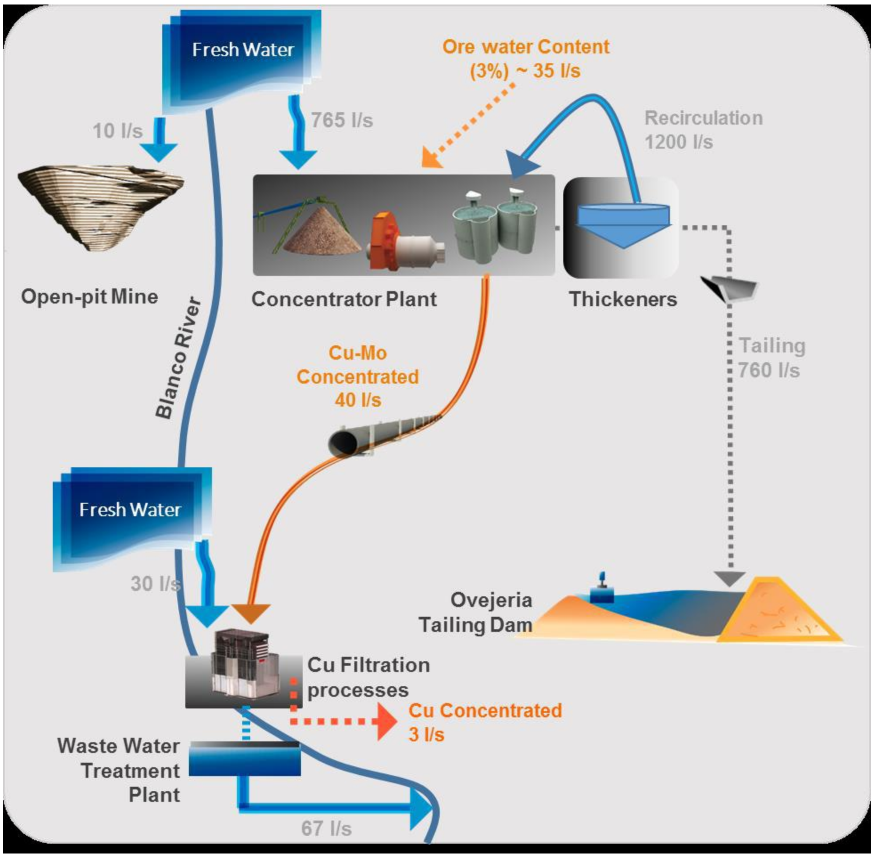

Figure 3.4 – Mine water balance of the project inside the Aconcagua River. Taken from (Correa Ibanez, 2015).

Statement of contribution to the paper submitted in Chapter 4

Contributor	Statement of Contribution
Author Juan Ossa-Moreno	Conception and Design (80%) Analysis and Interpretation (80%) Drafting and Production (80%)
Author Greg Keir	Conception and Design (15%) Analysis and Interpretation (5%)
Author Neil McIntyre	Conception and Design (5%) Analysis and Interpretation (7.5%) Drafting and Production (7.5%)
Author Michela Cameletti	Analysis and Interpretation (7.5%) Drafting and Production (7.5%)
Author Diego Rivera	Drafting and Production (5%)

4. Developing Improved Climate Variables for the Case Study

This chapter describes the analysis done on climate data, to facilitate its use as inputs of the Hydro-Economic Model (HEM). This section is based on the following publication:

Ossa-Moreno, J., Keir, G., McIntyre, N., Cameletti, M. & Rivera, D. (2018) Comparison of approaches to interpolating climate observations in steep terrains with low-density gauging networks. *Hydrology and Earth System Sciences - HESS* (submitted)[4].

The purpose of this chapter was to address one of the key challenges of implementing HEMs in mining regions, as highlighted in the Literature review: the lack of input data of acceptable quality. Although not necessarily a problem in all mining regions, this is a major obstacle in several of them worldwide, as mineral resources are often located in remote regions, and/or in countries lacking the funds to maintain high-quality networks of climate gauges. Several mining catchments throughout the Andes are a primary example.

This is not a problem for HEMs only, but for other analyses involving climate inputs as well (e.g. Environmental Impact Assessments - EIA). A consequence of this is that modellers are sometimes forced to oversimplify the water resources component in the HEM.

The objective here was to analyse different alternatives to interpolate point observations of climate variables, in order to select the one that better reproduced the climate dynamics in the catchment, and to support this by including alternative supporting datasets. Although results are specific for the case study, the methodology can be replicated elsewhere as the selected datasets are available worldwide.

A priori, it was desired to develop interpolated datasets of precipitation and temperature at a relatively high spatial and temporal resolution, to avoid climate inputs

[4] As of May 2019, this paper has been accepted as a HESS Discussion paper and is available at: https://www.hydrol-earth-syst-sci-discuss.net/hess-2018-505/
Also, the reviewers provided feedback and the paper was re-submitted after addressing their comments. The final decision is pending.

being a limiting factor in the development of the HEM. For reasons related to the economic component and the coupling methodology, which will be addressed in subsequent chapters, the HEM used climate inputs with a coarser resolution than the results in this chapter (see Chapters 5 and 6). This required aggregating climate results, sacrificing some of the value of the methods and alternative datasets tested here.

Nevertheless, it was decided to include the full explanation of the analysis of climate variables in this Chapter, in order to provide evidence of the results found, as HEMs in other catchments may benefit from the use of the interpolation approaches or the alternative datasets tested.

The Chapter includes a brief review of literature on interpolation of climate variables, and a description of the input data and the methodologies used. Then, results are presented and discussed. Finally, some closing remarks are included to explain how the data generated will be used in the development of the HEM.

4.1. Interpolation of climate variables in mountain regions – Literature Review

Climate variables such as temperature and precipitation are key inputs for hydrological modelling and water resources management. Generally, spatial interpolation of point observations is a necessary part of developing the climate inputs of models. Many interpolation approaches perform well for gentle terrains, however, their accuracy and precision decreases in mountain areas (Wu and Li, 2013, Frei, 2014, Buytaert et al., 2006).

As highlighted by Dorninger et al. (2008), challenges include observation errors, anisotropic climate patterns and sensitivity of results to density and location of observations. Strongly non-linear relations between temperature and altitude may be related to physiographic features (Stahl et al., 2006), to cold-air trapped in enclosing hill ranges (Frei, 2014), and also to the presence of glaciers (Ragettli et al., 2014). For precipitation, non-linearity can be related to physiographic features (Daly et al., 2008), to the interaction between topography and rain-storms (Falvey and Garreaud, 2007, Garreaud, 2013) and to summertime convective precipitation events (Viale and Garreaud, 2014).

The Andes Cordillera in South America is an example of a steep terrain with complex weather conditions. This mountain range is an important source of natural resources, including water for agriculture, mining and other industries. The stream-flows in the region are highly variable in both time and space (Pellicciotti et al., 2007, Mernild et al., 2017, Montecinos and Aceituno, 2003, Viale and Garreaud, 2014), therefore under such circumstances, quality of spatial climate data is a key issue when modelling water resources (Zambrano-Bigiarini et al., 2016, Mernild et al., 2017).

This challenge is further complicated by the lack of gauges (i.e. when compared to mountain regions in Europe or North America), particularly at high elevation points. As a consequence, several hydrological and water resources models in some regions of the Andes, such as central Chile, have applied deterministic interpolation approaches such as Lapse Rates (LR) (Ragettli and Pellicciotti, 2012, Ragettli et al., 2014, Vicuña et al., 2011, Stehr et al., 2008, Correa-Ibanez et al., 2017) to define climate inputs. Although easy to apply, LR in hydrological applications is usually a linear or logarithmic regression using elevation as the only covariate (Ragettli and Pellicciotti, 2012), and hence does not aim to maintain the spatial correlation between observations or to fully explore the spatial dynamics of the climate variables. Therefore, there is an increasing interest in the use of improved interpolation approaches together with alternative sources of data, beyond point observations, such as satellite and other gridded products (Manz et al., 2016, Zambrano-Bigiarini et al., 2016, Dinku et al., 2010, Hobouchian et al., 2017, Demaria et al., 2013).

In the Andes, Álvarez Villa et al. (2011) tested four stochastic interpolation approaches in Colombia and found that Kriging with External Drift (using long term averages of the Tropical Rainfall Measuring Mission - TRMM as the drift term) had the best performance, with RMSEs between 519 and 866 mm, however this analysis was restricted to annual precipitation estimates.

In Castro et al. (2014) the authors developed a deterministic method that separated the analysis of occurrence and magnitude of events, and that took into account the influence of topography (i.e. slope orientation and wind direction) to interpolate daily precipitation values in a catchment in central Chile. The authors found that this method outperformed inverse distance weighting (IDW) and other simple methods. This analysis was restricted to gauges below 1000 masl thus conclusions may not be valid for higher elevation points. This is a common limitation in the south Andes where there are few gauges above this elevation.

In Manz et al. (2016) the authors analysed a database of 735 gauges in Bolivia, Peru, Colombia and Ecuador (including 455 gauges above 1000 masl in the tropical Andes) and merged them with the Tropical Rainfall Measuring Mission Precipitation Radar product (TRMM 2A25). The authors used deterministic (including IDW of residuals between monthly precipitation observations and satellite estimates) and Kriging methods (including KED using mean monthly TRMM 2A25 values as the external drift term). It was found that for this case study, KED had the best performance amongst the Kriging methods, that the overall performance of Kriging methods was similar to the interpolation of residuals to estimate monthly precipitation values, and that this interpolation of residuals was less sensitive to low gauge densities. In that study performance was assessed using leave-one-out cross validation of the gauges, using metrics such as RMSE, and runoff ratios.

A broader review of the performance of satellite products for estimating precipitation in the Andes and other mountain areas (Nikolopoulos et al., 2013, Thiemig et al., 2012, Dinku et al., 2014), suggests that in these regions, satellite products tend to be good at detecting precipitation (except in very dry areas (Zambrano-Bigiarini et al., 2016, Manz et al., 2016)) and its overall spatial variability. However, they struggle to accurately predict the magnitudes of the events, particularly during extremely dry (e.g. in the north of Chile (Zambrano-Bigiarini et al., 2016)) or extremely wet regions (e.g. western slopes in the Colombian Andes (Dinku et al., 2010)), and for daily and subdaily resolutions (Dinku et al., 2010, Manz et al., 2016, Thiemig et al., 2012).

In a comprehensive analysis of precipitation estimates from satellite products in Chile, Zambrano-Bigiarini et al. (2016) found that the satellite product PGFv3 exhibited the best overall performance for the country, followed by CHIRPS, TMPA 3B42V7 and MSWEPv1.1. The authors mention that the superior performance of PGFv3 is likely due to the bias-correction of this product, which uses several gauges from Chile. The authors also found that for most products, the performance in central Chile was superior to that in the north of the country (the driest region), that better results were achieved during the wet season and that errors were lower in areas below 1000 masl.

In a similar analysis using three satellite products with long historical data records (CHIRPS, TMPA and PERSIANN-CDR) to estimate precipitation and monitor droughts in Chile, Zambrano et al. (2017) found that there were no major differences in the performances of the three products except in the southern most part of the country where PERSIANN-CDR highly underestimated values. The authors also confirmed that errors are lower during the wet season and in relatively humid parts of the country. In these two papers there was no interpolation or merging of satellite products and gauge data, but the authors recommended site-specific analyses before using satellite products in hydrological models. Furthermore, the authors also mentioned the limitations due to the lack of observations at higher elevation points.

In Alvarez-Garreton et al. (2018) authors describe CR2MET (DGA, 2017), a gridded product for Chile, which includes precipitation and temperature. This dataset was developed based on logistic (for precipitation occurrence) and linear (for precipitation magnitudes and temperature) regressions using covariates such as topography, slope, ERA-Interim reanalysis variables (Balsamo et al., 2015) and in the case of temperature, MODIS satellite data were also used. Estimates of both variables on a 5 km grid were generated, however, performance metrics, particularly at high elevation gauges, were not reported. There are few other analysis of temperature interpolation in the Andes, compared to other regions (Frei, 2014, Wu and Li, 2013). However, there are global gridded datasets such as WorldClim (Hijmans et al., 2005), which are based on regressions using observations from around the world (further details of this product are given in Section 4.2.3).

This review highlights that there is still a lack of knowledge of how to interpolate point observations at high elevations in the sparsely gauged sub-tropical Andes, and how this process can be supported on a catchment-specific basis by using alternative sources of data. Furthermore, it is not clear what approaches are more suitable for merging different datasets under these conditions (e.g. deterministic or stochastic), particularly when compared to simple alternatives such as LR often used to support hydrological and water resources models in this region.

It is not in the scope of this chapter to compare several stochastic interpolation methods such as in Nerini et al. (2015) or Álvarez Villa et al. (2011); rather the chapter selects one stochastic methodology (see Section 4.3.1) as representative of a complex, computationally expensive approach, for comparison with simple deterministic alternatives.

4.2. Case Study and Input Data

The Aconcagua River is an important source of water in Central Chile (Pellicciotti et al., 2007). The source is located in the Andean mountains near the border of Chile and Argentina, and the river flows west towards the Pacific Ocean. Topography fluctuates from coastal areas to peaks of approximately 5900 m above sea level. The catchment has an area of approximately 7500 km^2; however, the upper section, which is the subject of this research, is only around a third of this and includes the Andean mountains and a portion of the central valley (see Figure 4.1).

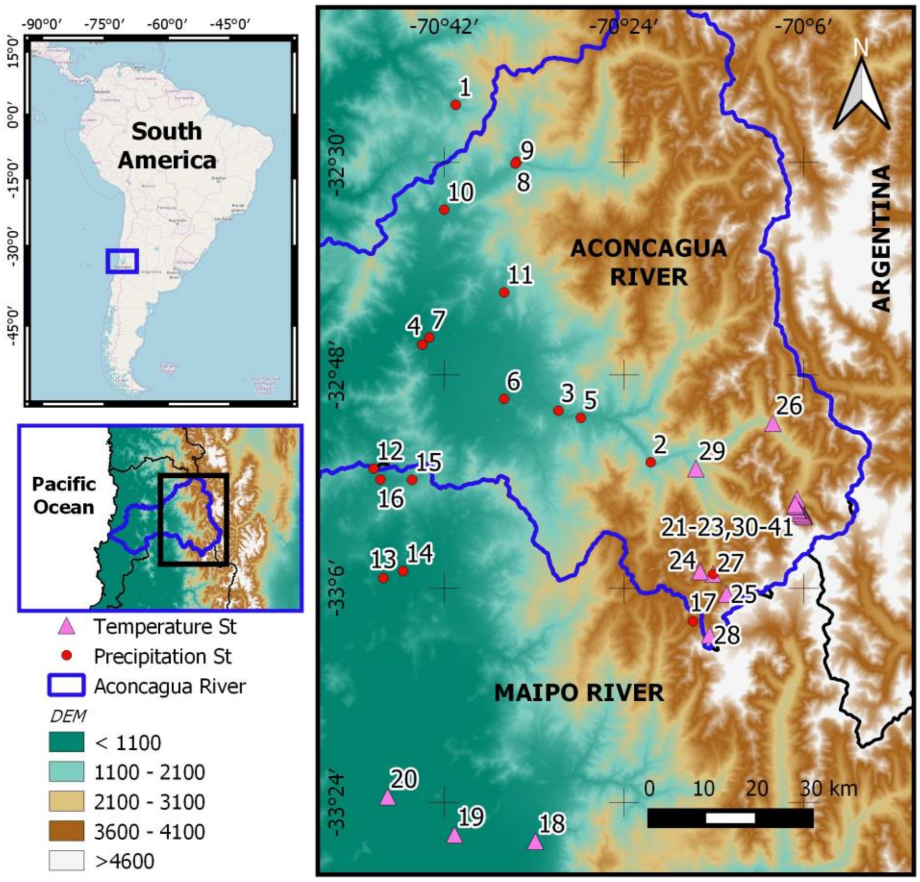

Figure 4.1 – Temperature and precipitation gauges in the catchment with available data during the period of analysis. Further details of the gauges are provided in the Appendix. Taken from (Ossa et al., 2018).

4.2.1. Climate Settings

Climate within the Aconcagua catchment is Mediterranean, close to semi-arid conditions (Ohlanders et al., 2013). Annual average precipitation is approximately 350 mm, however, most of this is concentrated during the austral winter (frontal rainstorms during June, July and August), when the South Pacific Anticyclone retreats from the region (Falvey and Garreaud, 2007, Montecinos and Aceituno, 2003). This is complemented by occasional convective storms (Garreaud et al., 2009, Viale and Garreaud, 2014). Furthermore, precipitation is also highly influenced by the orographic effects on the windward slope of the Andes (Viale and Garreaud, 2015). The occurrence of solid or liquid precipitation is determined by the location of the zero isotherm during winter, however, above 3000 masl, low temperatures prevail and precipitation is mostly snowfall. This thermal regime allows a relevant presence of snowpack and glaciers (e.g Juncal Norte) (Janke et al., 2017, Ohlanders et al., 2013).

There is considerable inter-annual variability related to El Niño and La Niña phases (ENSO) (Garreaud et al., 2009). La Niña is an anomalous cooling of the southeastern Pacific leading to dry conditions in Central Chile when the Pacific Anticyclone strengthens, while wet conditions occur during El Niño (Montecinos and Aceituno, 2003, Pellicciotti et al., 2007). Inter-decadal variability related to the Pacific Decadal Oscillation may also affect the case study, although the causes and impacts of these low-frequency fluctuations are less understood than those of ENSO (Garreaud et al., 2009).

Streamflow peaks at the beginning of the austral summer, although it remains high between late spring and summer (Pellicciotti et al., 2007) (i.e. the dry season). This means that during this period almost all runoff comes from snowmelt and glacier melt, although the contribution from the latter seems to be relevant during very dry years only (Ohlanders et al., 2013).

4.2.2. Precipitation and Temperature Gauges

Observations of daily average temperature and precipitation in the catchment were sourced from the Chilean General Water Directorate (DGA) and the Chilean Meteorological Directorate (DMC), through the Chilean Centre for Climate and Resilience Research. Most of these gauges are located in lowlands, whereas the mountain areas are sparsely monitored with the only available gauges sourced from mine projects in the area. Amongst these high-elevation gauges operated by mining companies, there are two that record liquid and solid precipitation (sites 27 and 17, see the Appendix for more details). The latter were transformed to snow water equivalents (SWE) before being analysed here.

This data were complemented with information from Universidad de Chile (Ohlanders et al., 2013) (available for some months only) and with measurements done by ETH-Zurich in the 2008-2009 summer season (sites 21-23 and 30-41 in Figure 4.1) (Ragettli and Pellicciotti, 2012, Pellicciotti et al., 2010). The latter was available during a very short period, but the measurements were done nearby a major glacier and in a different sub-catchment from the one where the private companies installed their gauges. Thus, they provide valuable information to test the interpolation approaches.

A total of 42 gauges were used in the project, 18 of them measured precipitation and 24 measured temperature. The 42 gauges covered 41 sites, with one site (site 27) having both temperature and precipitation gauges. The locations of the temperature and precipitation gauges are shown in Figure 4.1, while further details of the gauges (including the periods with information available and the percentage of missing values) are provided in the Appendix.

The period of analysis spans from September 2008 to August 2013 as the data obtained from the high elevation gauges was restricted to these years. Although not long enough to analyse long-term trends, the selected period allows testing of the interpolation approaches over both dry and wet years. Figure 4.2 provides an overview of the data by showing the monthly average temperature at four representative gauges over the five year period of analysis, and the monthly precipitation at three representative gauges throughout the same period (see Figure 4.1 for the location of these gauges).

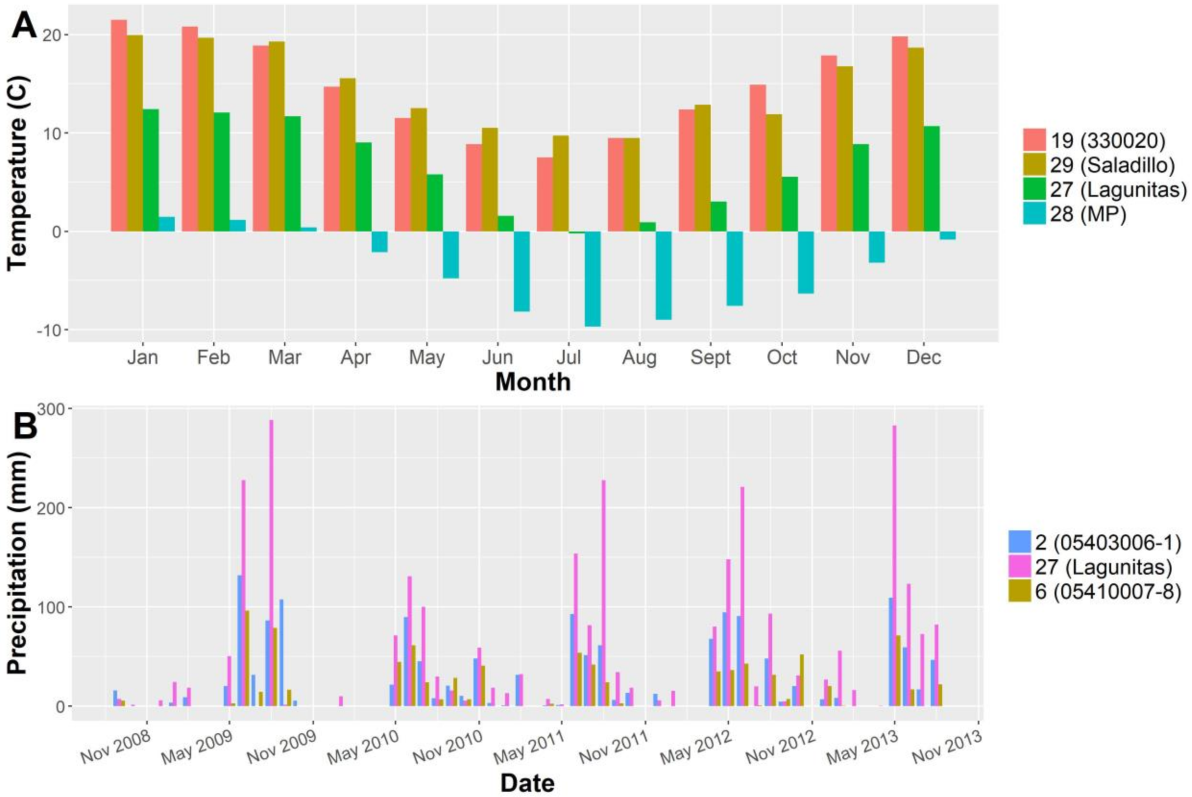

Figure 4.2 - (A) Monthly temperature averaged over the period of analysis, 09/2008 - 08/2013, for four of the gauges in the catchment (B) Monthly precipitation in the period of analysis for three of the gauges in the catchment. The numbers in the legend correspond to those in Figure 4.1, while the texts in parenthesis are the names of the gauges. 330020 (527 masl), Saladillo (1580 masl), Lagunitas (2765.5 masl), MP (4250 masl), 05410007-8 (820 masl) and 05403006-1 (1290 masl). Taken from (Ossa et al., 2018).

Quality control of climate data was done by analysing double mass plots and Pearson correlation values with patron gauges (e.g. long-term gauges previously used by academic and government sources (Jacquin and Soto-Sandoval, 2013, Ragettli et al., 2014, Correa-Ibanez et al., 2017)). This led to the exclusion of precipitation measurements at sites 26 and 29 (the temperature measurements at these sites did not show any anomaly). No further issues with data quality were noted.

4.2.3. Spatially distributed datasets

To complement the point observations, the Climate Hazards Group Infrared Precipitation with Station data (CHIRPS) satellite product (Funk et al., 2015) was used. Although there is a wide range of products available, this selection was done taking into account the good performance of this product in Chile, as reported by Zambrano-Bigiarini et al. (2016), and its spatial resolution (0.05° pixels). Most other products (e.g. TMPA 3B42v7, MSWEP and PGFv3) are relatively coarse for the size of the catchment (0.25 ° pixels). A sample image illustrating CHIRPS' resolution compared to the size of the case study is presented in Figure 4.3. CHIRPS does not include estimates of temperature and therefore was only used to support interpolation of precipitation.

The WorldClim (WC) Version 1 maps (Hijmans et al., 2005) were a further source of data (see Figure 4.3). WorldClim was suitable due to its spatial resolution (1 km), because it provides both temperature and precipitation values, and as for CHIRPS, because it is available worldwide and so may be used to support interpolation in any case study.

WC data provide a historical average for each one of the 12 calendar months (one map for every month) and originates from a statistical analysis of weather observations worldwide between 1950 and 2000, through an algorithm included in the ANUSPLIN interpolation package (Hutchinson, 2004), using latitude, longitude and elevation as independent variables in a regression. The developers of the WC data warn about its potential inaccuracies in mountainous areas (Hijmans et al., 2005). Therefore, the WC data were used only to complement point observations or as a benchmark for testing other interpolation approaches.

Although different in essence, both WC and CHIRPS can be used to complement to point observations to construct daily or monthly interpolated fields. None of the selected gauged data were used as input in the construction of WC or CHIRPS, furthermore the 5-year period of analysis here does not overlap with the period used to develop WC.

The third spatial dataset used was a Digital Elevation Model (DEM) based on the Shuttle Radar Topography Mission (SRTM) (Jarvis et al., 2008), with a spatial resolution of 90 m. The DEM was used to define the elevation in the catchment, in order to use this variable in some of the interpolation approaches. Finally, although not spatially distributed, a multivariate ENSO (El Niño-Southern Oscillation) index was included to analyse the inter-annual variability of precipitation in the catchment (Wolter and Timlin, 2011).

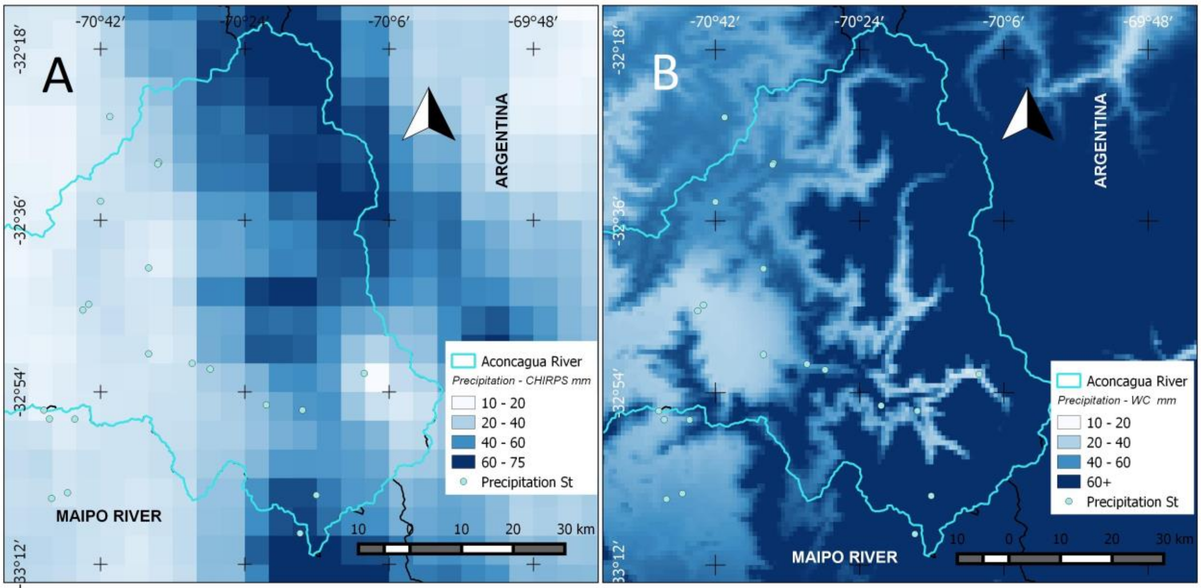

Figure 4.3 - (A) CHIRPS precipitation for May 2009 (B) Worldclim precipitation values for May (long-term average). Taken from (Ossa et al, 2018).

4.3. Interpolation of Climate Data

A stochastic approach, a Generalised Linear Mixed Model (GLMM), was compared to simpler deterministic approaches: IDW and LR (Pellicciotti et al., 2014, Ragettli et al., 2014), and one method that uses IDW to interpolate the residuals between WC maps and gauged values (precipitation and temperature), which from now on will be called WC Adjustment (WCA). A summary of all interpolation approaches including the data required is in Table 1. The following sections describe the methods in more detail and their application.

Before using the covariates mentioned in Table 1 (e.g. WC, elevation, CHIRPS), an analysis of their correlation with the climate variables was done. This included plotting temperature and precipitation observations versus the covariates, and computing Pearson Correlation coefficients.

Table 4.1 - Summary of approaches to interpolate climate variables.

Approach	Description	Input Data	Advantages	Disadvantages	References
IDW (Precipitation and Temperature)	Interpolation based on the inverse of the distance between gauges for each timestep independently.	Observations and distances between gauges	Simple and easy to implement approach.	Ignores the effects of elevation on the climate variables and does not include information from alternative datasets.	
LR (Precipitation and Temperature)	Interpolation based on linear (temperature) and logarithmic (precipitation) regressions using elevation as independent variable, for each time-step independently.	Observations and elevation of gauges	Simple and easy to implement approach that takes into account the effects of elevation on the climate variables.	Although alternative datasets could be included as covariates, in similar applications in nearby catchments it is more common to find elevation as the only independent variable.	(Ragettli and Pellicciotti, 2012, Ragettli et al., 2014, Vicuña et al., 2011, Stehr et al., 2008)
WCA (Precipitation and Temperature)	Interpolation of residuals between observations and values in WC maps. Each time-step is analysed independently.	WC Maps and observations.	Simple and easy to implement. The effects of spatial location and elevation are included to some extent through the WC values.	WC maps are not a continuous dataset but only a monthly long-term average.	(Hijmans et al., 2005)
GLMM (Temperature)	Spatio-temporal model whose parameters are estimated through approximate Bayesian inference. The model includes a first order autoregressive process with spatially correlated innovations for temperature.	Observations, elevation and coordinate of gauges, and WC maps.	Takes into account multiple covariates, and analyses the random component of the climate variable thought a spatiotemporal model.	Computationallyexpensive compared to the rest of the models.	(Cameletti et al., 2013, Rue et al., 2009)
GLMM (Precipitation)	Spatio-temporal model whose parameters are estimated through approximate Bayesian inference. Precipitation is modelled as a spatially correlated variable with monthly dummy variables.	Observations, elevation and coordinate of gauges, CHIRPS, ENSO index and WC maps.	Takes into account multiple covariates including satellite data, reproduces both occurrence and magnitude of precipitation events, and analyses the random component of this climate variable thought a spatial model.	Computationallyexpensive compared to the rest of the models.	(Rue et al., 2009, Blangiardo and Cameletti, 2015)

4.3.1. Stochastic Approach - GLMM

In addition to including the effects of covariates, GLMMs allow modelling of the spatio-temporal variability of the data (after removing the effect of the covariates) by means of random effects (Faraway, 2016). For example, the temporal correlation of temperature observations in this case study was analysed through an autoregressive (AR1) term (although further alternatives such as random walks could also be used). Furthermore, spatial correlation of precipitation and temperature was modelled as random variables whose covariance matrix is defined by a covariance function (in this case the Matern Function (Minasny and McBratney, 2005)) which depends on the distance between gauges and some spatial parameters (as opposed to intersite dependence functions that do not take into account distance between observations (Yang et al., 2005)).

In addition, inference on GLMMs is performed jointly for all the parameters, without having to split the estimation problem into separate steps (i.e. one for each time-step or doing the covariates regression first and the spatio-temporal analysis second (Hengl et al., 2003)). This approach differs from Kriging methods, as it avoids using the *method of moments* to define empirical/experimental variograms (Minasny and McBratney, 2005), and the subsequent adjustment of a theoretical variogram through a curve-fitting exercise (Ecker and Gelfand, 1997, Müller, 1999), as sometimes done for Kriging applications in hydrology (Goovaerts, 2000, Cameletti et al., 2013). Further details of GLMMs and the different alternatives to model spatio-temporal variables can be found in Faraway (2016), Rue et al. (2009), Lindgren et al. (2011), Cameletti et al. (2013).

The main drawback of using GLMMs with the Bayesian approach, as done here, is the computational requirements of the classical simulation-based methods such as Markov Chain Monte Carlo (MCMC) (Cameletti et al., 2011). However, here we use the Integrated Nested Laplace Approximation together with the Stochastic Partial Differential Equation approach (INLA-SPDE) (Rue et al., 2009, Lindgren et al., 2011, Cameletti et al., 2013), which represents a computationally efficient way to do approximate Bayesian inference on GLMMs (Rue et al., 2009).

In this approach, the climate variables in the case study (temperature and precipitation) are assumed to be realisations (e.g. observations) of a spatio-temporal process (random field) of the form:

$$\boldsymbol{Y}(\boldsymbol{s},\boldsymbol{t}) \equiv \{\boldsymbol{y}(\boldsymbol{s},\boldsymbol{t}) : (\boldsymbol{s},\boldsymbol{t}) \in \boldsymbol{D} \subseteq \mathbb{R}^2 \times \mathbb{R}\} \qquad \textbf{Equation 4.1}$$

where s and t denote the spatial location and time. This process has a mean μ and covariance function $Cov(y(s,t), y(s',t')) = \sigma^2\, C((s,t),(s',t'))$ (Blangiardo et al., 2013, Cameletti et al., 2013). Assuming that climate observations, $\boldsymbol{y} = \{y(s_i,t), i = 1,\ldots,N, t = 1,\ldots,T\}$, follow an exponential family probability distribution function (PDF), μ_i can be connected to a structured additive predictor η_i through a link function $g(\,)$ as shown below (Rue et al., 2009):

$$\boldsymbol{g}\big(\boldsymbol{\mu}(\boldsymbol{s_i},\boldsymbol{t})\big) = \boldsymbol{\eta}(\boldsymbol{s_i},\boldsymbol{t}) = \boldsymbol{\alpha} + \sum_{j=1}^{n_f} \boldsymbol{f}^{(j)}\big(\boldsymbol{u}_{j(s_i,t)}\big) + \sum_{k=1}^{n_\beta} \boldsymbol{\beta}_k \boldsymbol{z}_{k(s_i,t)} + \boldsymbol{\epsilon}(\boldsymbol{s_i},\boldsymbol{t}) \qquad \textbf{Equation 4.2}$$

where $\boldsymbol{x} = \big(\boldsymbol{\alpha}, \{\boldsymbol{f}^{(j)}(.)\}, \{\boldsymbol{\beta_k}\}, \{\boldsymbol{\eta}(\boldsymbol{s_i},\boldsymbol{t})\}\big)$ is the vector including the Gaussian latent processes (i.e. the parameters describing the random field), $\epsilon(s_i,t)$ is the random error component, the $f^{(j)}\big(u_{j(s_i,t)}\big)$ are functions of covariates u and the βs are the multipliers of covariates z.

For temperature, the model in this project was defined based on the one described in Cameletti et al. (2013) and Cameletti et al. (2011) for particulate matter, with daily time-steps. This selection was done taking into account that both variables are affected by their values in previous time-steps, but also because both of them have a spatial correlation. The model is described as follows:

$$\boldsymbol{y}(\boldsymbol{s_i},\boldsymbol{t}) = \boldsymbol{z}(\boldsymbol{s_i},\boldsymbol{t})\boldsymbol{\beta} + \boldsymbol{\xi}(\boldsymbol{s_i},\boldsymbol{t}) + \boldsymbol{\varepsilon}(\boldsymbol{s_i},\boldsymbol{t}) \qquad \textbf{Equation 4.3}$$

$$\boldsymbol{\xi}(\boldsymbol{s_i},\boldsymbol{t}) = \boldsymbol{a}\boldsymbol{\xi}(\boldsymbol{s_i},\boldsymbol{t}-\boldsymbol{1}) + \boldsymbol{\omega}(\boldsymbol{s_i},\boldsymbol{t}) \qquad \textbf{Equation 4.4}$$

where $y(s_i,t)$ represents a realisation of the gaussian field (GF) $Y(.,.)$ for site s_i and time t, $z(s_i,t) = (z_1(s_i,t),\ldots,z_p(s_i,t))$ are the covariates (fixed effects), βs are the coefficients of the covariates, ε is the measurement/observation error component, both serially and spatially uncorrelated ($\epsilon(s_i,t) \sim N(0,\sigma_\epsilon^2)$) and ξ represents the random component in the model. The latter is defined as a first-order autoregressive (AR) component with spatially correlated innovations $\omega(s_i,t)$ (a is the parameter of the AR1 process). The covariates included latitude, longitude, elevation and WC. Data from WC maps were included in the model as covariates, after extracting the values of the pixels containing the gauges.

The spatio-temporal model for precipitation was defined based on previous experiences of applications of INLA-SPDE for this variable. This involved dividing the analysis into occurrence and magnitude components, based on Equations 8.5 and 8.6 in Blangiardo and Cameletti (2015). However, it was decided to use monthly time-steps as preliminary results of daily runs were far from satisfactory. In addition, CHIRPS and the ENSO index were included as covariates to complement the ones used for temperature.

Dummy variables for each calendar month were included as additional covariates, in order to better represent the strong seasonality of precipitation in the case study (Falvey and Garreaud, 2007, Montecinos and Aceituno, 2003). In this way, the random process $\Phi(s_i, t)$ is spatially correlated but independent of other time-steps. The model is described as follows:

$$\boldsymbol{logit(\pi(s_i, t)) = z^P(s_i, t)\beta^P + \Phi(s_i, t) + \varepsilon^P(s_i, t)} \qquad \textbf{Equation 4.5}$$

$$\boldsymbol{log(\mu^P(s_i, t)) = z^P(s_i, t)\beta^P + \Phi(s_i, t)\beta^{P\prime} + \varepsilon^P(s_i, t)} \qquad \textbf{Equation 4.6}$$

Both Equation 4.7 and Equation 4.8 share the same $\beta^{\boldsymbol{P}}s$, but the latter has an extra parameter ($\beta^{\boldsymbol{P}\prime}$) connecting the random field in both equations.

It is acknowledged that other models (i.e. with different random effects) could be tested with these climate variables after changing covariates, spatio-temporal components, the prior distributions (currently we use the default in the R-INLA package) and correlation functions (e.g. as done in Cameletti et al. (2011) for particulate matter), and this represents a subject for future research. However, taking into account the scope of the paper, it was desired to work with existing GLMMs in the literature (or close adaptations) that have been analysed with the INLA-SPDE approach.

4.3.2. Deterministic approaches

It is assumed that the reader is familiar with IDW and LR. Briefly, the former estimates variables at unsampled locations $y(s_j,t)$ as a function of the inverse of the distance $d(s_j,s_i)$ between s_j and all sampled locations s_i following

$$\boldsymbol{y(s_j, t)} = \frac{\sum_{i=1}^{n} y(s_i,t)\frac{1}{d(s_j,s_i)}}{\sum_{i=1}^{n}\frac{1}{d(s_j,s_i)}} \qquad \textbf{Equation 4.7}$$

where $y(s_i,t)$ are the values at the *n* sampled locations. This method does not consider elevation effects. LR, on the other hand, uses linear and logarithmic regressions to model the relation between temperature or precipitation and elevation. The regressions could be extended to include all the covariates of the GLMM, however, the objective here was to apply the methods as they are commonly used to define inputs of hydrological and water resources models in nearby catchments (Ragettli et al., 2014, Vicuña et al., 2011, Meza et al., 2014).

The WCA method attempts to couple the benefits of the spatial variability of the WC maps and those of the temporal resolution of the observations in a simple way. This approach is similar to the RIDW in Manz et al. (2016) or the bias adjustment in Dinku et al. (2014), but in this case using WC maps. First, the residual between observations and WC is computed at each gauge location at a daily resolution for temperature and at a monthly resolution for precipitation. Then, these residuals are interpolated using Inverse Distance Weighting (IDW) to each point in the catchment, and this interpolated surface is added back to the original WC values. This procedure is repeated for every time-step.

For precipitation, due to the spatial smoothing that is inherent to all approaches, it is common to have very low values of precipitation where none is observed. Therefore, a threshold of 1 mm/month was set below which all values were deemed to be 0.

4.3.3. Comparison of interpolation approaches

In order to assess the performance of the approaches, one gauge was removed from the group used to interpolate the climate variable, and the set of errors for that gauge were recorded as the difference between the interpolation results for that location and the corresponding observations. After repeating this for all gauges, the concatenated errors are used to calculate the validation metrics. This leave-one-out cross-validation (LOOCV) procedure was applied separately for temperature and precipitation and for each interpolation approach.

For temperature there was a total of 24 gauges available, thus, the LOOCV analysed 24 combinations of 23 gauges. For precipitation there were 18 gauges available, thus the LOOCV involved analysing 18 combinations of 17 gauges.

For all tests, the average Root Mean Squared Error (RMSE) was used to assess the performance of temperature and precipitation predictions, following similar comparisons (Cameletti et al., 2013, Manz et al., 2016). Being a stochastic approach, for the GLMM this involved the analysis of the expected values of each variable (Equation 4.3 and Equation 4.6).

This was complemented with an analysis of the distribution of the residuals. Furthermore, two categorical statistics, the False Alarm Ratio (FAR) and the Probability of Detection (POD) (e.g. as applied in Zambrano-Bigiarini et al. (2016)), were used to assess to what extent the model is able to predict precipitation occurrence (see Table 4.2). These categorical statistics are relevant, even at a monthly time-scale, considering that in the case study there are several months without any precipitation, thus accurately simulating its occurrence is not a trivial exercise.

Table 4.2 - Categorical statistics used to assess the capacity of the interpolation approaches to predict the occurrence of precipitation. Taken from (Ossa et al, 2018).

Precipitation	Observed	Not Observed
Predicted	A	B
Not Predicted	C	D
	Categorical Metrics	
POD	$\frac{A}{A+C}$	
FAR	$\frac{B}{A+B}$	

4.3.4. Sensitivity to the number of estimation gauges

The sensitivity of the performance of the different approaches to the number of estimation gauges was also tested. For temperature, only 9 gauges with relatively long observation periods were used as estimation gauges in this sensitivity analysis. The other 15 gauges were operational for only one summer period, 2008-2009, and the variability in record length they introduced made it difficult to isolate sensitivity to number of estimation gauges. These 15, however, remained as validation gauges.

This allowed 9 combinations of 8 estimation gauges. The 9 validation results were averaged for the purpose of the sensitivity analysis. This was repeated using different numbers of estimation gauges: all possible combinations of 5 and 2 gauges out of the 9. The sensitivity analysis for the precipitation results was done in a similar way, but this time with all combinations of 14 and 4 gauges.

The sensitivity test was complemented with the estimation of precipitation and temperature values at all locations using raw WC maps and CHIRPS, in order to understand the accuracy of these data sets when used independently of the observations. This involved comparing the observed values at each time-step with those reported by CHIRPS or the WC maps, which in the latter case meant estimating the climate variables based on the long-term averages in the WC maps.

Regarding the computational requirements, the approximate Bayesian inference approach (INLA-SPDE), which was run on the INLA package for R (Rue et al., 2013), required using the Euramoo and Flashlite High Performance Computers (HPC) system from the Queensland Cyber Infrastructure Foundation (QCIF). All other interpolation approaches were run on a computer with 16 Gb of memory, an i7 processor and 4 cores.

4.4. Results

4.4.1. Preliminary analysis of correlations between covariates and climate variables

Figure 4.4 shows that monthly temperature values are inversely correlated to elevation (Pearson Correlation Coefficient $\rho = -0.81$). This figure also shows a strong correlation between WC values and monthly temperatures ($\rho = 0.98$). Likewise, daily temperature values show considerable correlation with elevation ($\rho = -0.77$) and WC ($\rho = 0.93$). In contrast, ENSO has a low correlation with temperature($\rho = 0.04$), thus it was decided not to include this covariate in the GLMM.

Figure 4.4C and Figure 4.4D show that the correlation between CHIRPS and daily precipitation observations is weak, but considerably improves when both are aggregated to monthly values ($\rho = 0.81$). The ρ for monthly precipitation and WC values is lower ($\rho = 0.62$ - see

e), while monthly correlation with elevation is above 0.6 for most months. ENSO shows a weak correlation with precipitation ($\rho = 0.12$), however, a monthly analysis shows that for several months the correlation is close to $\rho = 0.5$, therefore, it was decided to keep ENSO as a covariate for the precipitation GLMM. These correlations may be stronger in longer-term analyses that cover several Niño-Niña cycles, which last around 2-5 years each (Wolter and Timlin, 2011).

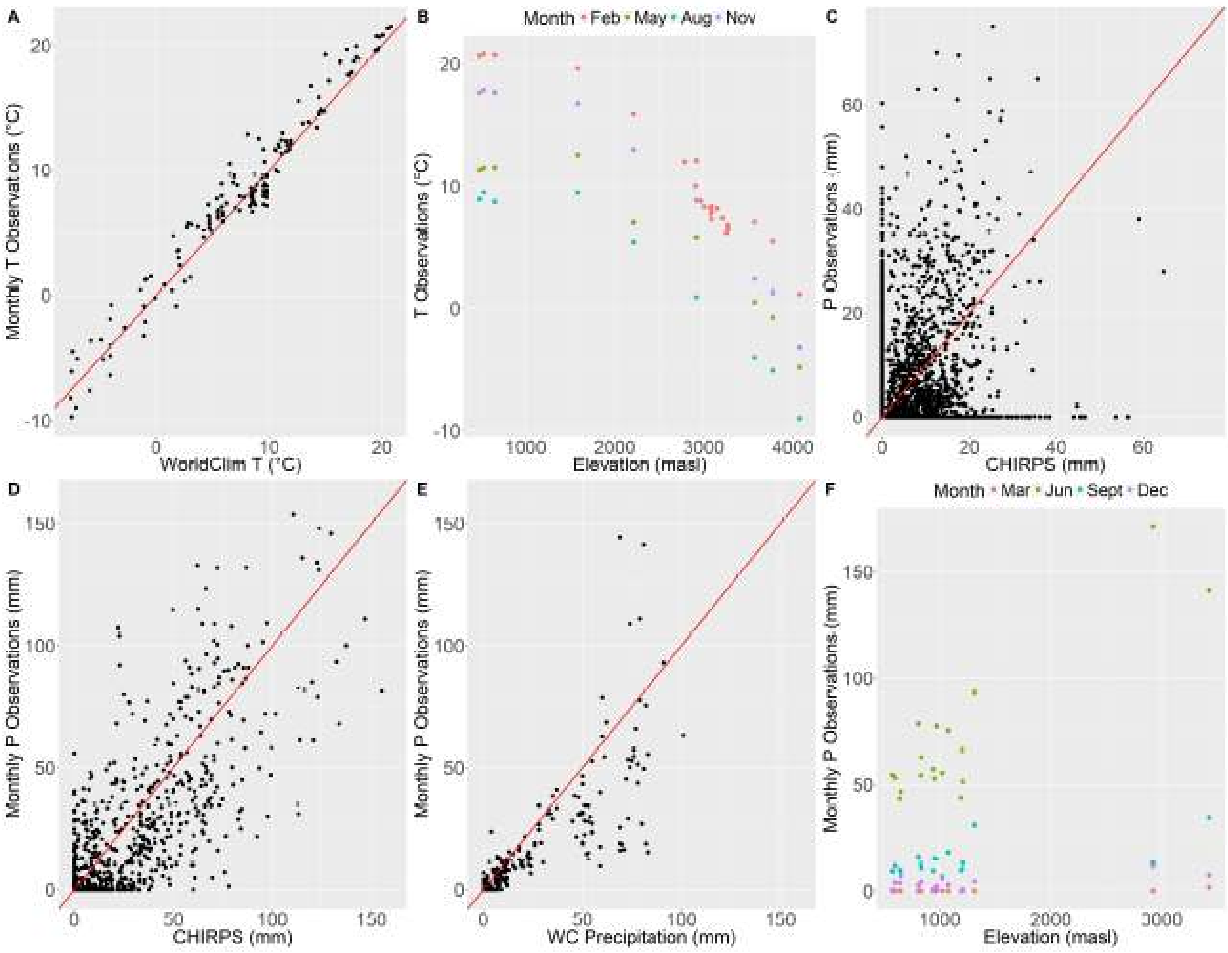

Figure 4.4 - (A) WC values versus monthly aggregated (averaged) temperature values. (B) Elevation of gauges versus average temperature in four months. (C) CHIRPS versus precipitation. Daily values for all stations used. (D) Monthly aggregated (sum) CHIRPS versus monthly aggregated (sum) precipitation values. (E) WC values versus monthly aggregated (sum) precipitation values. (F) Elevation of gauges versus average precipitation for four months. The red lines correspond to the 1:1 line.

4.4.2. Temperature results

Table 4.3 shows the results of all interpolation approaches in terms of the average RMSE of the validation gauges in the LOOCV (23 gauges). It was found that the GLMM and WCA have the best performance, while LR and particularly IDW have larger RMSE values.

Table 4.3 - Temperature RMSEs in the leave-one-out cross validation for each interpolation approach. Taken from (Ossa et al., 2018).

Approach	RMSE (^oC)
GLMM	1.2
WCA	1.22
LR	1.53
IDW	2.72

Table 4.4 shows the results of the sensitivity analysis. As expected, it can be seen that errors increase when the number of estimation gauges decreases. However, values for WCA increase the least, and its loss of performance is relatively small even when only two estimation gauges are used. On the other hand, the performances of all other approaches, including the GLMM, show a sharp decline, to the point that some of their RMSE values are comparable with the range of observed temperatures (see Figure 4.2).

Table 4.4 Sensitivity test of the temperature interpolation approaches. Taken from (Ossa et al., 2018).

Approach	Number of estimation gauges	RMSE (^oC)
GLMM	8	3.89
	5	3.99
	2	14.44
WCA	8	1.77
	5	1.98
	2	2.54
	0 (Raw WC Maps)*	3.36
LR	8	2.12
	5	4.14
	2	7.78
IDW	8	4.42
	5	6.15
	2	9.34

*** Using the monthly long term values provided by WC to approximate daily temperature at all sites (i.e. one value applied to all days in the month).**

Figure 4.5 illustrates the daily temperature averaged over the 5-year period of analysis for sites 18, 27 and 28 (similar results were found for the rest of the gauges). Values were averaged in this way purely to facilitate visualisation of results, as the daily variability over the five years makes it difficult to see what approaches over and under-estimate observations, by approximately how much, and how this changes as a function of the period of the year. The performance metrics were calculated with the non-aggregated data.

In the figure it can be seen that the GLMM and WCA reproduce the observed temperatures relatively well except for site 28 (the one at the highest elevation - 4250 masl). LR and particularly IDW tend to underestimate temperature at all gauges, except at site 28 where they overestimate it.

In Figure 4.5A, the anomalous overestimation of temperature with the LR method around March is because during March 2009 all other high elevation gauges stopped measuring, thus the predictions for site 27 were done with the lower elevation data only. This generated large errors for this gauge and this approach, which may highlight the limitations of the latter when few estimation gauges are available or when it is required to extrapolate results far beyond the elevation of available gauges. This will be further discussed later in this section.

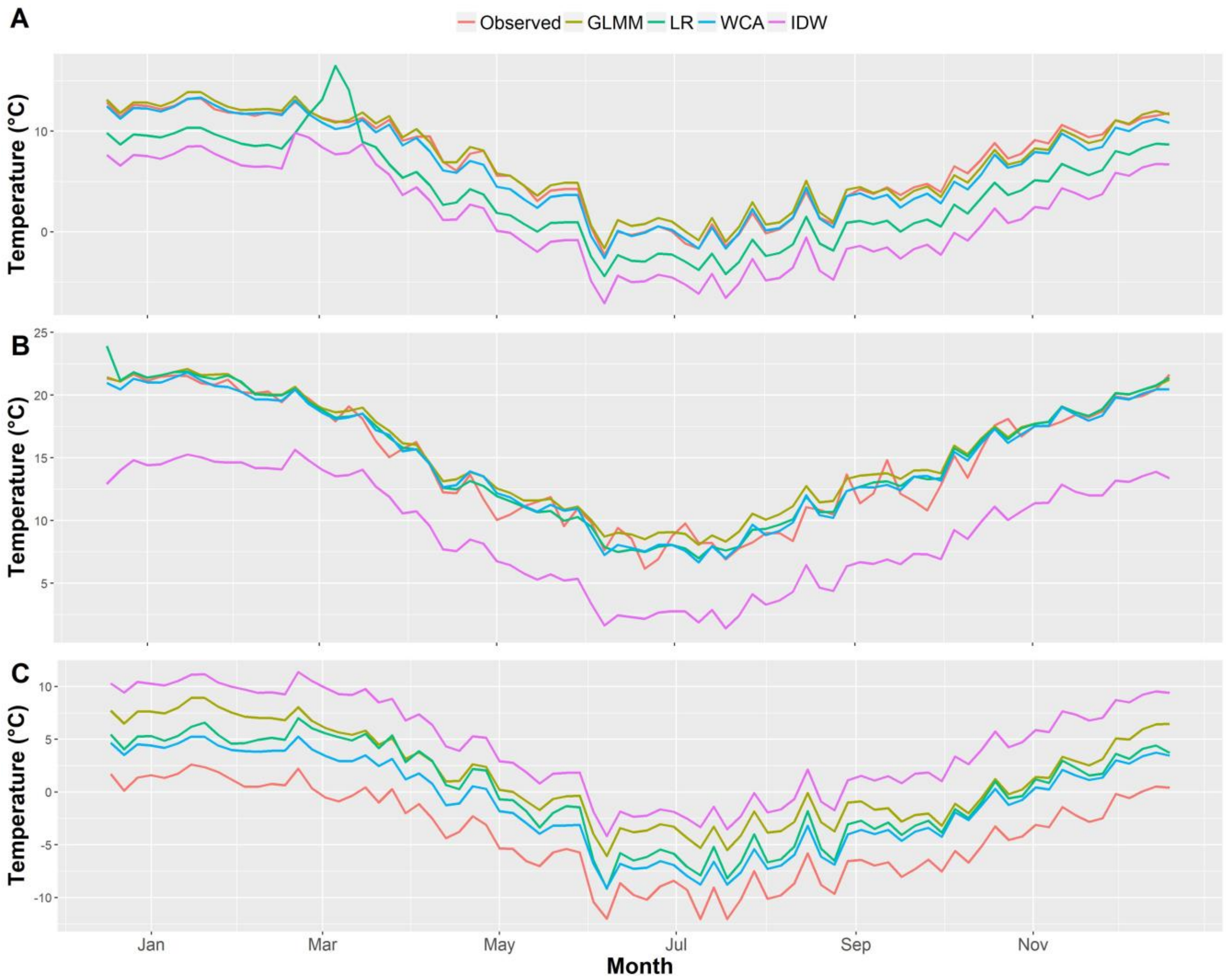

Figure 4.5 - Daily temperature averaged over the 5 years of analysis for gauge (A) Site 27 (Lagunitas) (B) Site 18 (330019) (C) Site 28 (MP) (All curves were smoothed using the LOESS method Jacoby (2000) with α= 0.045, this is similar to a moving average and is used to facilitate the visualisation of the main trends only). Taken from (Ossa, et al. 2018).

Figure 4.6 shows histograms of the validation residuals. It can be seen that the GLMM, WCA and LR give residuals that are more or less evenly distributed around zero, although those of the GLMM are more peaked. The distribution of IDW residuals is strongly multi-modal indicating consistent over or under-estimation at particular gauges. Figure 4.7 shows the relationship between temperature RMSE values and elevation.

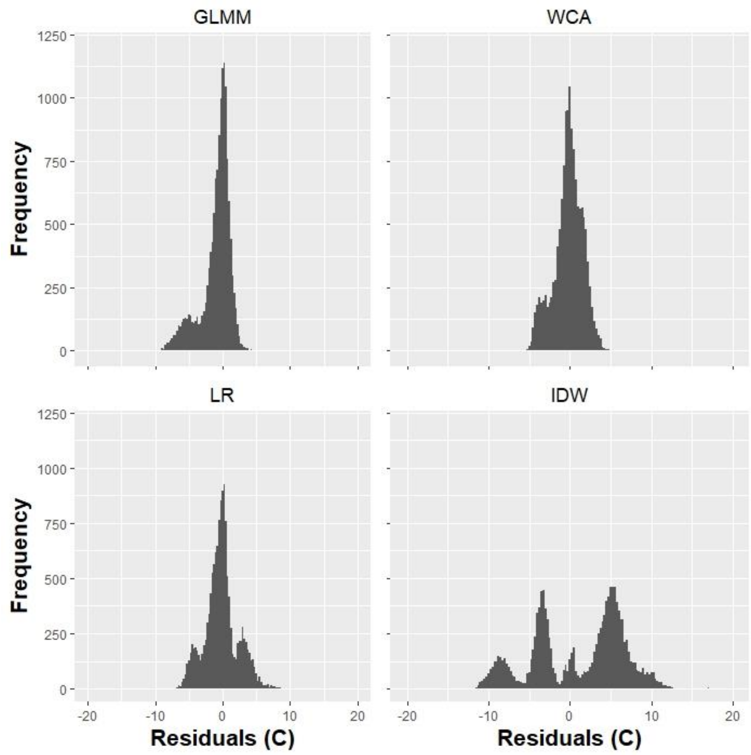

Figure 4.6 - Residuals of the temperature LOOCV for each interpolation approach. Taken from (Ossa et al., 2018).

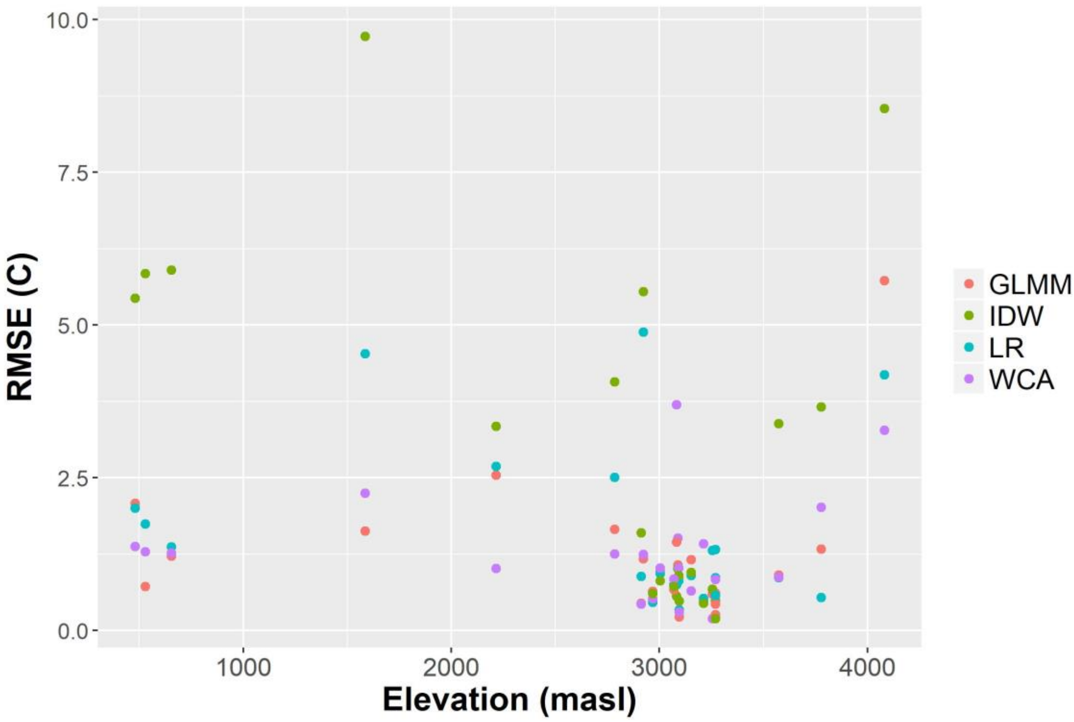

Figure 4.7 - Elevation of gauges vs Average temperature RMSE in the LOOCV.. Taken from (Ossa et al., 2018).

4.4.3. Precipitation results

Table 4.5 shows that the performances of all interpolation approaches are relatively similar in terms of RMSE. All probability of detection (POD) indices are above 90%, although WCA and IDW have values closer to 100%. Differences in false alarm ratios (FAR) are larger, as the GLMM has a ratio of only 7.1%, which is around half of the one for LR and less than a third of that of IDW and WCA.

Table 4.5 - Precipitation results in the leave-one-out cross validation for each interpolation approach. Taken from (Ossa et al., 2018).

Approach	RMSE (mm)	POD (%)	FAR (%)
GLMM	14.2	92.3	7.1
LR	15.5	93.7	12.9
WCA	13.4	97.3	24
IDW	13.5	98	22.7

Table 4.6 shows the sensitivity of performances to reductions in the number of estimation gauges. It can be seen that the GLMM is quite sensitive to these changes, and its RMSE performance decreases sharply when moving from 17 to 14 gauges, and even more from 14 to 4 gauges. Its POD and FAR remain similar. The RMSE performance of the other approaches decreases by a similar rate (3 - 4 mm) when moving to 14 gauges, although LR have lower POD and FAR. When moving from 14 to 4 gauges WCA shows the smallest increase in RMSE, while LR has a larger increment. PODs and FARs of these methods remain similar when moving to 4 gauges, except for the LR POD which drops around 6%.

Table 4.6 - Sensitivity test of the precipitation interpolation approaches. Taken from (Ossa et al., 2018).

Approach	Number of estimation gauges	RMSE (mm)	POD (%)	FAR (%)
GLMM	14	32.1	91.8	7.1
	4	135.8	87.8	10.6
LR	14	18.9	90.6	15.7
	4	26.4	84.4	11.7
WCA	14	17.4	97.5	25.8
	4	23.5	95.3	27.9
	0 (Raw WC Maps)*	34.1	98.6	40.5
IDW	14	17.8	97.2	22.1
	4	25.4	94	19.1
	Raw CHIRPS data **	26.2	88.5	28.6

*** Using the monthly long term values provided by WC to approximate daily temperature at all sites (i.e. one value applied to all days in the month).**

**** Using the monthly CHIRPS values at all sites.**

When these values are compared with raw CHIRPS and WC values, it can be seen that the performance of both alternative data sets by themselves is not competitive when there are 17 or 14 gauges available. The accuracy of CHIRPS gets closer to that of the interpolation approaches when only 4 gauges are used suggesting its potential value for poorly gauged regions; however, still, WCA performs better with 4 estimation gauges.

Figure 4.8 shows the observed and simulated monthly precipitation values for three representative gauges. Figure 4.8A shows the performance of the low elevation gauge at site 1, which is representative of the performance at the other low elevation gauges. It can be seen that most approaches reproduced observed precipitation at this lowland gauge well compared to the high elevation gauges. It can also be seen that IDW and WCA predicted small amounts of precipitation in several months during the dry season when no precipitation was observed, which causes a larger FAR for both of them (see Table 4.5).

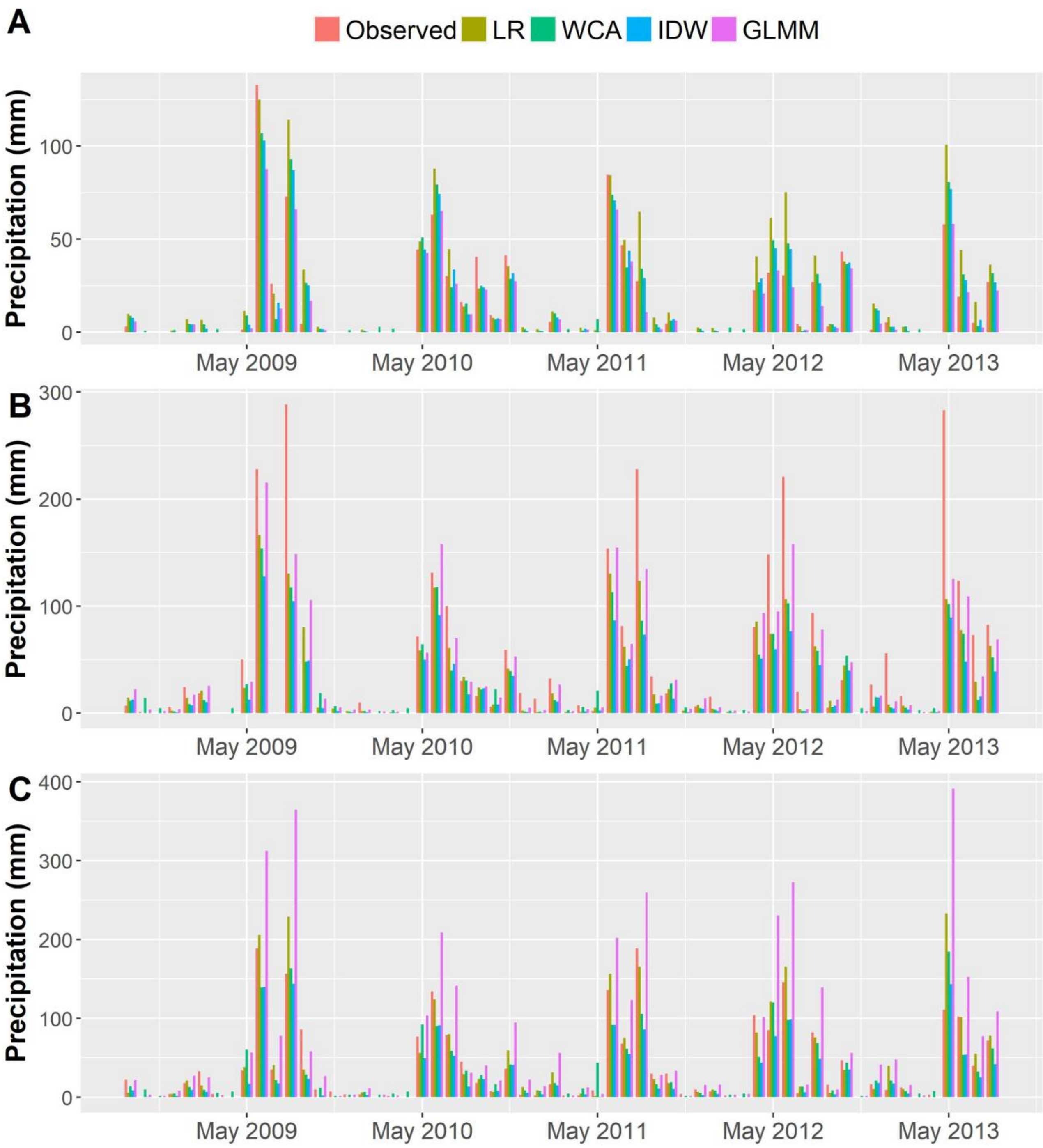

Figure 4.8 - Validation monthly precipitation estimates for sites (A) 1 (05200007-6) (B) 27 (Lagunitas) (C) 17 (Los Bronces). Taken from (Ossa et al., 2018).

Figure 4.8B shows the performance of all approaches for site 27, which is in the mountains at 2765 masl. In this plot it can be seen that observed precipitation is larger than in the lowlands, and that all approaches fail to reproduce observations with the level of accuracy seen for the lowland gauge (see Figure 4.8A). Figure 4.8C illustrates results for site 17, the highest of the precipitation gauges (3420 masl). Once more, larger errors can be seen compared to the gauges in the lowlands, particularly for the GLMM, although this approach has the best results in site 27.

This behaviour can be better appreciated after plotting the elevation of the gauges versus their average RMSEs (see Figure 4.9). While RMSE values below 1500 masl are rarely above 20 mm, all the RMSE values of the two gauges above 1500 masl are above this threshold, some of them are beyond 40 mm and two are above 60 mm. This suggests that the performance of all approaches is likely to be determined by inaccuracies at high elevation gauges, where frontal systems interact with the topography to create high precipitation during the wet season.

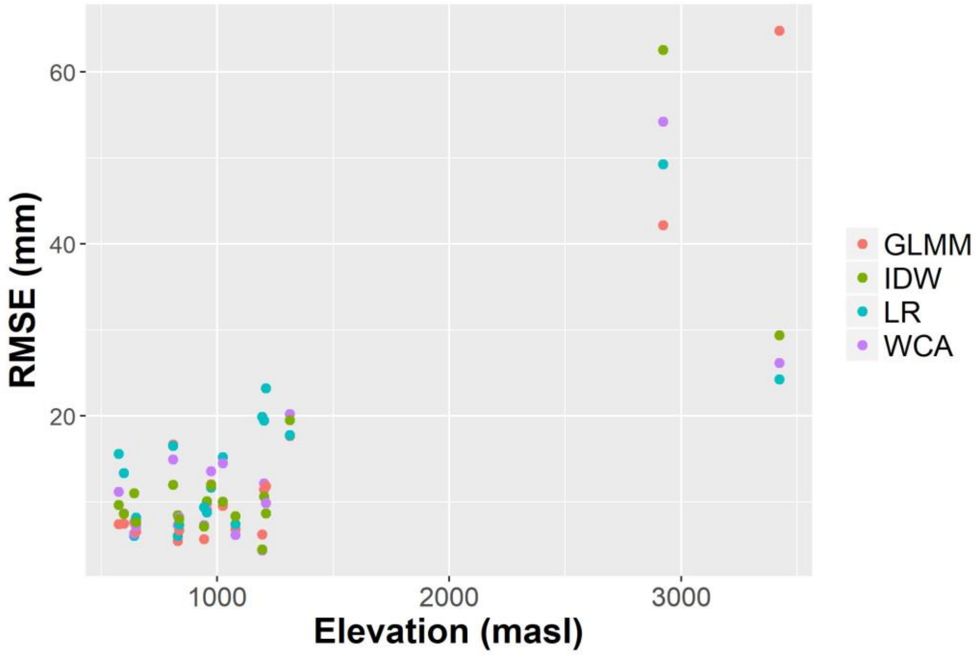

Figure 4.9 - Elevation vs Precipitation RMSE for all gauges in the validation groups of the LOOCV. Taken from (Ossa et al., 2018).

Regarding the distribution of residuals (see Figure 4.10), all approaches show values that are more or less equally distributed around 0. The GLMM residuals are particularly peaked at 0, nevertheless, its greater number of very large residuals gives the GLMM a higher RMSE than WCA or IDW.

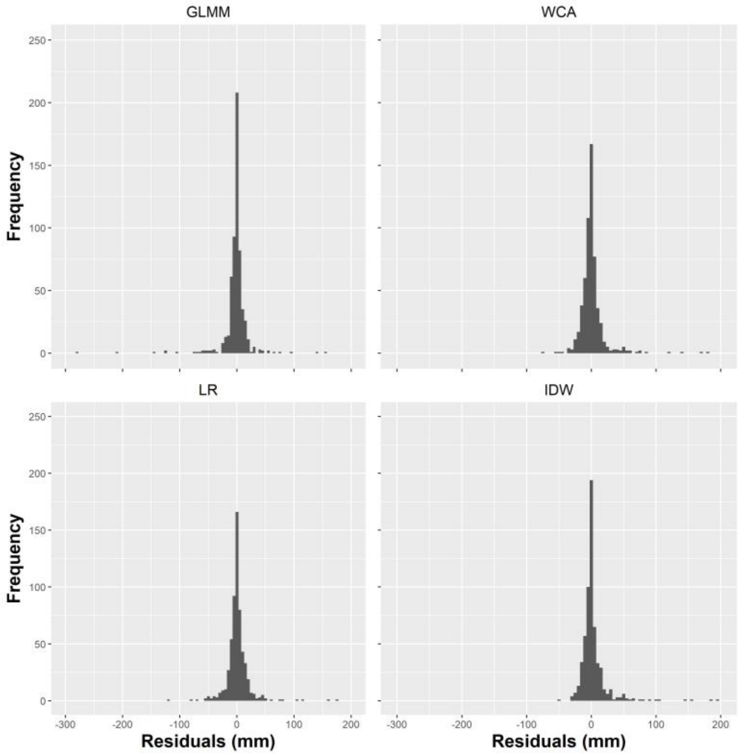

Figure 4.10 - Precipitation residuals of the validation gauges for each precipitation interpolation approach. Taken from (Ossa et al., 2018).

4.5. Discussion

The LOOCV analysis of air temperature in Section 4.4.2 shows that for this case study, the GLMM and the WCA have the best performance (i.e. smallest RMSE values - see Table 4.3). These results, and those of LR, are comparable with those obtained from similar analyses in USA and Canada (Stahl et al., 2006, Wu and Li, 2013). However, compared to the GLMM, WCA has less computational requirements thus is easier to implement (i.e. WCA was run on a desktop computer as described in Section 4.3.4, while the GLMM was run on 20 HPC cores in parallel).

On the other hand, IDW has the largest temperature errors and this, together with the skewed and multi-modal nature of its residuals, shows the limitations of this approach. Figure 4.5c and Figure 4.7 suggest that IDW residuals can sometimes be related to the high elevation (e.g. site 28) or isolation (e.g. site 29) of gauges. Temperature observations from the 2008-2009 summer season have the best RMSE values for IDW, but this is likely to be due to the proximity and quantity of gauges in this period.

In terms of the influence of the elevation of gauges on temperature results, WCA, LR and the GLMM show similar performance across all elevations, although the latter has an outstanding error at the highest gauge (site 28). This may suggest that compared to WCA and LR, this approach is more sensitive to the extrapolation of results beyond the altitude ranges of the estimation gauges.

Furthermore, it was found that the quality of results of the GLMM are particularly sensitive to the number and location of gauges measuring temperature. As shown in Table 4.4, the RMSE for this approach rises sharply when only 8 (3.89 ^oC), 5 (3.99 ^oC) and 2 (14.44 ^oC) gauges are used to estimate its parameters. The performances of IDW and LR also decrease considerably (RMSE of 9.34 ^oC and 7.78 ^oC respectively, with only two gauges), to the extent that using the raw WC maps for this case study (RMSE of 3.36 ^oC) may be preferable to any method other than WCA once the density of gauges becomes low.

On the other hand, WCA is quite resilient to the reduction of estimation gauges. Even with two estimation gauges the average RMSE was only 2.54 ^oC. This may be because the raw WC maps have internalised the average effect of elevation, longitude and latitude through the long-term analysis (a worldwide generalisation), which can then be adapted to local conditions by including a small number of gauges. This suggests that WCA is an accurate and easy to use alternative to model air temperature in the case study.

Regarding precipitation, the LOOCV shows that all approaches have similar performances in terms of RMSE, although the simple merge of WC maps and observations (WCA) has a slightly better value (13.4 mm). However, the GLMM also stands out due to its lower FAR (7.1%), which may be a positive outcome of separating the analysis of precipitation into occurrence and magnitude. This could also be related to the fact that the GLMM analyses the randomness of occurrences and their spatial correlation (see Equation 4.5), thus limits the possibility of one or few gauges with non-zero precipitation overly influencing the precipitation estimate at all points (e.g. smoothing).

As opposed to this, other alternatives, particularly WCA and IDW, tend to predict precipitation when at least one (IDW) or even when no gauges (WCA - due to the inclusion of long-term averages) record non-zero values. This is evident from the prediction of dry-season precipitation events that were never observed (see Figure 4.8). Preliminary results obtained using a different threshold (0.3 mm) for the detection of precipitation were similar, thus, the preference for GLMM in terms of FAR and POD performance seems not to be sensitive to the selection of this threshold.

When the precipitation interpolation approaches are tested with a reduced number of estimation gauges, it is found that the RMSE values of the GLMM rise drastically (beyond

100 mm with 4 gauges only). Once more, this suggests that compared to the alternatives, in this case study the GLMM is more sensitive to the number and distribution of estimation gauges. The importance of the latter is highlighted when using only 14 gauges for model estimation but including at least one of the high elevation gauges at site 17 (Los Bronces) or site 27 (Lagunitas). This gives an RMSE of 19 mm, which is considerably less than the average RMSE for the GLMM with 14 gauges (32.1 mm).

The other precipitation interpolation approaches decrease their performance at a relatively similar rate, when facing a reduction in the number estimation gauges. As shown for the LOOCV (see Figure 4.9), this may be because errors at high elevation gauges strongly influence the overall RMSE. When only 4 gauges are included, however, WCA shows a slightly better RMSE (23.5 mm), although a larger FAR (27.9 %). It was also found that CHIRPS as a standalone product is a useful alternative to the interpolation approaches when 4 or fewer gauges are available, with only marginally worse RMSE value than IDW and better RMSE than LR and GLMM (RMSE=26.2 mm, POD=88.5% and FAR=28.6 %).

The results in this paper show how simple approaches, which can be easily reproduced elsewhere, may perform at least as well as other more complex or more commonly used approaches, in a catchment with sparse monitoring networks and complex climate dynamics. Based on this evidence and its simplicity, it would be desirable to use WCA to estimate temperature in this case study. For precipitation, WCA may also be preferable, unless the modeller is particularly interested in the occurrence of precipitation in the dry season, in which case the GLMM would be desirable if computational requirements are not an issue and there is a reasonable coverage of gauges. Analyses of further case studies are required to test the generality of these findings.

Beyond the issues with the number and location of gauges to estimate the parameters of the GLMM, this paper shows how approximate Bayesian inference methods can be applied to estimate parameters of these models in a hydrological context. Despite there being high computational requirements with the the R-INLA package, these are lower than those of MCMC, and this facilitates the use of GLMMs. It would now be useful to test if the benefits of GLMMs and Bayesian approaches discussed in this paper and in the non-hydrology literature (Pilz and Spöck, 2008, Ecker and Gelfand, 1997) can equally be achieved by stochastic approaches like Kriging and GLMs that are more common in hydro-climate applications. It would be particularly interesting to analyse how these approaches behave in well and poorly monitored regions, and how this influences hydrological modelling.

Results in this case study are of course limited by the fact that 15 temperature gauges in the mountain areas measured during one summer season only. For precipitation, it would also have been desirable to have good quality gauges between 1300 and 2700 masl, to better understand what happens between the low and high elevation gauges.

4.6. Closing remarks

Lack of input climate data is an issue for the development of the water resources component of HEMs, which may hinder their implementation in several mining regions. This chapter considered how this problem can be addressed by using a range of different interpolation approaches and alternative datasets, which can be readily applied worldwide.

This Chapter showed that the WCA approach had a very good performance (often the best), for estimating precipitation and temperature values in the case study, and was the least sensitive to the reduction in the number of observation gauges in the calibration. Furthermore, this approach has very low computational requirements compared to the GLMM. Based on these results, it was decided to use the WCA method to generate the precipitation and temperature datasets, required to develop the water resources component of the HEM (see Chapter 5). Furthermore, as precipitation was estimated in monthly time-steps, it was required to aggregate all other variables to fit this temporal resolution.

The spatial resolution of the outputs from this Chapter provide considerable flexibility for the development of the water resources component of the HEM, as they allow developing distributed, semi-aggregated and lumped models. Due to the characteristics of the economic component, it was decided to use the second alternative, which required some degree of aggregation of the results here.

It was still considered appropriate to describe the results of the comparative analysis here, because the approaches and alternative sources of data may be useful for further applications of HEMs in mining regions with climate data scarcity issues. Thus, they contributed towards one of the main objectives of this project, which is developing insights into how to facilitate the use of HEMs in mining regions.

Beyond the direct applications in this project, results in this section support the quest for improved climate data sets for water modelling, which is a relevant research topic in hydrology. Amongst others, it was shown that approximate Bayesian inference methods (e.g. INLA-SPDE) have the potential to facilitate the use of GLMMs in hydrology, and should be compared in more detail with alternatives (e.g. kriging or maximum likelihood) in further case studies. Also, WorldClim maps were found to be useful to support the interpolation of climate variables, while it was shown how CHIRPS performed similarly to other methodologies when only four gauges were made available for calibration. This means that these global data products, could provide an alternative source of input data for water resources models when there are very few or no climate measurements, particularly if monthly time-steps are used.

5. The water resources component of the Hydro-Economic Model

This chapter describes the development, calibration and validation of the water resources component of the HEM. Developing a detailed representation of this component was one the objectives of this PhD project, in order to obtain insights into the value of this, as opposed to simpler representations in HEMs focused on the economics. The temperature and precipitation input data used here correspond to the results of Chapter 4, although it was required to extend the period of analysis to 17 years (April 2000 – March 2017) as it was not possible to calibrate the water resources model with the 5 years period used in Chapter 4.

Some of the gauging stations used in the previous chapter were not available during the 17-year period, however, this was not an issue for the WCA method used to interpolate climate data, taking into account its resilience to a reduced number of gauges (see Chapter 4).

It is important to mention that water quality was not part of the scope of this project, although future research could include this in HEMs, as this is a relevant topic in mining regions. This chapter starts with a brief review of literature on hydrological and water resources modelling, model development is then explained, and finally, results of the calibration and validation are provided.

5.1. Literature review on hydrological modelling

Hydrological and water resources modelling is a field of research that seeks to understand the behaviour of water in the physical realm, and more importantly how water fluxes can be analysed through equations and models. It is not the scope of this section to undertake an in-depth review of this concept and about recent developments in this field(this can be found in Yang et al. (2000), Pechlivanidis et al. (2011) and Praskievicz and Chang (2009), amongst others). Here, it is intended to review some hydrological models in the light of their applicability to HEMs.

In order to develop a list of possible hydrological models to use in this project, the reviews of HEMs in Harou et al. (2009) and Bekchanov et al. (2015) were employed. This was complemented with a search on Google Scholar using the following key words: “Hydro-Economic Model”, “Hydro-Economic Modelling” and “Economic hydrologic model”. Many of these papers are described in Chapter 2. The whole review included more than one hundred references, but these were filtered by applying the following criteria:

- Early literature (i.e. before 2000) on hydro-economic model applications was reviewed to understand general concepts of HEMs. However, assuming that more recent publications use more applicable tools, they were left aside. Furthermore, high impact old papers/tools are still referenced in more recent articles, thus it is possible to have an idea of the former by analysing the latter.
- Papers *purely* focusing on subjects beyond the scope of this work (e.g. water quality, water markets, economic methods, ecosystem services) were left aside as well.

Roughly 40 papers were shortlisted and analysed in more detail taking into account the considerations discussed in Chapter 2, in order to define several features of the water resources component of this project. These are described as follows:

- A monthly resolution was chosen to take into account the effects of intra-annual seasonality on hydrological processes (this was the best possible resolution with available precipitation data). The review showed that with this temporal resolution, the water resources component could be merged with the economic analysis using the same time-step, or after aggregating the former into yearly values.
- A continuous analysis (e.g. several years) was chosen, even if some information about agricultural crops and mine requirements was limited to some years only. The reason of doing this was that it enabled the analysis of catchment behaviour over several dry, wet and wet/dry years.
- Climate inputs allowed doing either semi-distributed or fully distributed hydrological modelling, but information on the volumes of water demanded and economic data were less spatially detailed thus the former option was preferred.
- The model does not include stochastic input data. However, the sensitivity of the model to changes in precipitation and temperature values (based on discrete changes) was tested and described in Chapter 7.1.

With these considerations in mind the initial set of 40 papers was narrowed down to 16. This last group of references was analysed in further detail, and it was found that most water resources components involved conceptual hydrological models (usually involving two reservoirs), monthly time-steps, and continuous analyses (see Table 5.1 – Lines 1 to 16).

Table 5.1 – Comparison of modelling options for the water resources component.

Number	**Consideration**	**Time-step**		**Spatial resolution**					**Hydrological model or platform used**	**Timeframe**		**Integration**	
	Reference	Monthly or less	Seasonal or Yearly	Large Areas	Micro or Small (< 20,000 km2)					Static*	Continuous **	Modular	Holistic
				Lumped catchments	Node-Links	Semi-distributed	Lumped	Pixels					
1	(Cai et al., 2006)	X			X				NHM - HF	X			X
2	(Medellín-Azuara, 2006)		X		X				NHM	X			X
3	(Fernández et al., 2016)		X			X			SWAT		X	X	
4	(George et al., 2011)	X					X		SimHYD		X	X	
5	(Satti et al., 2015)		X	X					NHM - HF		X		X
6	(Medellín-Azuara et al., 2015)		X	X					C2VSim		X	X	
7	(Kim and Kaluarachchi, 2016)	X					X		FAO AquaCrop***		X		X
8	(Esteve et al., 2015)	X				X			WEAP		X	X	
9	(Hurd and Coonrod, 2012)	X		X					WATBAL		X	X	
10	(D'Agostino et al., 2014)		X	X					SCS Curve Number Method	X		X	
11	(Graveline et al., 2014)	X				X			Geotransf		X	X	
12	(Dale et al., 2013b)	X		X					C2VSim		X	X	
13	(Jeuland and Whittington, 2014)	X		X					NHM - SF		X	X	
14	(Pande et al., 2011)	X		X					Other Conceptual Model	X		X	
15	(Srinivasan et al., 2010)		X		X				Other Conceptual Model		X	X	
16	(Forni et al., 2016)	X		X					WEAP		X		X

17	(Stehr et al., 2008)	X		X		SWAT		X	HO
18	(Ragettli and Pellicciotti, 2012)	X			X	Topkapi		X****	HO
19	(Ragettli et al., 2014)	X		X		WEAP		X	HO
20	(Vicuña et al., 2011)	X		X		WEAP	X		HO
21	(Young et al., 2009)	X	X			WEAP		X	HO

*** One year analysis (may include several runs, but all are 1 year runs)**

**** Multiple year analysis**

***** Seems to be an irrigation requirement model only**

****** The model is continuous in the sense that is run for several days on hourly time-steps, although is only run for one year.**

NHM No hydrological Model Used

HF Historical Flows Used

SF Stochastically generated Flows based on historical records used

HO Hydrological Model only

Note: This table was filled with the best understanding of the papers analysed, however, in some cases information was not completely clear.

It was also found that tools like C2VSim, WEAP and SWAT were common, thus it was decided to complement this analysis with a further review of applications of these models in Chile or in similar catchments, even in cases where there was no HEM involved (see Table 5.1– Lines 17 to 21).

Out of the models listed in Table 5.1, C2VSim was not an option as this model is exclusive to California. Other distributed models like Topkapi were overly complex approaches whose advantages calculating water supply would be lost, as information of the demand for water in the case study is not available in a distributed format. Taking this into account, its applicability to HEMs, and previous experiences in Chile (including one example in an small section of the case study in this project (Ragettli et al., 2014)), it was decided to use the Soil Moisture Model (SMM) available in the Water Evaluation and Planning (WEAP) platform (Yates et al., 2005).

The SMM in WEAP represents hydrological processes with two buckets (Sieber and Purkey, 2015). The first one represents the upper soil layer and controls the amount of water that infiltrates into the soil, the amount that is transformed into surface runoff and the evapotranspiration. Water in this layer can then become interflow or percolate to a deeper layer represented by the second bucket, which in turn controls base-flows. Snow melt, which is key in the case study, is represented with a temperature index method controlled by two parameters (melting point and freezing point). A representation of the model is shown in Figure 5.1, and further details about it and about WEAP can be found in Appendix C.

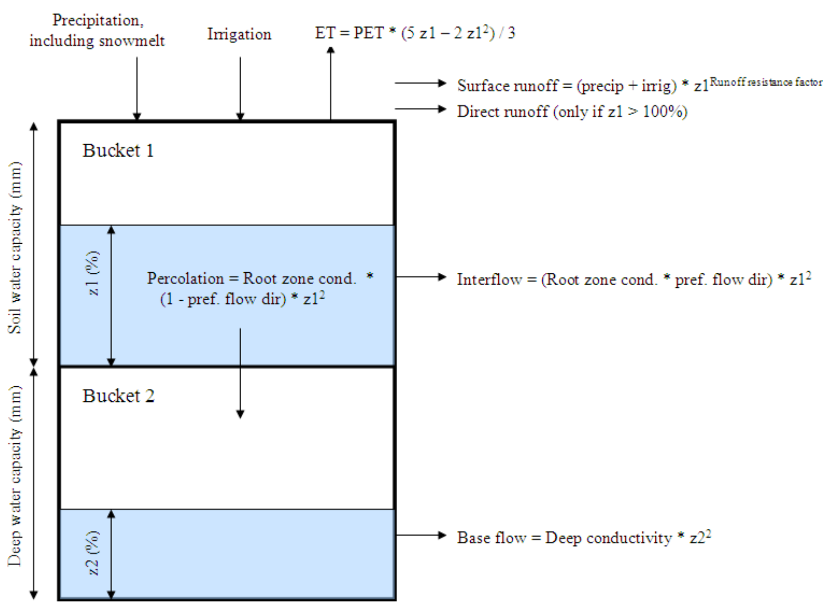

Figure 5.1 – Diagram of hydrological processes modelled in the Soil Moisture Model in WEAP. Taken from (Sieber and Purkey, 2015).

In addition to the calculation of water supply, WEAP includes an optimisation routine that facilitates the allocation of resources to all demanding users in order to maximise their coverage (proportion of the demand met). This process is influenced by a scheme of priorities in which each water user is assigned a number between 1 to 99, and precedence is given to the smallest numbers.

For this application, all users were given the same priority, so this allocation routine could be seen as the normal allocation in the case study, which gives each user its corresponding share of available volumes, as a function of their WRs. In Chapter 7.2, when analysing the effects of including environmental flow requirements, these were given a higher priority than all users. Future refinements of the model could include temporal WRs that are only allocated during wet years.

This allocation, however, does not allow to model potential inter-user transactions (e.g. agriculture to urban) based on economic data, as WEAP does not allow including the latter in the allocation system. Therefore, the possible transactions between users are simulated with the full coupled HEM (see Chapter 6), by means of a water market.

5.2. Development of the water resources model in WEAP

The development, calibration and validation of the water resources model was implemented in WEAP, however, several steps also required using additional software including R, Python, ARCGis and QGis.

5.2.1. Water Supply

The first step to analyse supply was identifying all flow gauges available in the case study (see Table 5.2), and downloading the observed values from the CR2 database (the same one used in Chapter 4). With the spatial location of these gauges and the same Digital Elevation Model (DEM) used in Chapter 4, it was possible to delineate the areas draining to each one of them, and the trajectory of the main streams of the river (see Figure 5.2). The latter was done up to the point where tributaries drained an area of at least 4 km^2 (less than 0.2% of the total area analysed), as to manage the trade-off between detail and computational complexity of the model.

Table 5.2 – Flow gauges available in the case study.

DGA Code	Name	Elevation (m.a.s.l.)	Latitude	Longitude
5410005	Rio Aconcagua en San Felipe	650	-32.7572	-70.7367
5410002	Rio Aconcagua en Chacabuquito	950	-32.8503	-70.5094

5406001	Rio Colorado en Colorado	1062	-32.8572	-70.4122
5401003	Rio Juncal en Juncal	1800	-32.8625	-70.1675
5403002	Rio Aconcagua en Rio Blanco	1420	-32.9067	-70.3036
5402001	Rio Blanco en Rio Blanco	1420	-32.9072	-70.2978
5402015	Rio Blanco Antes Junta Rio de los Leones	2090	-32.98	-70.2547

The DEM was also used to define 500 m contour lines in the catchment. Although smaller intervals would have allowed a more detailed analysis of elevation bands, it is not clear if this would have resulted in benefits to the model worth the increased complexity in calculations (i.e. increased computational time). Although this could be explored in more detail in future research, for this project it was decided to use 500 m, as this allows a reasonably large number of bands (10) without excessive computational cost. This is the same value that has been applied in other analysis in similar catchments in Chile (Correa-Ibanez et al., 2017, Vicuña et al., 2011).

The contour lines were overlapped with the river and its tributaries to define all sub-catchments in the case study (see Figure 5.3 for a sample of the Blanco River, one of the main tributaries in the upper section). These sub-catchments represent the basic unit of the water supply analysis in WEAP, as homogeneous climate conditions are assumed within them when running the hydrological calculations. All the GIS manipulation of the DEM was done using the Arcpy python module of ARCGis.

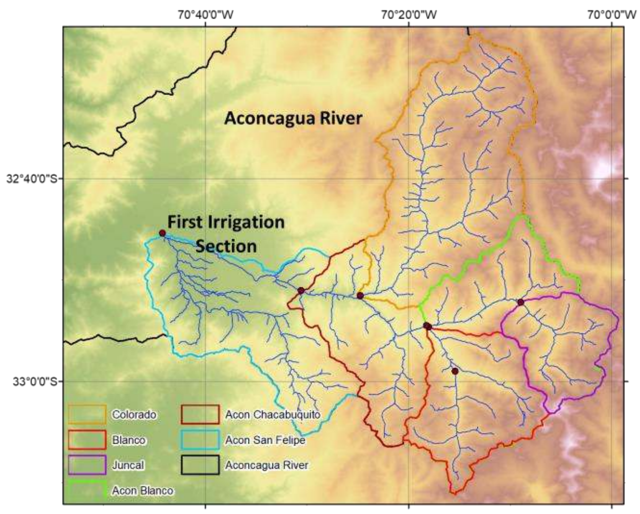

Figure 5.2 - Delineation of the areas drained by the tributaries in the case study.

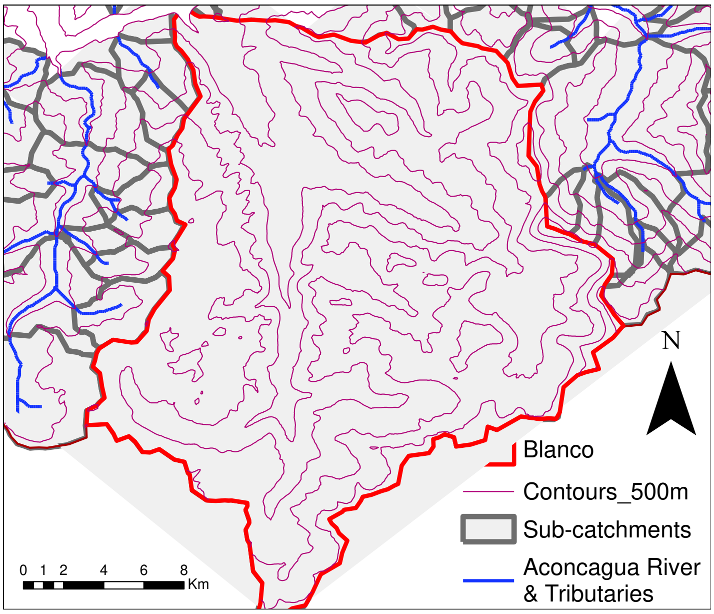

Figure 5.3 – Example of the definition of sub-catchments (grey lines) based on the overlapping of the Aconcagua River and its tributaries (blue lines), with the 500 m contour lines (purple lines). The image is focused on the Blanco River only.

Once the sub-catchments were defined, it was possible to include a *"Catchment"* object in WEAP to represent each one of them. The main channel of the Aconcagua River, its main tributaries (Colorado, Blanco and Juncal Rivers) and other creeks where also included either as *"River"* or *"Runoff-Infiltration"* objects (see Figure 5.4). The next step involved arranging all input data in the format required by WEAP. This was straightforward for Precipitation and Temperature (after aggregating it to monthly values), as they were already available from the analysis in Chapter 4.

Although temperature, and especially precipitation, are the key inputs of the hydrological model, it was also required to approximate other climate variables needed to run the model in WEAP. Most of this work was done in R and it is explained as follows:

- Total area and latitude of each catchment's centroid was obtained after analysing the sub-catchments.
- For relative humidity (RH), only the six gauges that measured this variable were analysed (see Appendix B). First, the observed RH and mean temperature were used to define the actual vapour pressure e_a at these gauges, using Equation 5.1. Then, using Equation 5.2 it was possible to define the dewpoint temperature at the gauge T_{dew}. A simple linear regression $(Dewpoint\ Temperature \sim Elevation)$ for each time-step was used to interpolate this variable to all centroids of the sub-

catchments. Finally, the actual vapour pressure e_a and the RH at all centroids were estimated using Equation 5.1 and Equation 5.2.

- $\boldsymbol{e_a = \frac{RH}{100}[e^o(T_{mean})]}$
- **Equation 5.1**
- $\boldsymbol{e_a = e^o(\,T_{dew}) = 0.6108\, exp\left(\frac{17.27\, T_{dew}}{T_{dew}+237.3}\right)}$
- **Equation 5.2**

These equations were adapted from Allen et al. (1998). As the gauges used to measure RH were only available from 2008 onwards, values for previous years were defined as the monthly averages of the period with available data.

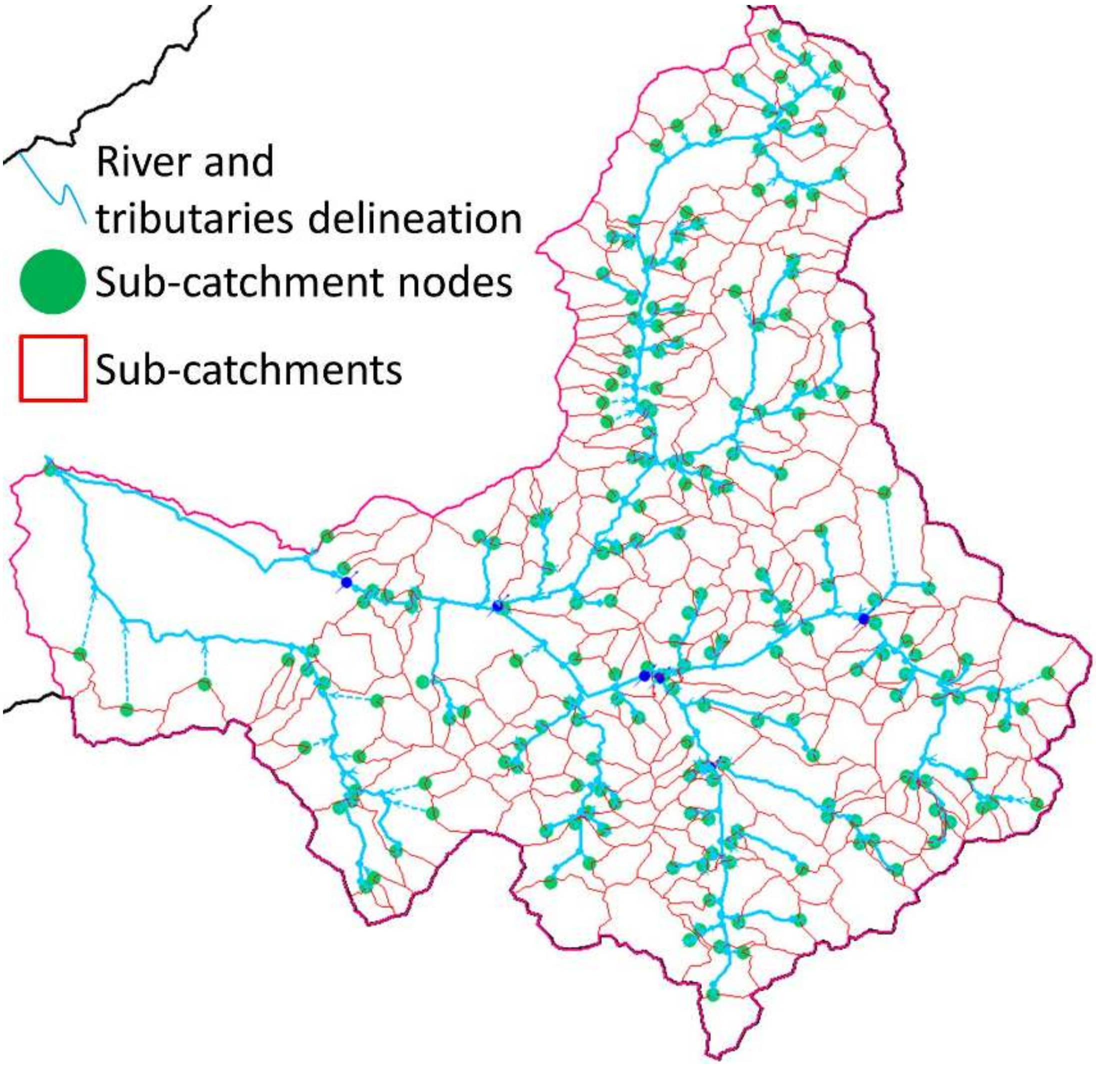

Figure 5.4 - Representation of the sub-catchments in the case study in WEAP.

- Snow Water Equivalent (SWE) values were taken from Cortés and Margulis (2017). These values were generated using Landsat observations together with a snow model run with the Modern-era Retrospective Analysis for Research Applications (MERRA) (Mernild et al., 2017). The SWE values are available until March 2015 only and are considered *observed* SWE values to differentiate them from the values modelled in WEAP, even if they were obtained from the merging of observations and another model.

- Wind speed values were taken from WorldClim maps (Hijmans et al., 2005).
- Cloudiness fraction was defined as the percentage of cloud coverage in an area, based on MODIS satellite data V5 (Hall et al., 2006).

The last three calculations were used to define the climate variables in a map with raster format. Afterwards, the sub-catchments outlines were overlaid with the raster maps, in order to define the mean value in the former..

5.2.2. Demand for Water

Demand for water in WEAP can be represented with demand nodes, and this was done for the mine and for the urban users, as their consumption was assumed to be located in the same place (see Figure 5.5). For the mining user, the location of the consumption nodes was assumed to be the processing plant facility, as this is the largest consumer of water in the mine site (Correa-Ibanez et al., 2017).

In addition, instead of analysing each mine WR separately, a transmission link from Blanco River, starting downstream of the WRs owned by the mine site was created. Doing an individual representation of each WR for this user was not possible, as it is not known how much water is obtained from each of them on a daily/monthly basis. There was an exception for a groundwater WR located downstream of the rest whose water is pumped to the mine area.

Including the irrigation demand was more challenging because it is difficult to know the exact position of all abstraction points. Also, the valley where the first irrigation section is located is above a large aquifer. The DGA developed models of this aquifer, however, this project did not have access to them, thus it was not possible to include them in WEAP. Furthermore, the coupling and set up of the surface and groundwater models would have required a considerable effort, which would have shifted the scope of the project away from the HEM and towards a purely hydrological research.

Taking this into account, the irrigation demand was simplified by aggregating it into one node, located just after the *Rio Aconcagua en Chacabuquito Gauge*. Furthermore, hydrological processes downstream (e.g. including the aquifer) were not modelled. However, a minimum flow requirement was enforced after the irrigation node, to make sure that the HEM does not consume the water that would normally flow downstream to other irrigation areas or that would percolate to the aquifer.

Minimum flow requirements are another object in WEAP, which can be located at any point along a river to force the optimisation algorithm to guarantee, whenever possible, that the flow at this point is at least the predefined value. During very dry periods this minimum requirement may not be fulfilled, but by having the same priority as the consumption nodes, it was ensured that the coverage was the same for both, even during droughts.

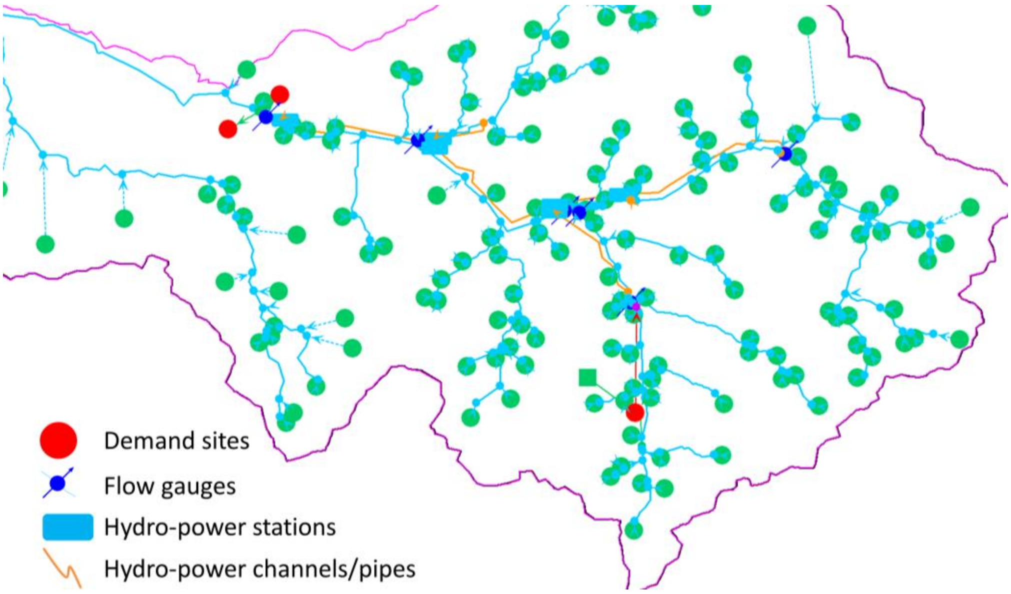

Figure 5.5 – Overview of the representation of the demand for water of the case study in WEAP.

It is acknowledged that representing downstream hydrological processes and water use, through a minimum flow requirement, is a major assumption. However, a considerable review of the available DGA documentation of the aquifer was undertaken (DGA, 2001, DGA, 2002, DGA, 2007, DGA, 2015a, DGA, 2016, DGA, 2011), to make sure that this was modelled as realistically as possible. Some of the key findings of this review are summarised as follows:

1. In the first irrigation section, the Aconcagua River recharges the aquifer with a yearly average of around 11 m^3/s.

2. Most of the groundwater inflow to the aquifer comes from the case study, although it also comes from other mountain areas like Estero Pocuro. However, the total groundwater influx is small (~0.5 m^3/s) compared to the surface flows entering the first irrigation section. The Rio *Aconcagua En Chacabuquito* gauge has a range of observed flows between 10 and 160 m^3/s.
3. Some of the total recharge to the aquifer comes from precipitation in the area during the wet months, but during the rest of the year, the key source is the percolation from the Aconcagua River. There are two further streams, the Pocuro Creek and the Putaendo River, and although these are not measured as accurately as in *Rio Aconcagua en Chacabuquito,* they are smaller.
4. Water pumping from the aquifer is smaller than the surface abstractions in this section of the river, however, there are no monthly estimates of aquifer pumping to compare with the irrigation requirements used in this project.

With this information in mind, it was determined to use a minimum flow requirement of 7.5 m^3/s to model downstream users. This number was defined assuming that most of the recharge to the aquifer (11 m^3/s) comes from water leaving the area analysed by WEAP. The remainder was assumed to come from precipitation, and percolation from other streams. This will be complemented with a sensitivity analysis explained in Chapter 6, in which an alternative of 5 m^3/s and 10 m^3/s for this value are tested. The former would be a scenario in which percolation mostly comes from alternative sources, while the later assumes that almost all of the percolation comes from the area analysed by WEAP.

In addition, all the irrigation demand will be concentrated in one node just downstream of *Rio Aconcagua en Chacabuquito* gauge. This does not assume that there is no pumping for agricultural purposes in the first irrigation section, but rather that water for pumping comes from the outlet of the area modelled in WEAP as well. In other words, it is assumed that this water leaves the case study and then percolates to the aquifer, thus from a modelling perspective, it is equivalent to including it in the consumption node.

This means that water supply calculations in the WEAP model will be implemented up to *Rio Aconcagua en Chacabuquito* gauge. The *Rio en Aconcagua en San Felipe* gauge will not be included in the analysis (see Table 5.2).

The urban user was defined with a demand site node in WEAP, using information of the local water utility (ESVAL, 2014). The location of their surface WRs is in *La Petaca* channel, whose starting point is a couple of kilometres downstream of the *Aconcagua en Chacabuquito* flow gauge. Thus, in the WEAP model the urban demand for water site is located to the left margin of the river after the gauge.

It is important to mention that this is not the only source of water for the local water utility, they also have groundwater WRs in the first section of the River and several WRs in other sections. However, their groundwater WRs in the first section are assumed to be included in the minimum flow requirement in WEAP, partly due to the lack of information of their location, but also because the economic calculations were recommended for surface water only (more details will be given in the next section) (Cai et al., 2006). This means their groundwater consumption is accounted for in the water resources component, but the full HEM only analyses their surface consumption, as done in (Cai et al., 2006).

The hydro-power stations in the case study were included in WEAP as *Run of River Hydro* objects (see Figure 5.5), while *Diversion* objects were used to model the channels and pipes that are used to channel water from the river and between stations. There are a total of four major hydro-power stations in the river that were included in WEAP: Hornitos, Aconcagua (which takes water from Blanco and Juncal Rivers), Los Quilos (which takes water from Colorado as well) and Chacabuquito (see Figure 5.6).

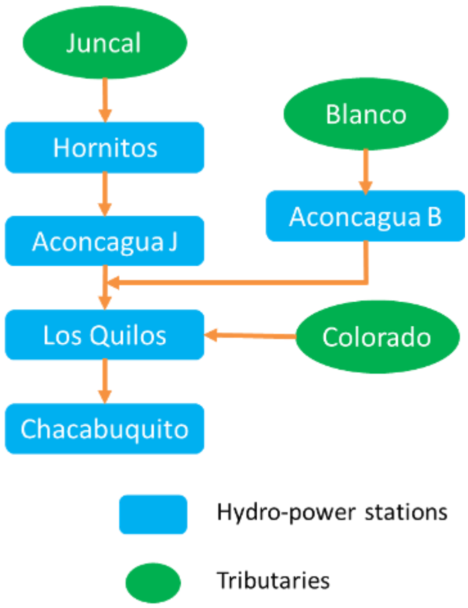

Figure 5.6 – Location of run-of-river hydro-power stations in the catchment.

5.2.2.1. Input Data of the Demand for Water

The Chilean agricultural census of 2007[5] developed by the *Instituto Nacional de Estadísticas* (INE) was used to define crop areas in the first irrigation section. While this information may be relatively old, there has not been another census since then (although there was some discussion about doing another one in 2017 or 2018). Furthermore, although INE attempts to update this information with estimates derived from the sampling of a small number of farms (in the case study this was done in 2008 and 2014), these are not as accurate and do not include as much information as the census. The main issue with the latter was that for some of the crops, estimations are only done by region and not by commune (the smallest administrative unit in Chile) as in the census.

Given the aforementioned data limitations, the census dataset was employed assuming the 2007 production applies for the whole period of the model. This is another major assumption of the project. However, it was discussed with local experts[6] and it was found suitable for the HEM, although it would be desirable for future versions to incorporate more recent data once it becomes available. The list of the crops analysed and their respective areas are shown in Table 5.3. This list does not include all the crops in the census, as there were crops with very small areas whose data was difficult to define (price, cost and water requirement – see Chapter 6). This list, however, includes 91% of the total crop area of the first irrigation section.

Table 5.3 – Types of crops in the first irrigation section of the Aconcagua River in 2007.

Crop	Area (ha)
Alfalfa*	1,705
Wheat	69
Corn	326
Potato	112
Table Grapes	9,376
Avocado	676
Walnut	1,369
Peach**	2,632
Olives	354
Plum	146
Total	16,768

***Aggregates all forage plants. ** Includes apricots, nectarines and peaches.**

[5] Available at http://ine.cl/estadisticas/economicas/estad%C3%ADsticas-agropecuarias

[6] Dr. Guillermo Donoso Harris, Professor at Universidad Catolica de Chile and Dr Diego Rivera, Professor at Universidad de Concepción.

This information was complemented with an analysis of the irrigation requirements of the crops, to define the total volume consumed by agriculture. This analysis was implemented following the next steps:

1. The ASCE Standardised reference evapotranspiration equation was used to calculate the reference evapotranspiration in the area (Walter et al., 2000).
2. The input data for this equation was taken from *La Cruz* gauge of the Agrometeorological network of the Instituto de Investigaciones Agropecuarias (Agricultural Research Institute - INIA). This gauge was not included in Chapter 4 as it was further away from the mountain area, and also because it has only been active since October 2013, however, INIA recommends its use as the basis for evapotranspiration calculations in the valleys. Daily evapotranspiration from October 2013 until June 2018 was averaged to define the mean value for each day of the year, to provide the most representative value possible with available data.
3. Crop coefficients (k_c) for each of the crops (see Table 5.3) were taken from Allen et al. (1998) and SEPOR (2017), while the dates of the different stages of crops in Chile was taken from Faiguenbaum (2003).

Table 5.4 shows the water requirements per area for each of the crops included in the analysis, and their total yearly consumption. The total amount of water required by the crops analysed is shown in Table 5.5. Then, taking into account that the latter value corresponds to the requirements of 91% of the crops, it was assumed that the 9% that could not be analysed had a similar consumptive use. In this way, the total use included in the WEAP model is 93,786 Megalitres per year (ML/yr).

Table 5.4 – Crop water requirements in the case study.

Crop	Water requirement (m^3/ha)	Total Water Required (ML/yr)
Alfalfa*	4,676	7974.0
Wheat	2,736	189.9
Corn	4,125	1345.9
Potato	3,573	400.9
Table Grapes	4,978	46679.2
Avocado	6,978	4717.3
Walnut	5,889	8063.4
Peach	4,928	12969.9
Olives	4,911	1740.7
Japanese Plum	4,928	721.9

Table 5.5 – Total estimated annual irrigation water use in the case study.

Total analysed in census (ML/yr)	**84,803**
Total in WEAP (ML/yr)	**93,786**

Finally, as the model was run in monthly time-steps, WEAP required the monthly share of the yearly total. This was done by calculating the monthly irrigation requirements of each crop, and then aggregating values per month (see Table 5.6). As expected, most of the irrigation occurs during the austral summer, while during winter, irrigation requirements are considerably reduced.

Table 5.6 – Monthly share of the total yearly irrigation requirements.

Month	Monthly share (%) of yearly total
Jan	20.9%
Feb	16.0%
Mar	9.8%
Apr	4.5%
May	1.7%
Jun	0.2%
Jul	0.2%
Aug	0.8%
Sep	2.4%
Oct	9.6%
Nov	14.9%
Dec	19.1%

Mining demand was estimated as 25.5 million m^3 in 2013 (Correa Ibanez, 2015) and it was assumed that this corresponds to the volume required to produce the largest amount of copper concentrate during the period of analysis (2000 – 2017). This corresponds to 2000 when there was a production reached 258,000 tonnes. Then, taking into account that the agricultural demand was calculated for 2007 only, it was decided to use the mining water use for the same year only, in order to do a fairer comparison amongst all users. The mining production for 2007 was 218,400 t, which means that the mine water consumption for the WEAP model is 21.58 million m^3 per year. Water use from this user is assumed to be constant throughout the year.

The water use for the urban sector was taken from the five-years plan that all water utilities in Chile, including ESVAL (i.e. the one in the case study), must present to the regulator. From this information it was possible to obtain information about the average historical consumption from surface water sources in the area included in this case study, which is

79.7 l/s (2.5 million m^3 per year), corresponding to about 55% of the total urban consumption in the area. As explained before, the urban groundwater consumption was not included as a demand site node in WEAP, but as part of the minimum flow requirement at the outlet.

The run-of-river hydro-power stations in the area do not significantly consume water, but they abstract it from the tributaries in the mountain area, and then give it back just before *Rio Aconcagua en Chacabuquito* gauge. Information on their abstractions is not publicly available, and perhaps it is not even metred with precision. Furthermore, the non-consumptive WRs from the energy company may not necessarily match their exact consumption, as they may hold more WRs than what they use, and also their historic abstractions may have been restricted by the DGA during dry periods.

Taking this into account, the energy generated by each station (which must be reported to the regulator on a daily basis) is the best source of information to approximate the abstracted volumes. The energy generated by each station can be downloaded from the website of the *Coordinador Electrico Nacional* (National Energy Coordinator - **CEN**[7]). This information was complemented with the characteristics of each station, including the maximum possible flow Q_{max}, the height difference between the inlet and the generator H, and the location of inlets and generators (4C Ingenieros, 2013, DGA, 2001, DGA, 2011, EDIC Ingenierios, 2003).

The list of stations included in this analysis and their features are shown in Table 5.7. Two smaller stations called Juncalillo and Sauces Andes were not included in WEAP because they are relatively small compared to the others, and because it was not possible to obtain their data.

Table 5.7 - Characteristics of the run-of-river Hydro-power stations included in WEAP.

Station	Height difference (m)	Max Flow* (m^3/s)
Hornitos	540	12.1
Aconcagua Blanco	689	8.6
Aconcagua Juncal	282	11.6
Los Quilos	227	20
Chacabuquito	137	20

*** Some of these values had to be increased in WEAP after the flow calculations showed that some stations required larger flows to generate the energy reported to the regulator.**

[7] https://sic.coordinadorelectrico.cl/informes-y-documentos/fichas/operacion-real/

Assuming that the energy E is generated at a constant rate throughout the month ($24\,hr * Days\ of\ the\ Month = T$), the generation of each station can be transformed into power P using Equation 5.3. This assumption is justified by the fact that these are run-of-river hydro-power stations rather than reservoirs, which means that the elevation head between the abstraction point and the turbine is almost constant. For example, *Los Quilos* station produced 28,880.8, 23,857 and 15,928 MWh in January (744 hours), February (all years are assumed to be non-leap years - 672 hours) and April 2000 (720 hours) respectively, corresponding to 38.82, 35.5 and 22.12 MW of power during the three months.

$$\boldsymbol{P = \frac{E}{T}}$$

Equation 5.3

Once the monthly power values were calculated, it was possible to transform these to flows Q abstracted from the River by using Equation 5.4. In the latter, it was assumed a water density of $\rho = 1000\ \frac{Kg}{m^3}$, a gravitational acceleration of $g = 9.81\ \frac{m}{s^3}$ and an efficiency of $\eta = 0.95$. These calculations imply that water is abstracted at the same rate as energy is produced, which may not necessarily be true at every moment because there are small reservoirs next to the inlets regulating abstractions. However, their size is very small, compared to the total volumes abstracted in a monthly scale, so they can be ignored.

$$\boldsymbol{\frac{P}{\rho g H \eta} = Q}$$

Equation 5.4

As opposed to mining, agriculture and urban uses, water required for hydro-power generation was defined for the whole period of analysis, and not only for 2007. Using only the 2007 demand for the other three users was done to do a fairer comparison, however, hydro-power is slightly different because they do not consume but only temporarily abstract water. Furthermore, although some calculations were required to transform energy into flows, this data represented a reliable benchmark that could be used to refine the calibration of the model, to complement flow observations. Thus, not using the whole record of hydro-power data would have represented a missed opportunity for better calibrating the HEM.

Figure 5.7 illustrates the flow requirements to generate energy at each station for the whole period of analysis 2000-2017. Following Figure 5.6, it can be seen that water is not abstracted separately for each station, but that the same flow generates energy at different stations. This means that flows required to generate energy in Hornitos should be similar to the ones of Aconcagua Juncal, and those of Los Quilos should be similar to those of

Chacabuquito. Although the curves are not exactly equal, Figure 5.7 shows that the differences are relatively small, except for a period in which Chacabuquito station was closed (Sep 2015 – Jun 2016), and during the first months after Hornitos was constructed.

The average difference between Aconcagua Juncal and Hornitos is 0.7 m^3/s, which is only 15% of the average flow required for Hornitos station. The average difference between Chacabuquito and Los Quilos, excluding the period when the former was not working, is 0.23 m^3/s, which is only 2% of the flows required by Los Quilos. This suggests that the calculations used to transform energy into flows are of adequate quality to be used in this model. Finally, it is important to mention that it was not known how Los Quilos split the abstractions between the channel coming from Aconcagua station and the abstractions in Colorado River. Thus, it was assumed that the latter only provided water whenever the water that had passed through the former was not enough to generate the energy values reported for Los Quilos.

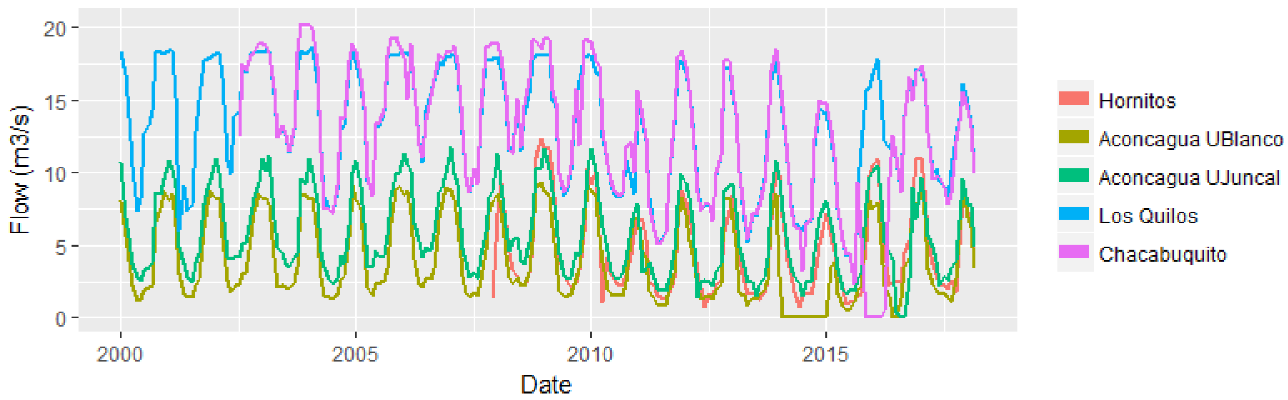

Figure 5.7 – Flows required by the four main hydro-power stations. See Figure 5.2, Figure 5.5 and Figure 5.6 to check the location of the hydro-power stations.

5.3. Calibration and Validation

WEAP includes a tool called PEST (Parameter ESTimation (Doherty and Hunt, 2010)), which can be used to calibrate the parameters of the model. Nevertheless, this approach was not very flexible when defining the calibration periods and it was cumbersome when multiple parameters were calibrated at the same time. Furthermore, it only allowed calibration with flow observations, reservoir levels and SWE (i.e. comparison of energy generation could not be included in the calibration). Due to this, it was decided to use

WEAP's Application Programming Interface (API[8]), which basically allows the user controlling the whole model from an external program, in this project Python. The latter allowed using Monte Carlo sampling to calibrate all parameters (Pechlivanidis et al., 2011).

The whole period of analysis (April 2000 - March 2017) was divided in one warm-up year (April 2000 – March 2001), 8 years for calibration (April 2001 – March 2005 and April 2013 – March 2017) and 8 for validation (April 2005 – March 2013). The calibration period was divided in two to make sure that calibration and validation covered wet and dry years. All years started on 1st April and finished on 31st March of the next calendar year, following the hydrological year in Chile (Cortés and Margulis, 2017). Several rounds of Monte Carlo sampling were undertaken to become familiar with the parameters, and each of them involved between 1500 and 5000 samples of parameters for each one of the calibration areas (see Figure 5.2 and Figure 5.8).

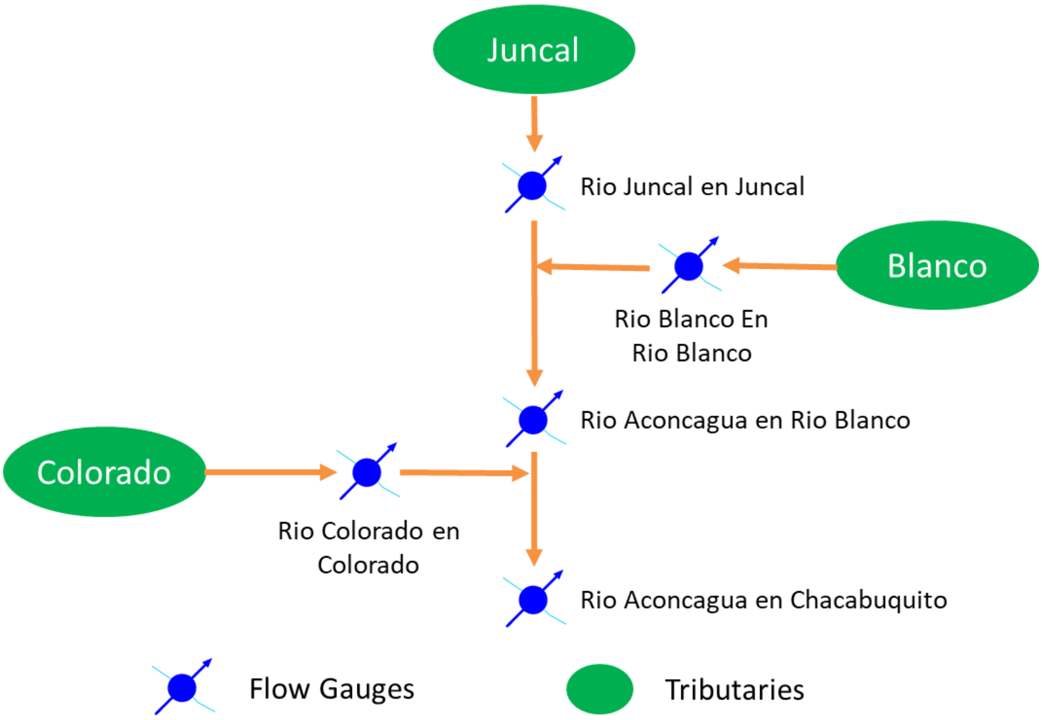

Figure 5.8 – Calibration areas and their flow gauges in the case study.

The calibration procedure started in the Juncal River (see Figure 5.8), the upstream-most tributary, followed by the Blanco River. Then, all other sub-catchments upstream of *Rio Aconcagua en Rio Blanco* gauge were calibrated together. The sub-catchments upstream

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[8] An API is a set of routines that allow manipulating a program (e.g. WEAP, Microsoft Excel, etc.) from an external programming software like Python, JavaScript or Perl, amongst many others. WEAP's API allows changing almost everything in the model, like parameters, climate conditions, input data, demand for water, priorities of demand, etc.

of the Colorado River gauge were then calibrated and finally, all sub-catchments upstream of *Rio Aconcagua en Chacabuquito* that had not been calibrated already. There was a sixth gauge (*Rio Blanco Antes Junta Rio de Los Leones,* inside Blanco River see Figure 5.9) with data for a brief period in 2012 and then from 2014 on. However, taking into account the large number of missing values, it was decided to use it for validation only.

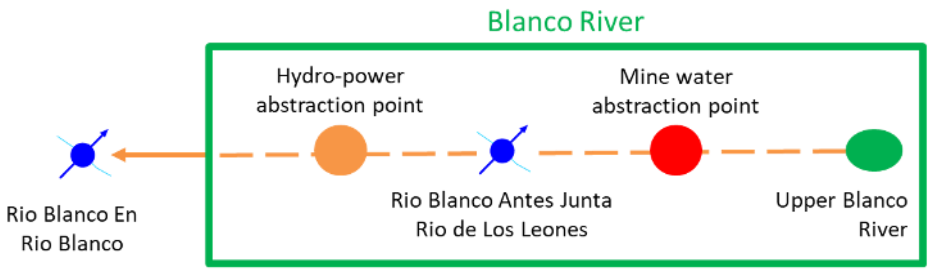


Figure 5.9 – Location of the extra flow gauge inside Blanco River.

Initial analyses of the Juncal River showed that runoff in the outlet during the entire period of analysis was larger than precipitation in the area. This was also seen for the Rio Blanco en Los Leones gauges. This was probably caused by the limitations of the interpolation methodology in the upper most areas. Therefore, it was decided to do a Bias correction of 60% and 45% respectively (i.e. increment of 60% and 40% in precipitation values in all sub-catchments upstream of these two gauges). This correction was done to make sure that the long-term (i.e. the 17 years of analysis) volumes of water measured in the gauges, were similar to the volume of water precipitated during this period.

The Soil Moisture Model (SMM) in WEAP includes 11 parameters, Table 5.8 list them and provides a brief description, while a detailed explanation can be found in Yates et al. (2005) and Sieber and Purkey (2015). The ranges of values that each parameter could take for each Monte Carlo sampling in the last calibration round were defined taking into account other WEAP models (Vicuña et al., 2011, Young et al., 2009), the previous calibration rounds, and discussions with experienced WEAP users. All sub-catchments in the same calibration area shared the same set of parameters, although they could change between areas.

Table 5.8 – Parameters in the Soil Moisture Model in WEAP.

Parameter	Unit	Description	Range of values for calibration
Soil Water Capacity (SWC)	mm	Maximum amount of water that can be held in the upper bucket	100-600
Deep Water Capacity (DWC)	mm	Maximum amount of water that can be held in the lower bucket	50-400

Runoff Resistance Factor (RRF)	NA	Empirical factor influencing the volume of precipitation that turns into surface runoff	1-8
Root Zone Conductivity (RZC)	mm/month	Fully saturated conductivity rate of the upper soil	50-800
Deep Conductivity (DC)	mm/month	Fully saturated conductivity rate of the deep soil	50-400
Preferred Flow Direction (PFD)	NA	Empirical factor to split the flow from the lower bucket between interflow and flow to lower bucket	5-10
Freezing Point (FP)	°C	Threshold for transforming liquid precipitation into the solid phase (e.g. snow)	-2 - 4
Melting Point (MP)	°C	Threshold for transforming solid precipitation or snow into the liquid phase	6-12
Albedo Lower Bound (Old snow)	NA	Fraction of solar radiation reflected by new snow	0.3
Albedo Upper Bound (New Snow)	NA	Fraction of solar radiation reflected by old snow	0.7
Crop Coefficient (K_c)	NA	Crop coefficient relative to the reference crop.	0.4 – 1 (0.2 – 1)*

*** Although the lower bound of this range may appear quite small when compared to crop coefficients frequently used for irrigation calculations, it was chosen taking into account that almost all the area analysed is mountainous with bare soil or rocks, and extended dry periods during the year (Allen et al., 2005, Ding et al., 2015, Snyder et al., 2000). The range (0.2-0.1) was used for Juncal River only, as this one is the upstream most tributary, and thus has the lowest amount of alternative land uses compared to the other 4 areas calibrated.**

Out of the 11 parameters only 9 were calibrated, as the Albedo for old and new snow were fixed at 0.3 and 0.7 respectively. This was done following previous applications of this model in similar catchments (Vicuña et al., 2011, Young et al., 2009), but also based on the initial calibration rounds which showed that these parameters could be fixed without sacrificing the quality of the outputs.

Taking into account the large number of parameters in the model used, equifinality problems (i.e. compensation of errors caused by poor modelling of more than two hydrological processes (Beven, 2002)), were a potential threat when calibrating the model to observed streamflows. This was addressed, to some extent, by comparing SWE observations (Cortés and Margulis, 2017) with modelled values as well, to promote internal consistency of the model and have a more robust calibration.

Nevertheless, some authors are cautious about using satellite images (e.g. MODIS or Landsat) to calibrate the SWE magnitudes in semi-distributed models (Ragettli et al., 2014). Thus, in this project the comparison was only done in terms of the timings and by using a graphical comparison. Being a manual procedure, this comparison was done for a small set of parameters only, but thanks to it, it was possible to refine the range of values of FP and MP to better simulate snow accumulation and melting periods, and to avoid having long-term accumulation of snow. Furthermore, the Pearson correlation coefficient was used to analyse the calibrated snow results as to have a better idea of their suitability.

In addition, the model was also calibrated to make sure that the hydro-power stations could generate at least 90% of the energy production that was reported by the company to the regulator (i.e. the sets of parameters generating less than 90% were rejected). This is particularly important taking into account that each calibration area had several sub-catchments, thus there could also be compensation of errors amongst them. This is a common issue in similar models and was particularly relevant for Blanco and Juncal River areas. However, by including this type of information it is possible to mitigate these problems. Although the mining water consumption estimations are not as detailed as the hydro-power ones, it was also required that the model provided at least 90% of their demand.

The metrics used to compare simulated and observed values were RMSE, which was already explained in Chapter 4, and the Nash-Sutcliffe Efficiency (NSE) that is "*a normalised statistic that determines the relative magnitude of the residual variance ("noise") compared to the measured data variance ("information")*" (Moriasi et al., 2007). The closer to 1 the better NSE, any value > 0.5 is often consider acceptable, and any value < 0 means the performance of the model is quite poor, as the mean observed flow is preferable. The NSE is calculated with the following equation:

$$NSE = 1 - \left(\frac{\sum_{i=1}^{n} \left(Y_i^{obs} - Y_i^{sim} \right)^2}{\sum_{i=1}^{n} \left(Y_i^{obs} - Y^{mean} \right)^2} \right)$$

Equation 5.5

In addition, although not used for calibration, the Mean Absolute Relative Error (MARE) was calculated for all calibration areas. As opposed to the RMSE and the NSE, the MARE aggregates relative errors (see Equation 5.6), which provides further insight into the performance of the model.

$$MARE = \frac{abs(Y_i^{obs} - Y_i^{sim})}{Y_i^{obs}}$$

Equation 5.6

5.4. Results

Figure 5.10 shows the plots comparing observed and simulated flows for calibration (April 2001 – March 2005 and April 2013 – March 2017) and validation periods (April 2005 – March 2013), while Table 5.9 includes the average observed flow of each station during the period analysed, and the calibration results. Furthermore, Table 5.10 shows the calibrated parameters for each one of the areas.

Table 5.9 – Results of the calibration and validation of the water resources model.

Gauge	Short Name	Average observed flow (m^3/s)	Calibration			Validation		
			RMSE (m^3/s)	NSE	MARE (%)	RMSE (m^3/s)	NSE	MARE (%)
Rio Juncal En Juncal	**Juncal**	**5.5**	1.40	0.87	21.2	1.65	0.85	25.4
Rio Blanco en Rio Blanco	**Blanco**	**4.05**	2.72	0.70	47.1	2.62	0.81	57.6
Rio Aconcagua en Rio Blanco	**Aconcagua en Blanco**	**7.18**	4.95	0.7	47.8	5.01	0.63	48.3
Rio Colorado En Colorado	**Colorado**	**4.01**	2.67	0.85	658	4.87	0.72	636
Rio Aconcagua En Chacabuquito	**Chacabuquito**	**30.21**	8.51	0.88	21.9	13.16	0.8	26.2
Rio Blanco Antes Junta Rio de los Leones	**Los Leones**	**4.88**				3.82	0.52	40.9

Table 5.10 - Calibrated sets of parameters for each area.

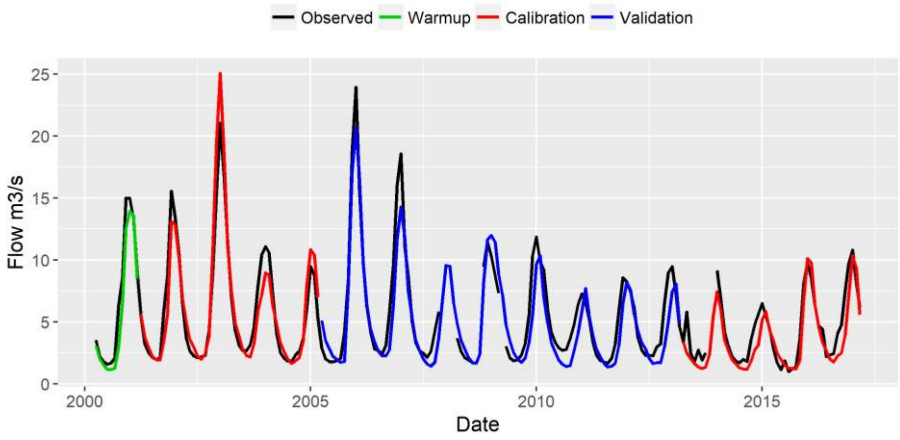
Parameter	Unit	Areas				
		Juncal	Blanco	Aconcagua En Blanco	Colorado	Aconcagua En Chacabuquito
Soil Water Capacity (SWC)	mm	431	362	211	102	105
Deep Water Capacity (DWC)	mm	284	207	167	316	272
Runoff Resistance Factor (RRF)	NA	5	1	4	6	1
Root Zone Conductivity (RZC)	mm/month	642	798	568	540	502
Deep Conductivity (DC)	mm/month	73	121	77	142	390
Preferred Flow Direction (PFD)	NA	0.6	0.9	1	0.8	0.3
Freezing Point (FP)	°C	0	-1	-1	-2	4
Melting Point (MP)	°C	10	12	7	7	9
Albedo Lower Bound (Old snow)	NA	0.7	0.7	0.7	0.7	0.7
Albedo Upper Bound (New Snow)	NA	0.3	0.3	0.3	0.3	0.3
Crop Coefficient (K_c)	NA	0.2	0.4	0.4	0.4	0.4

Results of the comparison between observed and modelled SWE are presented in Figure 5.11. As previously mentioned, magnitudes of SWE values were not compared with the RMSE or NSE, but by means of a visual comparison of values (sub-catchment results were aggregated by 500 m elevation bands to facilitate the comparison). This helped to refine the ranges of parameters FP and MP prior to the Monte Carlo calibration. In addition, Pearson correlation coefficients between observed and modelled values in the calibrated model are presented in Table 5.11.

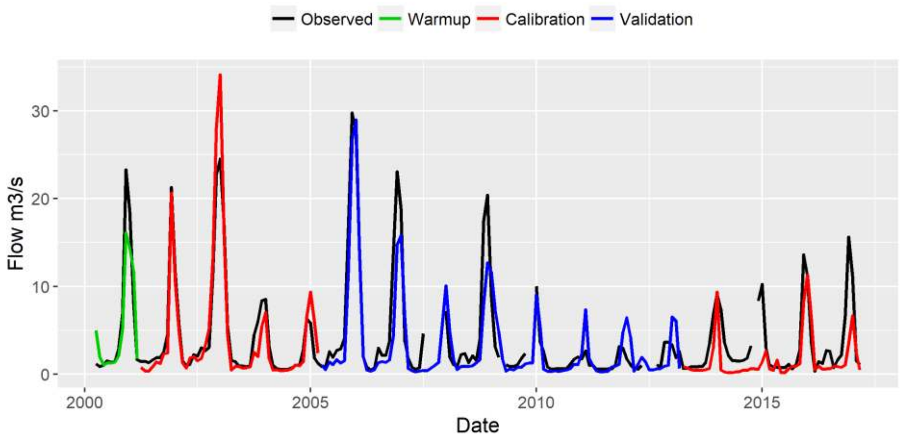
Table 5.11 – Correlation between observed and modelled SWE. Results were aggregated by the elevation of the centroid of the sub-catchments.

Elevation band (masl)	Pearson Correlation
Above 4500	0.7
Between 4000 and 4500	0.6
Between 3500 and 4000	0.82
Between 3000 and 3500	0.82

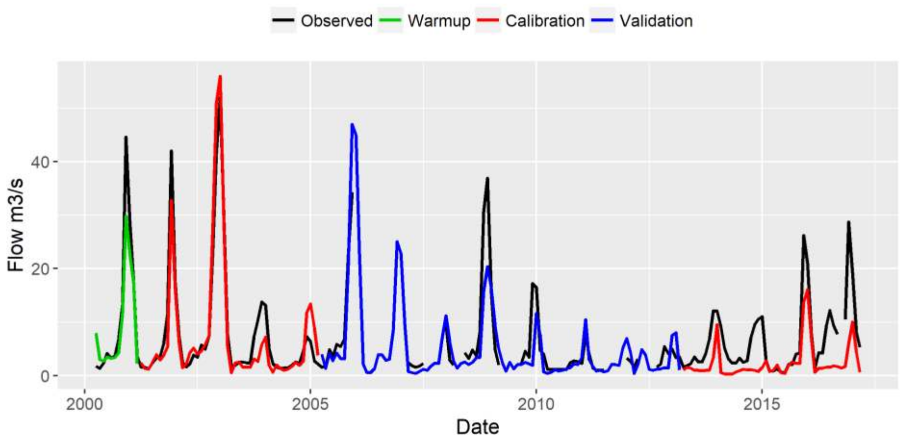
Between 2500 and 3000	0.69
Between 2000 and 2500	0.72



(A) Juncal River Area.

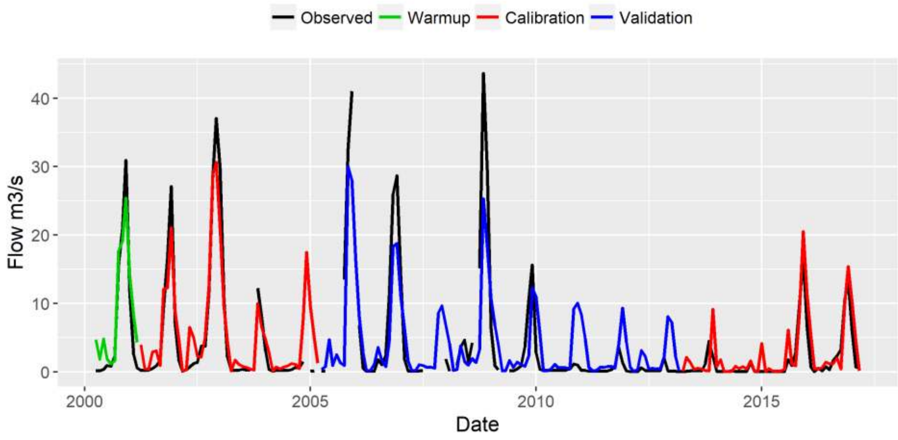


(B) Blanco River Area.

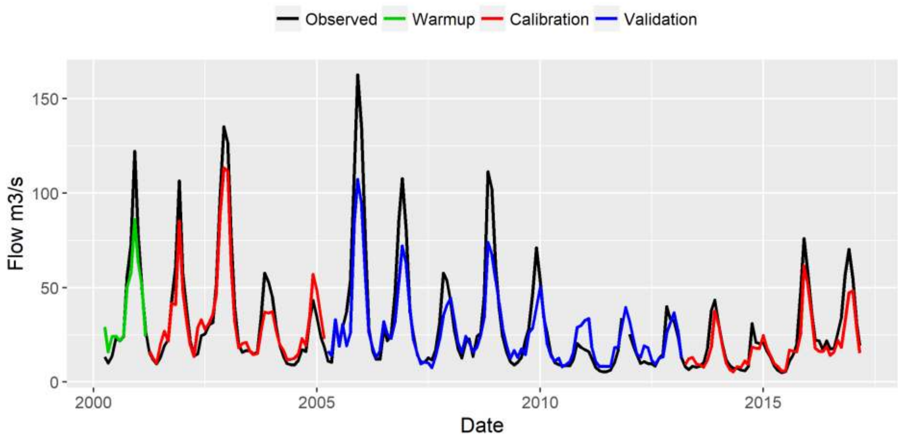


(C) Aconcagua En Blanco Area.

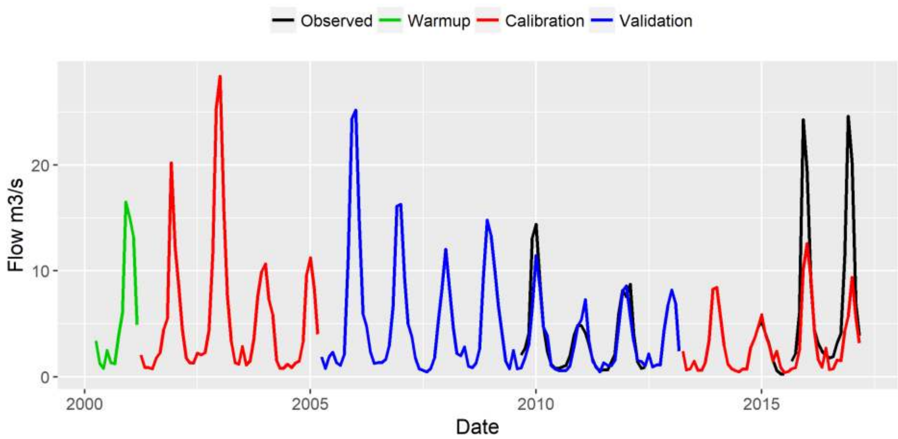
Figure 5.10 – Observed versus Simulated streamflows at the outlet of each one of the 5 calibration areas during calibration and validation periods.



(D) Colorado River Area.

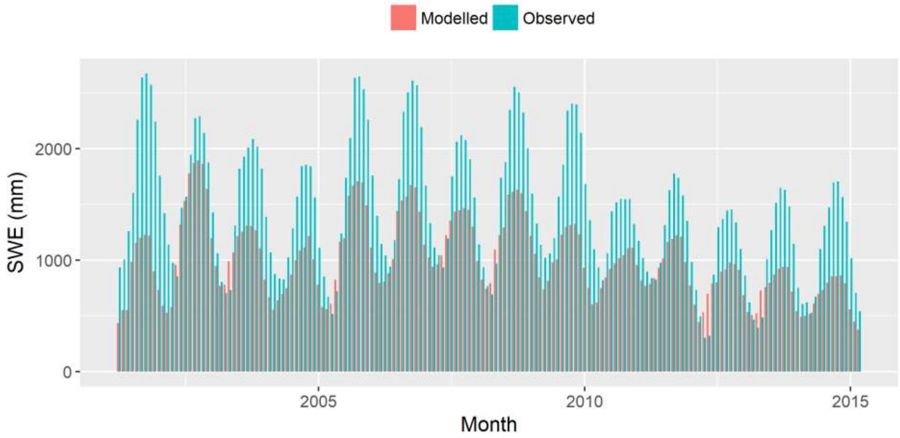


(E) Aconcagua en Chacabuquito Area.

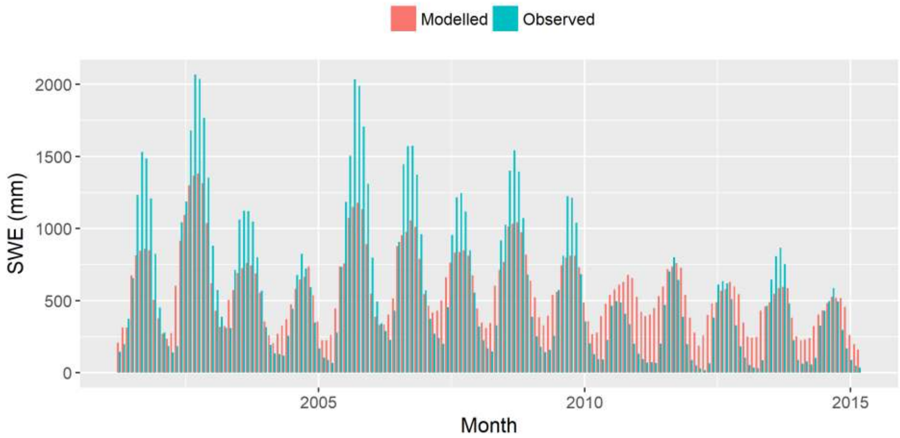


(F) Blanco Antes Junta Rio de los Leones Area.

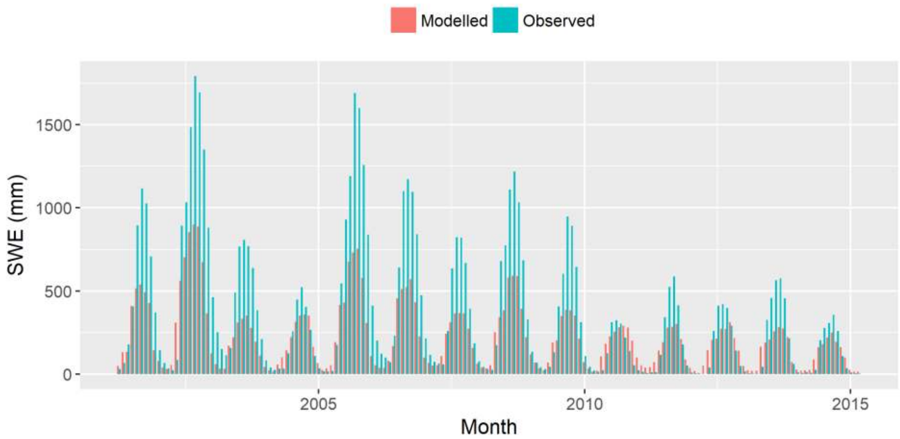
Figure 5.10 (Cont.) – Observed vs Simulated streamflows at the outlet of each one of the 5 calibration areas during calibration and validation periods.



(A) SWE for catchments above 4500 masl.

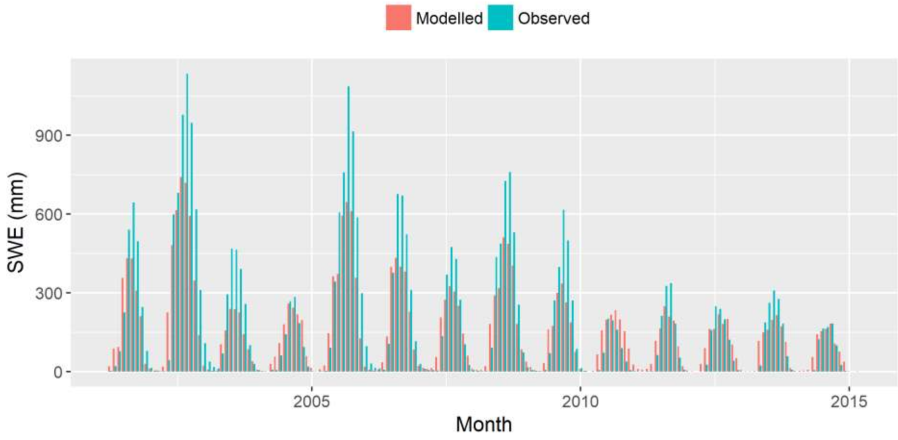


(B) SWE for catchments between 4000 and 4500 masl.

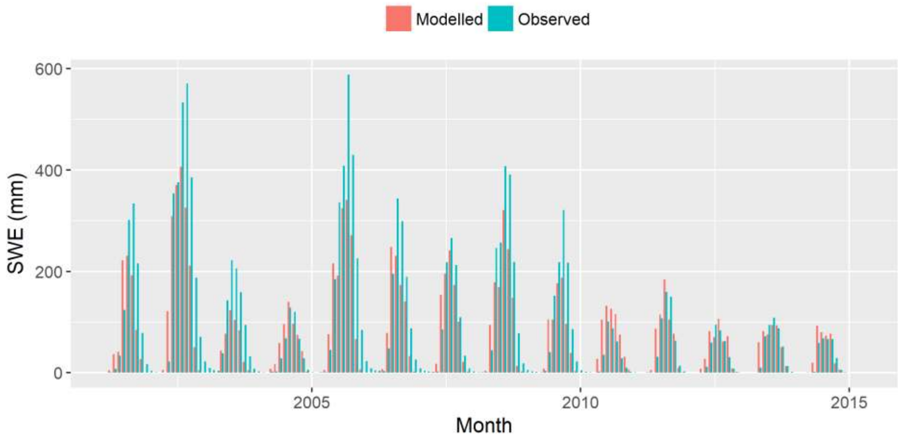


(C) SWE for catchments between 3500 and 4000 masl.

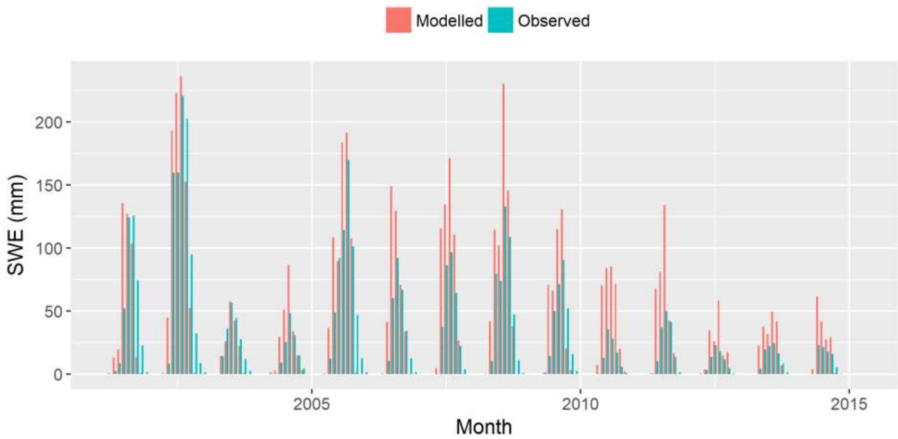
Figure 5.11 – Average SWE Observed and Modelled for catchments in six different elevation bands for the period with available observed data.



(D) SWE for catchments between 3000 and 3500 masl.



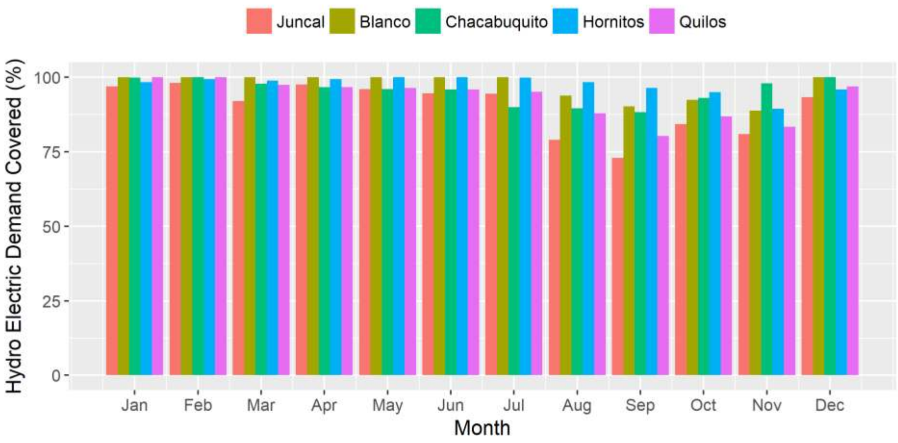
(E) SWE for catchments between 2500 and 3000 masl.



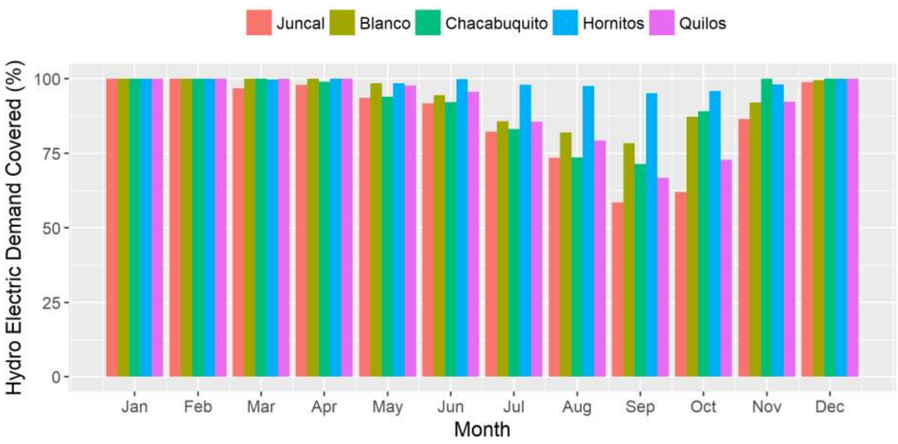
(F) SWE for catchments between 2000 and 2500 masl.

Figure 5.11 (Cont) – Average SWE Observed and Modelled for catchments in six different elevation bands for the period with available observed data.

The calibration based on the comparison of streamflows and SWE, was complemented with the requirement of the fulfilment of at least 90% of the energy generation values reported by the energy company. Figure 5.12 presents the monthly averaged demand coverage for the 5 stations during calibration and validation periods (the Aconcagua station comprises two abstraction points, Blanco and Juncal, thus for flow comparisons results are presented separately). It is important to mention that the 90% requirement had to be fulfilled for the entire period, and not month by month, thus some months for the calibration period have values slightly smaller than the threshold. In addition, Figure 5.13 shows the demand coverage for all stations together for the whole period of analysis.



(A) Calibration.



(B) Validation.

Figure 5.12 – Monthly averaged Hydro-power demand coverage for the calibration and validation periods.

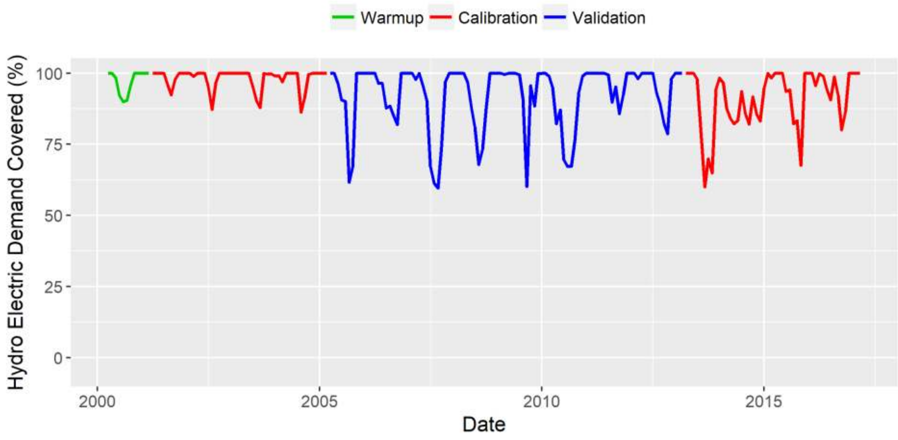
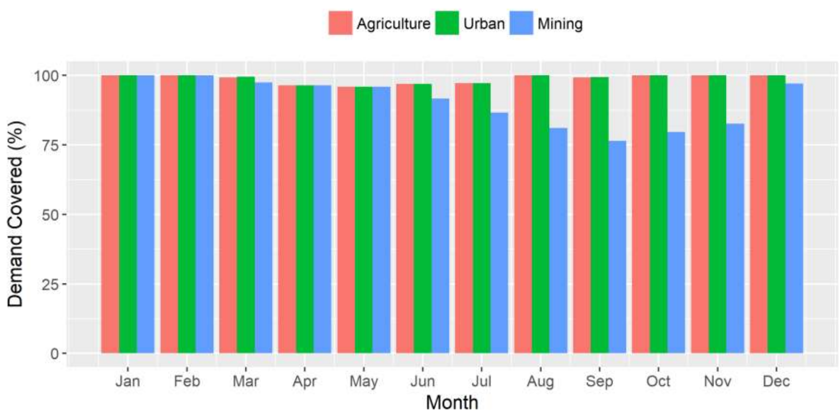
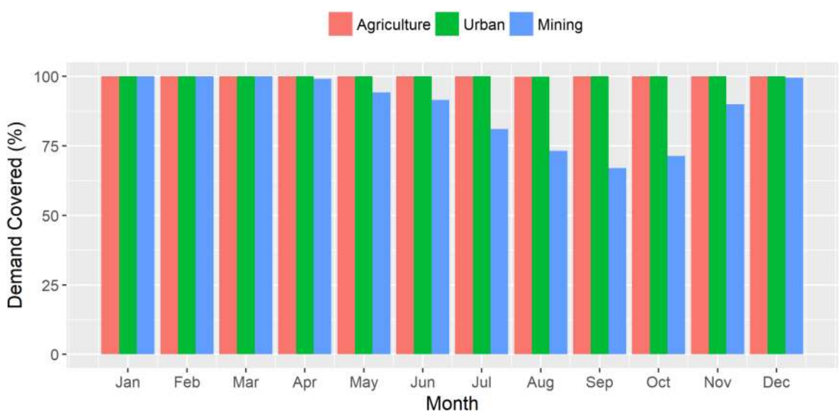


Figure 5.13 – Hydro-power demand coverage aggregated for all stations.

Demand coverage results for all other users (Mining, Urban and Agriculture) are presented in Figure 5.14. In the same way as for Hydro-power, these results were aggregated by month to facilitate its analysis and are presented separately for calibration and validation periods.



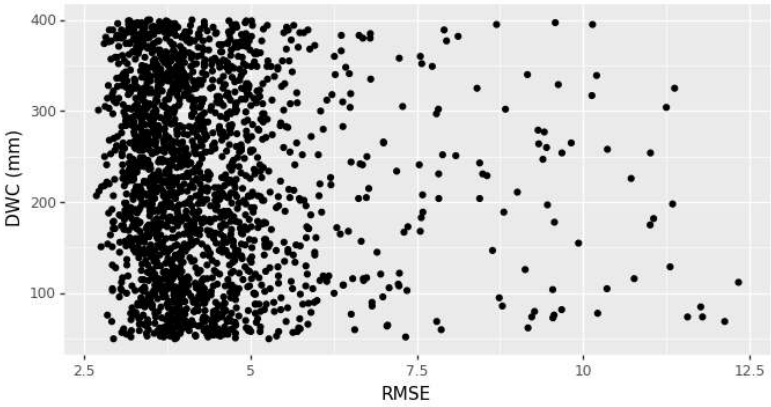
(A) Calibration.



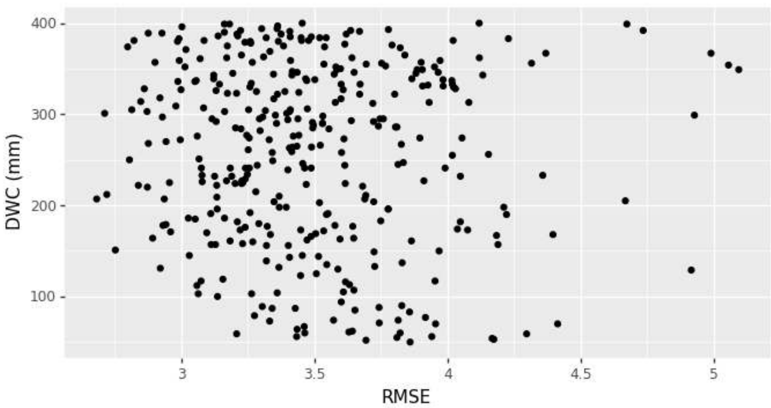
(B) Validation.

Figure 5.14 – Monthly averaged demand coverage for all other users for the calibration and validation periods.

Finally, calibration results were further assessed by plotting the parameters vs the RMSE, which was the main metric to assess the performance of models (see Figure 5.15, Figure 5.16 and Figure 5.17). The intention here was to obtain a better idea of the behaviour of the model, particularly its sensitivity to the parameters. For brevity purposes an image for every parameter of every calibration area is not included, but some key figures from the Blanco sub-catchment are shown, which present the general trends for all the case study. Furthermore, these figures also illustrate the effect of enforcing a minimum coverage on the hydro-electricity demand, when analysing the sensitivity of the model to the parameters.

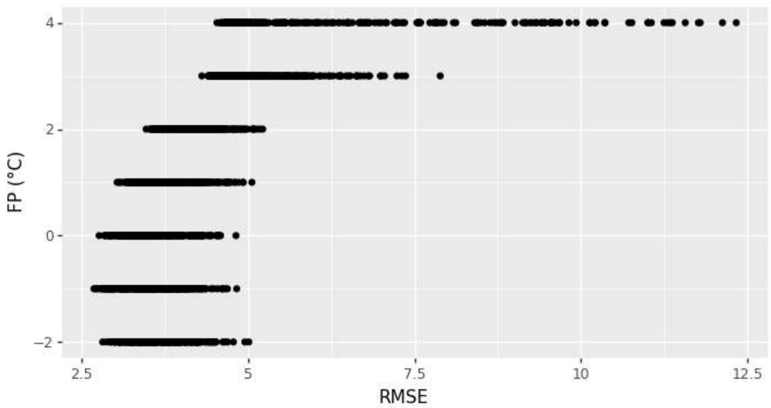


(A) All model runs.

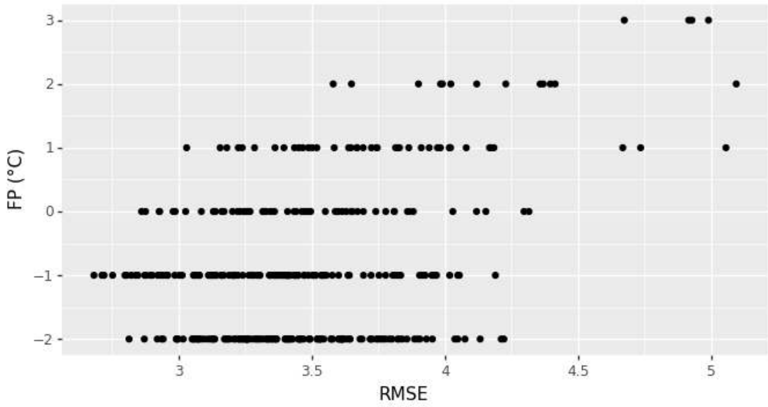


(B) Only runs that fulfilled the hydro-electricity minimum coverage restriction.

Figure 5.15 – Analysis of the performance of the model for different Deep Water Capacity (DWC) values in the Blanco calibration area.

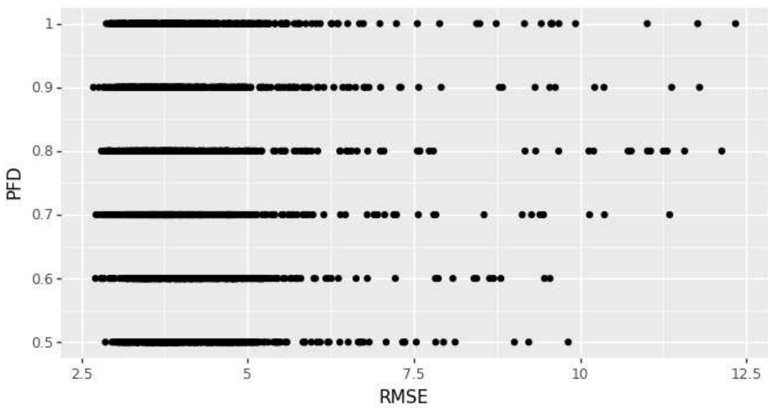


(A) All model runs.

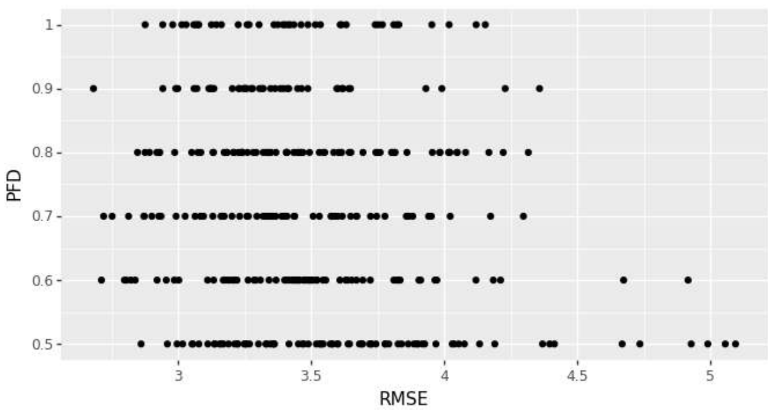


(B) Only runs that fulfilled the hydro-electricity minimum coverage restriction.

Figure 5.16 - Analysis of the performance of the model for different Freezing Point (FP) values in the Blanco calibration area.



(A) All model runs.



(B) Only runs that fulfilled the hydro-electricity minimum coverage restriction.

Figure 5.17 - Analysis of the performance of the model for different Preferential Flow Direction (PFD) values in the Blanco calibration area.

5.5. Discussion

From the results, it is considered that the water resources model acceptably reproduces the observed conditions. The RMSE values are below the average observed flows, most NSE for calibration and validation periods are above 0.7, and all of them are above 0.5, which some authors consider the threshold for acceptable results (Moriasi et al., 2007). For most part of the period of analysis, simulated flows follow closely observed ones, particularly for Juncal River and Aconcagua en Chacabuquito sub-catchments (Plots A and E in Figure 5.10).

Results for Blanco, Colorado and Aconcagua en Blanco are good for most of the period, however, there are some issues between the 2011 and 2014 hydrological years. These years correspond to a very dry period where observed values fell to very low levels. Simulated flows, despite being relatively small, are larger during these four years, particularly during the austral winter. Although other years had experienced similar levels of low rainfall (e.g. 2003 and 2004), observed flows in these gauges for those years were not as low as between 2011 and 2014.

It could be thought that despite water scarcity, users could have continued using similar volumes of water as in other years, which may have generated this behaviour. However, Figure 5.10**F** shows that at least between 2010 and 2012 observed flows in *Rio Blanco en Los Leones* are different from zero and are similar to simulated ones, thus problems are not related to the mining user but downstream of it.

It was found that during this period the River User Committees (RUCs) imposed several restrictions on users, but it was not possible to determine exactly how this affected consumption, thus it is difficult to fully understand the relation between these and the observed flows. Nevertheless, apart from the issues during this period, which is relatively small compared to the whole period of analysis, the model is considered to have a good performance overall.

This is supported by Table 5.9**,** which shows that most NSE values are above 0.7 for both validation and calibration years, and never fall below 0.5. Also, most RMSE values are small compared to the average observed flow in all stations, even in *Rio Blanco en Los Leones*, which was only used for validation purposes. The latter can also be seen in Figure 5.10F, and means that the model is able to predict flows in several points of the case study, even if they were not used for calibration.

Table 5.9 also shows that apart from Juncal and Chacabuquito calibration areas, MARE values are not as good RMSE or NSE. Indeed, the ones for Colorado are very poor (>600%). This is partly explained by the previously mentioned modelling issues between the 2011 and 2014 hydrological years. If this period was excluded from the calculations, the MARE values are reduced almost by half.

However, this is also explained by months with very low observed flows in both wet and dry seasons (which may even be influenced by measurement errors), where the model predicted larger flows. Although the absolute differences are not necessarily very large, when these are analysed relative to the very small observed flows, the relative errors end up being quite high. Table 5.12 shows an example for Colorado sub-catchment, although other areas presented a similar behaviour.

Table 5.12 – Analysis of the relative errors in the Colorado sub-catchment.

Date	Observed (m^3/s)	Modelled (m^3/s)	Absolute Difference (m^3/s)	Absolute Relative Error
Feb-14	0.017	1.782	1.765	10403%
Jan-15	0.029	4.122	4.093	14051%

Although they are not numerous, these large relative errors condition the MARE (see Figure 5.18). It was attempted to address this by using the MARE as objective function in the calibration, but there were not large improvements, thus it was decided to continue using the RMSE only. This means that despite some areas of the model have relevant issues during very dry moths, during most of the period of analysis the model is considered to perform satisfactorily for the objectives of this research.

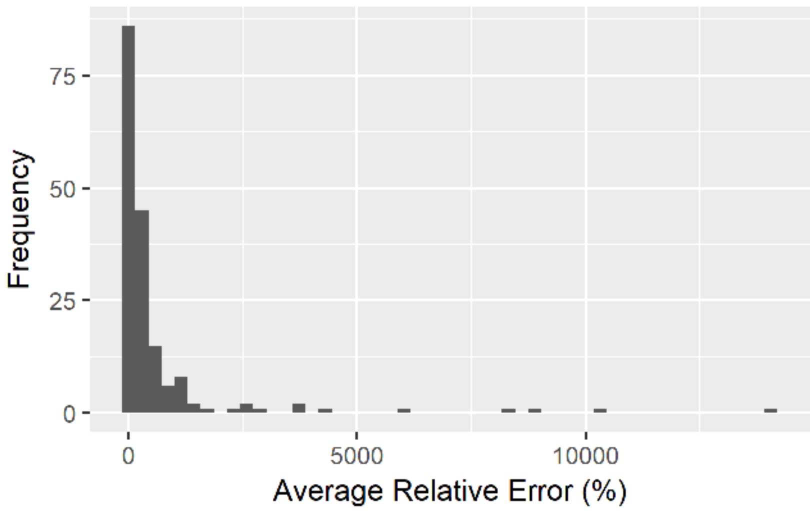


Figure 5.18 – Histogram of Absolute Relative Errors in the Colorado sub-catchment).

Comparison of the modelled SWE melting and accumulation periods, with independently estimated values was done to review the internal consistency of the model (i.e. to avoid error compensation), as described in Ragettli et al. (2014). In the previous reference, erroneous snow parameters caused melting to start earlier (compared to observed values and to a physically based model of the same area), but these errors were compensated with increased soil retention capacity.

Figure 5.11 shows SWE in the six key elevation bands after aggregating results in all sub-catchments with similar altitude. It can be seen that observed values are always larger than the simulated ones, particularly during the wet years. Here, it is important to remember that what are referred to here as observed values, come from a merging of observed satellite images and a snow model forced with MERRA data. In other words, these values are not measurements of SWE, but the output of satellite observations and another model, which means that there is a degree of uncertainty in them. Taking this into account, it was not ideal to compare the magnitudes between these observed values and the ones modelled in WEAP, and it was preferable to focus on comparing the timings of snow melting and accumulation, following previous experiences with semi-distributed models (Ragettli et al., 2014).

The melting and accumulation periods are well described, particularly below 4000 m. Above 4000 m there are some years in which the observed snow melting season finishes later than the simulated one, and this entails that snow accumulation starts earlier for the next year. These lags, however, are not very large and they are only seen in some years.

Table 5.11 complements this by showing correlation coefficients between observed and simulated time-series for the same elevation bands. It can be seen that there is good correlation between both series, and also that the weakest correlation is for sub-catchments between 4000m and 4500m. This could have consequences in the performance of the model at these elevations, particularly in the demand coverage of the most upstream users (i.e. the mine).

Despite lags of one or two months in the melting or accumulation periods in the upper most areas, the correlation for other elevation bands is strong. This analysis shows no evidence of large internal inconsistencies in the model related with snow.

Figure 5.12 and Figure 5.14 present the results of the demand coverage for the different users. It can be seen that generally, a considerable percentage of the demand of all users is covered. Percentages are smaller during validation periods, but still rarely below 80%. Agriculture and urban consumption have a very high demand coverage during calibration and validation years. This includes the minimum flow requirement at the outlet, which has the same coverage as it is located very close and has the same priority as the other two.

Following the model, the key period when users suffer water deficits is between July and November, and the users the most affected are hydro-power and mining. This is mainly because snow accumulates during winter but only starts melting by November in the upper-most areas of the case study. However, these issues could also be related to the problems in the calibration of the Colorado, Blanco and Aconcagua En Blanco areas, which affect the most upstream users. Nevertheless, taking into account the complexity of the catchment and the lack of more detailed input data, results are considered to be satisfactory, and the model is considered to be a useful tool for the objectives of this project.

Regarding the parameters, Table 5.10 summarises the final sets for each one of the calibrated areas. It was found that most parameters are not identifiable when plotted against performance metrics (see Figure 5.15**A**), which means that the model is not very sensitive to changes in them. Some parameters like PFD (see Figure 5.15**C**) and MP are not identifiable, but it can be seen that some values always give relatively poor results (e.g. 0.5 and 1 for PFD). This type of behaviour was seen more often during previous calibration rounds (not reported here), and thanks to this, it was possible to refine the calibration ranges. Finally, FP was the only parameter during this last round that clearly showed that the best performance was achieved by fixing the parameter to -1.

There is an entire research field in hydrology to analyse parameter uncertainty, and particularly how different sets of parameters can achieve almost equal behaviour (Beven, 2002, Pechlivanidis et al., 2011). Future research could analyse how the selection of parameters, and the equifinality problem, may affect the final results of HEMs.

At this point it is important to mention that as the WEAP model described in this chapter is based on an system of priorities to allocate water, which means that its decisions may not be optimal from an economic perspective. This was useful for this project because in the case study there is a system of water rights (see Chapter 3), where water is allocated to all water right holders with the same priority (i.e. in a similar way to the WEAP model). However, in the catchment there is also a water market where some, but not all users participate (i.e. mining is rarely involved thus it is easier to analyse this user through the system of priorities only). The water market component of the model will be explained in the next chapter, together with its limitations and the merging methodology.

5.6. Closing remarks

1. A water resources model was calibrated and validated in the upper Aconcagua River, which will allow estimating time-series of water flows at all relevant points of the HEM.
2. Despite the limitations of the water resources component of this HEM, including a relatively low demand coverage during late winter and spring for some users, the results found are considered to be satisfactory taking into account the complexity of the catchment (i.e. high degree of anthropogenic activity) and the lack of detailed input data.
3. The assessment of the timings of snow accumulation and of the energy demand coverage, is a sign of internal consistency amongst the different hydrological processes. This increases the reliability of the model when analysing changes in climate conditions that involve precipitation and temperature, as the latter affects the snow accumulation and melting periods. The inclusion of a snow-melt predictive model is a clear added value of the selected water resources model, relative to using historical or stochastic flows or a simpler (e.g. more spatially or temporally aggregated) models.
4. The methodology used to connect Python with WEAP is a relevant contribution of this project, as it gives a lot of flexibility to extend the capacity of WEAP to interact with other software and plaftorms, and may be more suitable for HEMs than previously used sequential approaches based purely on WEAP (Forni et al., 2016).
5. Future developments should improve:
    a. The coupling of this model with the ones that the DGA has developed for the downstream aquifer in the first irrigation section of the Aconcagua River.
    b. The mining demand for water estimation and the location of its abstraction points.
    c. The methodology used to transform energy generation into flows abstracted from the River.
    d. The assumption that the volume of water required by crops is the same as the volume irrigated. Farmers usually use more water than what is actually required by crops, and this is related to the efficiency of the irrigation technology.
    e. The urban and agriculture demand values as to change on a yearly basis.

6. Finally, some aspects of the model could represent interesting research topics for future projects. These include:
    a. The analysis of the sensitivity of results to the use of elevation bands of different height.
    b. The analysis of the identifiability of parameters of the Soil Moisture Method (SMM) in WEAP and the sensitivity of the model to them.
    c. The issues of the model in some sub-catchments during particularly dry months. This may even require analysing the quality of measurements during these periods.

6. The Hydro-Economic Model

The main objective of this PhD thesis is to understand how hydro-economic models (HEMs) can help analysing water conflicts in mining regions, and this chapter explains the development of the HEM for this project.

It is important to take into account that the WEAP model explained in Chapter 5 does not provide an optimal allocation from an economic perspective, as water is distributed amongst users based on a system of priorities related to the water rights in the catchment. In many cases this means that water may not be allocated to the most economically efficient uses.

This chapter will provide an economic analysis of the value of water for the different users in the catchment, which will complement the model in Chapter 5 by describing the results in terms of three economic metrics: Total Value of Water, Shadow Value of Water and Water Scarcity Cost. The generation of these metrics will in turn help model potential transfers of water between users (the model in this project allows transfers between agriculture and urban users only).

At first glance, it could be argued that doing an allocation based on a system of priorities first, and then complementing this with the transfer of water between users based on the assessment of the economic value of water, does not follow an economic logic. Nevertheless, this was done to better reproduce real conditions in the catchment. As it has been mentioned in previous chapters, in Chile there is an established system of Water Rights that allocates water to users based on the amount of rights they hold. During cases of water scarcity, users get volumes of water proportional to the shares they have[9]. This is better reproduced through a system of priorities where all users (i.e. all water right holders) have the same priority, and its access to water during dry years is limited equitably (the WEAP model in Chapter 5).

However, in the case study there is also a water market where users can trade temporal or long-term water rights (some of the limitations of this market were discussed in Chapter 2 and will be reviewed later in this Chapter). This component is described in this Chapter and is based on the analysis of the economic value of water for the users assumed to be involved

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[9] There are many types of Water Rights and some of them have more priority than others, however, here it is assumed that all water rights have the same priority.

in the trades. In this way, the whole water system in the case study (water rights allocation and water trade) is modelled through a system of priorities (Chapter 5) and simplistic but relevant water market assumptions (this Chapter).

The outline of this Chapter is as follows: first, a review of HEMs is done, together with an analysis of some key concepts. This is followed by the description of the economic analysis of the water demand from each user and the coupling methodology. Afterwards, key results are presented, followed by a discussion and some closing remarks.

6.1. Review of HEMs

Table 6.1 analyses the models from Table 5.1 that also included an economic component. Table 6.1 also describes some models that were not previously included, as they did not provide enough details of the water resources component. In the table, it can be seen that the time-steps for some of the papers are different to the ones reported in Table 5.1, this is because they use different temporal resolutions for both components, usually after aggregating the results from the water resources component.

Table 6.1 also shows that the General Algebraic Modelling System (GAMS) software is widely used to analyse the economic component, and eventually the water resources one is also included in this software. It is important to remember that the objective of the economic component is to define a set of functions that describe the value that different users get from water. This may involve optimisation algorithms that analyse farmers behaviours to define their water demand curve (e.g. as done in Positive Mathematical Programming - PMP), demand functions, or more simple mathematical expressions that link the volumes supplied to the economic value obtained.

Another common tool to analyse irrigation demand is the State Wide Economic Agricultural Production Model (SWAP), however, SWAP is specific for models in California. Nevertheless, SWAP is based on the concept of Positive Mathematical Programming (PMP), which is a common approach to analyse irrigation demand (Howitt, 1995). It is important to mention that some papers did not clearly describe their economic approach, thus, although model details are reported as accurately as possible, they are the interpretation of the author of this dissertation.

Table 6.1 – Analysis of Hydro-Economic Models (HEMs) in the literature.

Number	Consideration	HEM Time-step		Integration		Economic models used to analyse water demand	Software used for the economic component
	Reference	Monthly or less	Seasonal or Yearly	Modular *	Holistic*		
1	(Cai et al., 2006)		X		X	• Crop Yield and Irrigation Profit function for agriculture. • Inverse demand function for urban uses. • PMP for agriculture as a second alternative.	GAMS
2	(Medellín-Azuara, 2006)		X		X	• PMP for agriculture. • Block rate pricing structures for urban uses. • Opportunity costs for environmental values.	GAMS and STATA
3	(Fernández et al., 2016)		X	X		• PMP integrated with a risk model for agriculture.	NS
4	(George et al., 2011)		X	X		• Residual method for agriculture.	NS
5	(Satti et al., 2015)	X			X	• Predefined marginal values for agriculture.	GAMS
6	(Medellín-Azuara et al., 2015)			X		• PMP for agriculture.	SWAP
7	(Kim and Kaluarachchi, 2016)		X		X	• Farm based single season mathematical model to develop producers' pre-season decisions.	Matlab
8	(Esteve et al., 2015)		X	X		• Non-linear mathematical programming optimisation model for agriculture.	NS
9	(Hurd and Coonrod, 2012)	X		X			GAMS
10	(D'Agostino et al., 2014)	X		X		• Non-linear optimisation model.	GAMS
11	(Graveline et al., 2014)		X	X		• Linear programming model for agriculture.	GAMS
12	(Dale et al., 2013b)	X		X		• PMP for agriculture.	CVPM
13	(Jeuland and Whittington, 2014)		X	X			NS
14	(Pande et al., 2011)	X		X			GAMS
15	(Srinivasan et al., 2010)		X	X			NS
16	(Forni et al., 2016)		X		X	• PMP for agriculture.	SWAP
17	(Hasler et al., 2014)		X		X		GAMS

18	(Qureshi et al., 2013)		X	X	• PMP for agriculture.	GAMS
19	(Ringler and Cai, 2006)	X		X		GAMS
20	(Lee et al., 2011)		X	X	• Non-linear model for all users.	NS
21	(Baresel et al., 2006)		X	X		GAMS

NS Non-specified

***The definition of holistic and modular can be found in the published article referenced in Chapter 2.**

As found in the literature review (see Chapter 2), Table 6.1 evidences that the type of integration of the water and economic components in a HEM is closely related to its purpose. Holistic models are usually connected to optimisation approaches, where all equations are programmed together and the user maximises or minimises an objective function. Modular approaches, on the other hand, may involve some optimisation (e.g. using a PMP to analyse agriculture, together with other approaches for other users), but are more focused on analysis of scenarios. The latter approach usually involves more detailed analyses of hydrological processes, which was the third objective of this PhD thesis (see section 1.2).

The economic depth of most models includes only the direct impacts (microeconomic analyses). Few of them even mention the indirect impacts, and when they do, they often use simple approaches like social accounting matrices (Hurd and Coonrod, 2012) or input-output models (Medellín-Azuara et al., 2015). These approaches provide a quantitative measure of the potential spillover effects of economic activities and events such as agricultural revenue losses due to water shortage. Impacts on macroeconomic variables such as employment, gross domestic product and income, amongst others, are often analysed.

This does not mean that indirect effects are never addressed, as there is a very rich field of research in macroeconomic analyses of water allocation, including the use of Computable General Equilibrium (CGE) models. Nevertheless, these approaches tend to use larger spatial extents (states or countries), coarser temporal resolutions (years) and often over simplify the water resources component substantially. This means that the focus of the research is shifted towards pure economics, and that is why they were not reviewed here.

Regarding the analysis of uncertainty and sensitivity, this is a relevant component of several of the HEMs reviewed, although not all of them address it. Two types of uncertainty/sensitivity analyses are usually considered; the first one uses Probability Distribution Functions (PDF) instead of fixed parameters or deterministic input data, and runs the HEM for each set of parameters/inputs sampled from the PDF. The output of this not only includes the most likely results, but also boundaries describing what could happen in less likely conditions. This is usually applied to specific parts of the model, like the generation of streamflow values (Fernández et al., 2016) or crop yields.

An alternative, and perhaps more common approach, is to analyse how the model changes as a function of discrete modifications of some of the parameters or input data. This includes increasing or decreasing climate conditions or water quality values by a specific percentage (e.g. + 20% and -20%) (Cai, 2008, Satti et al., 2015), changing price or cost estimates (Ringler and Cai, 2006, Cai, 2008), and using outputs of climate change models to predict future streamflow or precipitation values (D'Agostino et al., 2014).

Another feature that some HEMs include is a risk component for agriculture. This is often incorporated as a term in the objective function which is calibrated to adjust yield or profit functions to follow observed values. This is usually justified by the fact that many farmers are risk averse, thus their behaviour may be different from a theoretical maximisation of their economic returns (D'Agostino et al., 2014, Fernández et al., 2016, Kim and Kaluarachchi, 2016). These findings were used to define the characteristics of the HEM of this project.

6.2. The economic component of the HEM

This section describes the approaches used to value water for each one of the four users in the HEM (mining, agriculture, urban and hydro-power). While environmental requirements will be included in the model, they were not analysed in the same way as other users but through a cost of opportunity approach (see Chapter 7). For the economic component, most methods used information from 2007 thus the terms calibration/observed period are used interchangeably to denote this year.

6.2.1. Economic analysis of agriculture demand

6.2.1.1. Positive Mathematical Programming (PMP)

PMP is a deductive methodology to calibrate the parameters of a non-linear agricultural production model (Howitt, 1995, Forni et al., 2016, Medellín-Azuara et al., 2015). According to Howitt et al. (2012), its key advantages compared to alternative approaches are:

1. The model is calibrated to observed values of crop areas and water consumption. This is why the *"positive"* term is used.

2. PMP does not assume that costs are linear, thus adds flexibility to the profit function.
3. The methodology does not require very large datasets for calibration.

The calibration of the model is done in three steps. In the first a linear model of farm profit maximisation is defined with two sets of constraints. The first one is for resources constraints, which have to be normalised to land, and the second one is a restriction to reproduce observed crop areas. Water and Land were the only resources analysed in this project as explained in Equation 6.1.

$$\boldsymbol{max\ linprofit} = \sum_i \boldsymbol{XL_i}(\boldsymbol{v_i yld_i} - \sum_j \boldsymbol{c_{ij} a_{ij}})$$

Equation 6.1

$$\boldsymbol{s.t.} \sum_i \boldsymbol{XL_i} \leq \boldsymbol{b} \qquad \sum_i \boldsymbol{XL_i a_i} \leq \boldsymbol{wat}$$

Equation 6.2

$$\boldsymbol{XL_i} \leq \boldsymbol{\widetilde{XL_i}} * \boldsymbol{\varepsilon}$$

Equation 6.3

where i represents each crop, XL_i is the farmers' decision variable (crop areas), v_i is the marginal revenue per unit of output for crop *i*, j denotes the production inputs (in this case all inputs apart from water were lumped in a unitary cost per ha), c_{ij} is the cost of each input and a_{ij} is a coefficient relating the amount of input required per area of crop. Equation 6.2 describes the resource constraints, where b and wat are the maximum area and volumes of water available. Equation 6.3 defines the calibration constraint where $\widetilde{XL_i}$ is the observed area of each crop, while $\varepsilon = 1.0001$ is a perturbation constant that allows the calibration.

The second step of the PMP involves using the Lagrange multipliers λ of the calibration constraints (Equation 6.3) in the first step, to parameterise a quadratic cost function as follows:

$$Total\ Costs = TC = \alpha_i XL_i + \frac{1}{2}\gamma_i XL_i^2 \qquad \alpha_i = c_i - \lambda_i \qquad \gamma_i = \frac{2\lambda_i}{\widetilde{XL_i}}$$

Equation 6.4 – Definition of parameters of the cost functions of the PMP.

The last step involves optimising a non-linear model for agriculture production with a quadratic cost function parameterised in step 2, using the previously defined parameters (see Equation 6.5) and the constraints in Equation 6.2.

$$\boldsymbol{Max\ nonlinprofit = Z = \sum_i XL_i v_i yld_i - \alpha_i XL_i - \frac{1}{2}\gamma_i XL_i^2}$$

Equation 6.5

6.2.1.2. PMP Model Calibration

The 2007 agricultural census was used to define the type of crops and their areas in the case study (see Table 5.3). In addition, irrigation requirements were defined using evapotranspiration estimates for the Aconcagua valley done by INIA, crop coefficients from the FAO guides (Allen et al., 2006) and harvest dates from the literature (Faiguenbaum, 2003) (see Table 5.4, Table 5.5 and Table 5.6). For the economic analysis, this was complemented with technical sheets based on farmer surveys by the *Oficina de Estudios y Politicas Agrarias* (ODEPA – Bureau of Agricultural Policy and Research) (ODEPA, 2018)[10].

They include yields per area, market prices and costs, for the most frequently employed technological systems in the farms surveyed. The latter include some financial costs (e.g. interest on the loans taken at the beginning of the season to buy fertilisers and other supplies) but do not include major capital costs (CAPEX - e.g. cost of land and irrigation infrastructure, amongst others), except in the case of corn where they were included by ODEPA.

The sheets are developed for each crop independently, and most of them are provided separately for each region of the country. Some crops in this project had sheets calculated specifically for the Aconcagua River, although in some cases sheets for the *Region Metropolitana* or *O'higgins* regions were used.

[10] Although the link to the Technical Sheets is provided in the reference, during this project it was evidenced that this may change with time. This data is available in ODEPA's website following statistics→ productive statistics → the technical sheets are in the bottom of this page. https://www.odepa.gob.cl/estadisticas-del-sector/estadisticas-productivas

Data on the water rights fees[11] were available in two sheets from 2014 only (Table grapes and Peach) and it was found to be $40,000 CLP per ha per year (Chilean Peso - CLP). Taking into account the average water consumption of these two crops (see Table 5.4) means that the yearly water rights fee is around $8,075 CLP/ML. This value was applied to all crops.

As many of the input values used were calculated in different years, inflation rates were applied to convert all price data to 2007 equivalents. The input data and agricultural results in this section are presented as 2007 prices, to match the year of the census. Nevertheless, most of the final calculations of the HEM were taken forward to 2017 prices. In order to achieve this, inflation rates based on Consumer Price Indices (CPI) were taken from the *Instituto Nacional de Estadísticas* (INE – National Statistics Institute) and are presented in Table 6.2 (INE, 2018).

Table 6.2 – Yearly changes of Consumer Price Indices in Chile.

Year	CPI*
2000	3.7%
2001	2.1%
2002	3.5%
2003	0.6%
2004	2.7%
2005	3.7%
2006	2.9%
2007	8.9%
2008	3.0%
2009	1.5%
2010	3.3%
2011	3.1%
2012	0.9%
2013	5.4%
2014	4.0%
2015	4.2%
2016	2.6%
2017	2.0%

Values were calculated using *Calculadora IPC* between June of the year and May of the next year.

[11] These fees should not be confused with the costs of irrigation infrastructure inside each farm. These fees are paid by all water right holders to their local River User Committees (RUC), to maintain the shared infrastructure in the channel. This is paid by users as a function of their amount of water rights independent of the crops they grow.

Furthermore, to facilitate the understanding of the economic magnitudes, many values were transformed to US Dollars (USD) with the exchange rates taken from OANDA (OANDA, 2018). These values were double-checked with data from the Chilean Central Bank until 2011 (see Table 6.3). Both the CPI and exchange rates presented in this section were used throughout this project.

Table 6.3 – Average yearly exchange rate for Chilean pesos to 1 USD.

Year	Average Exchange Rate
2000	540
2001	636
2002	688
2003	692
2004	609
2005	560
2006	530
2007	522
2008	523
2009	559
2010	510
2011	484
2012	487
2013	496
2014	571
2015	654
2016	677
2017	649

Table 6.4 summarises the input data required to calibrate the case study PMP. Appendix D includes a detailed explanation of how these values were defined using the previously mentioned sources. In the table, some of the values for wheat and corn are presented in Quintals (i.e. 100 kg), because input data were found in these units. This is only for illustrative purposes and does not have consequences on calculations, as the latter are done with revenues, which in all cases are presented in CLP per ha.

Table 6.4 – Agricultural input data for the PMP model. Economic values in 2007 CLP.

Value	Price (CLP/kg) (CLP/qqm)*	Yield (kg/ha) (qqm/ha)*	Revenue (CLP/ha)	Cost (CLP/ha)	Crop Areas (ha)	Applied Water (m3/ha)
Alfalfa	$ 59	9,850	$ 578,087	$ 518,093	1,705	4,676
Wheat*	$ 10,210	70	$ 714,724	$ 650,692	69	2,736
Corn*	$ 8,997	150	$ 1,349,617	$ 1,323,964	326	4,125
Potato	$ 132	26,000	$ 3,427,681	$ 2,771,060	112	3,573

Table Grapes	$	324	29,000	$	9,384,961	$	7,768,150	9,376	4,978
Avocado	$	465	10,500	$	4,885,608	$	3,581,969	676	6,978
Walnut	$	1,318	4,000	$	5,273,355	$	3,805,538	1,369	5,889
Peach	$	124	30,000	$	3,722,368	$	3,278,946	2,632	4,928
Olives	$	447	7,000	$	3,131,800	$	2,696,037	354	4,911
Japanese Plum	$	488	9,000	$	4,393,120	$	3,638,376	146	4,928

As previously mentioned, costs in the technical sheets and in Table 6.4 do not include Capital Expenditure (CAPEX), thus, they were defined using agricultural data from the USA (University of California - Davis, 2018), as no local information was found (only corn included CAPEX in the technical sheets). Based on the data from California, it was found that for most crops, CAPEX is around 26% of the yearly total costs (based on the comparison of Annualised Capital Costs - ACC[12]), while for wheat and alfalfa this is 5%. Taking into account the similarities in crops raised, weather and irrigation infrastructure in both regions, using this data in this project is seen as an acceptable assumption.

Taking into account that this is a coarse approximation, it was decided to analyse the sensitivity of the HEM to changes in the ratio of CAPEX to Total Costs (from now on defined PeCAPEX). The sensitivity to the model to the PeCAPEX of wheat and alfalfa was not tested, as the margins of these crops are smaller (i.e. with values of PeCAPEX larger than 5%, negative net revenues may be obtained), and the areas of these crops are not very large.

With the input data in Table 6.4, it was possible to determine the total volume of water required by the crops analysed in the PMP (84,803 ML/yr), which corresponds to the sum of all individual water requirements. This is not the same value of the node in WEAP (see Table 5.5), as in the latter it was necessary to use the estimation of the total consumption of water (93,786 ML/yr), and not only that of the crops with economic data available (91%), which were the ones included in the PMP.

[12] This concept is also defined Equivalent Annual Cost and represents the fraction of capital costs that is split amongst the number of periods of the lifespan of an investment, including the effects of discount rates.

The land constraint was defined based on the total area available for crops, as reported in the census (18,551 ha). In addition to crops (16,768 ha), this value also includes fallow, resting and unused land. This project assumes that farmers were unable to use all available land due to the lack of water, in other words, there was a water scarcity cost equivalent to the foregone profits of using the extra land.

The PMP was coded in R to determine the shadow value of water for farmers. As previously defined, the higher this value is, the more urgent/pressing the requirements of water are, and the more likely it is that conflicts will arise between users. Furthermore, after the parameters of the CES production function and the quadratic cost function have been calibrated, it is possible to analyse how farmers in the case study may react to dry periods, which allows defining a water demand curve for irrigation water.

6.2.1.3. Results of the economic analysis of agriculture demand

The PMP calibration results are presented in Table 6.5, and they were validated by comparing the solutions with the original crop areas (differences were always below 1%). This table shows that, for the region as a whole, corn is the product with the lowest net revenue and net revenue per water consumption. This means that the shadow value of water corresponds to corn's net revenue per water consumption, and that the model redistributes its area (as much as the calibration constraint allows) to other crops ($\lambda_{corn} = 0$).

Table 6.5 – PMP results. Economic values in 2007 CLP.

Crop	Net Revenue (CLP/ha)	Linear Solution (ha)	Lagrange Multiplier λ	Alpha α	Gamma γ	Non-Linear Solution (ha)	Difference in predicted and actual crop areas (%)
Alfalfa	$ 59,994	1,706	30,914	487,180	36	1,706	0.007%
Wheat	$ 64,032	69	47,015	603,676	1,355	69	0.008%
Corn	$ 25,654	324	-	1,323,964	-	324	-0.598%
Potato	$ 656,620	112	634,400	2,136,661	11,306	112	0.010%
Table Grapes	$ 1,616,811	9,377	1,585,849	6,182,301	338	9,377	0.010%
Avocado	$ 1,303,639	676	1,260,240	2,321,730	3,728	676	0.010%
Walnut	$ 1,467,817	1,369	1,431,193	2,374,345	2,090	1,369	0.010%
Peach	$ 443,422	2,632	412,772	2,866,174	314	2,632	0.010%
Olives	$ 435,763	355	405,222	2,290,816	2,286	355	0.010%
Japanese Plum	$ 754,744	147	724,094	2,914,281	9,885	147	0.010%

The shadow value of water under the full modelled level of water consumption was found to be $ 6,219 CLP/ML (i.e. the value for current consumption – 100% in Table 6.6). Different volumes of water (e.g. as a percentage of the original volume available) were used to run the third step of the PMP several times and define the water demand curve for agriculture (see Table 6.6 and Figure 6.1). When water availability goes beyond 110% the shadow values are 0, meaning that water is not the constraint anymore, as farmers are using all land available (i.e. area is the new constraint of the model).

Table 6.6 – Shadow value of water in the first irrigation area of the Aconcagua River. Economic values in 2007 CLP.

Percentage (%)	Shadow Value (CLP/ML)	Volume (ML)
20	$ 426,698	16,961
30	$ 337,052	25,441
40	$ 256,582	33,921
50	$ 176,965	42,402
60	$ 131,769	50,882
70	$ 88,167	59,362
80	$ 44,565	67,842
90	$ 15,113	76,323
100	$ 6,219	84,803
110	$ 0	93,283

Figure 6.1 illustrates the water demand curve for agriculture in the case study, and shows that for very low water volumes the shadow value of water is quite large, as farmers have a very high willingness to pay for it. Further right in the curve, values approach the shadow value for observed conditions ($ 6,219 CLP/ML), and then it becomes 0 when more than the total amount of water currently required is made available. In this situation land, rather than water, becomes the binding constraint.

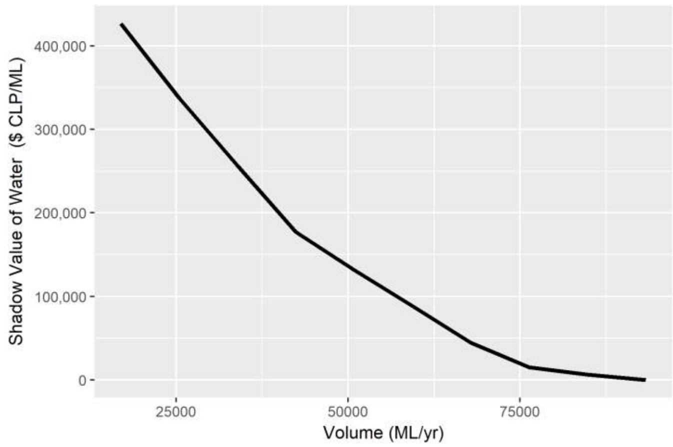

Figure 6.1 – Water Demand Curve for agriculture in the first irrigation area of the Aconcagua River. Values in 2007 prices.

In order to explore the potential importance of the ratio of CAPEX to total costs on these results, Figure 6.2 plots how different values of PeCAPEX affect the water demand curve. It can be seen that the shape of the curves are similar but the magnitudes change. Larger PeCAPEX decrease the net revenues of crops (i.e. they are less profitable), thus farmers forego less revenue during droughts (i.e. their willingness to pay for irrigation water decreases). The right hand side of the curve does not change, as the least profitable crops that influence this part of the curve had a constant PeCAPEX (i.e. were not included in this sensitivity analysis).

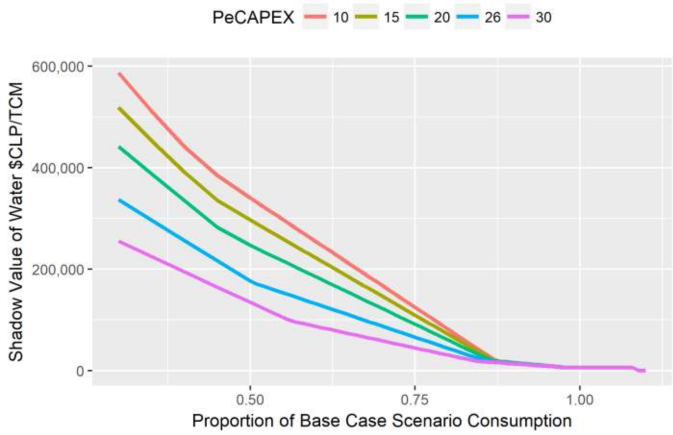

Figure 6.2 – Effects of the selection of ACC percentage on the Water Demand Curve. Values in 2007 prices.

The two other key economic metrics for this project are the total value of water and the water scarcity cost. The former is expressed by the objective function of the PMP model, thus it is also possible to plot how this value changes as a function of the volume of water available in the catchment (see Figure 6.3). It is important to mention that the curve in Figure 6.1 is the derivative of Figure 6.3, which means that net revenues can also be defined by integrating the water demand curve.

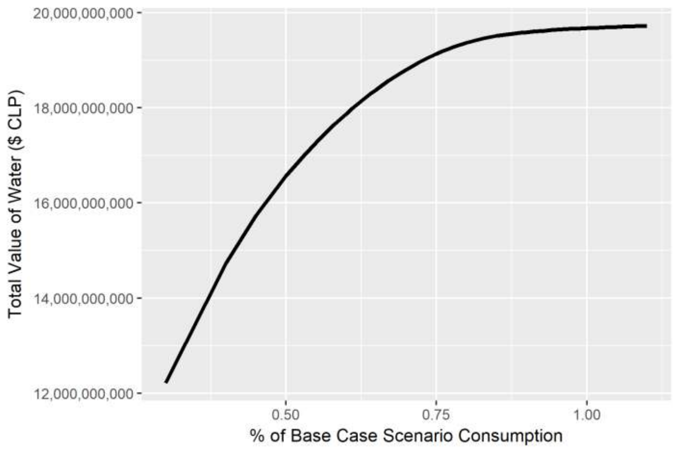

Figure 6.3 – Total value of water for agriculture in the first irrigation area of the Aconcagua River. Values in 2007 prices.

Water scarcity cost is also related to the area under the water demand curve, which makes it similar to the previous metric. However, in this case it is only accounted the area between the point of available water in a determined year and the intersection of the curve with the x-axis (i.e. where land starts being the resource constraint). Table 6.7 summarises all metrics.

Table 6.7 – Summary of metrics for agriculture in the calibration scenario[13]. Values in 2007 prices.

Metric	Unit		Value
Shadow Value of water	CLP / ML	$	6,219
Total value of water	CLP / yr	$	19,673,748,809
Water Scarcity Cost	CLP / yr	$	52,739,048

6.2.1.4. Limitations of the economic analysis for agriculture

In addition to the issues arising from the lack of information about CAPEX and the uncertainty from the lack of a more up-to-date agricultural census, there are other

[13] The ***Calibration Scenario*** is the year for which the economic calculations were defined. These values can be transformed to other years by means of inflation rates. This concept should not be confused with the ***Base Case Scenario***, which corresponds to the benchmark for the whole HEM (i.e. including both the water resources and economic components) between 2000 and 2017 described later in this section.

considerations that should be mentioned. First, PMP models have limitations including:

- PMP models are less suited to analyse multiple observations (e.g. from several years) on production outcomes for the same crop (e.g. to incorporate a set of marginal cost conditions for the same product). These rather work on the average cropping decisions for a set of years.
- PMP models are not able to analyse crops or farms whose production is zero during the reference period. In other words these cannot predict new crops in a given year if these were not part of the average of the base time period in the dataset.

A detailed discussion on these and other limitations can be found in Heckelei and Wolff (2003), de Frahan et al. (2007) and Howitt (2005). One of the conclusions drawn from these references is that PMP models may not make the best use of information when large datasets are available (i.e. several years of data). However, within scenarios of data scarcity like the one in this case study, these issues tend not to be a problem, and PMPs are well suited to analyse agriculture production based on the few data available.

In addition, it is important to mention that PMP results represent an ideal scenario where water is allocated with the aim of maximising its economic value. The closest representation of this in reality may only be achieved by using water markets, although there may be limitations as the latter involves transaction costs, and farmers behaviour in water markets departs from PMP ideal allocations.

For example, it has been reported that farmers prefer to trade water inside the same irrigation channel only, some of them do not trade water separated from land, and sometimes water is not metered to make sure that each person takes only their appropriate share (Donoso et al., 2010, Hearne and Donoso, 2014, Donoso, 2015). These are practical issues for the use of PMP but also for most alternative models, yet limitations and assumptions have to be discussed.

Finally, the PMP in this project assumed that the water volumes required by the crops are the same as the applied volumes by farmers. In reality, farmers may apply larger or smaller volumes as a function of their irrigation infrastructure, and based on their experience. Thus, adjustments at the intensive margin of water use in crop farming (i.e. irrigation intensity), will occur as farmers balance yields and water availability conditions. This could be a subject for future refinement of this HEM.

6.2.2. Economic analysis of urban water demand

In order to define the water demand curve for the urban user, it was applied the *Point Expansion Method* (Griffin, 2016, Young and Loomis, 2014), which is a common tool to analyse urban water demand, particularly when there is not too much data available. Cai (2008) used to this approach to analyse surface water demand from urban users in the Maipo River in Chile (just south of the Aconcagua River). One approach for applying this method is to use a known consumption Q and price P combination (i.e. the volume that is being currently consumed and the associated price per unit consumption), and to assume an estimate for the price elasticity of water demand α (see Equation 6.6), if it is not possible to calculate one from available data. Cai et al. (2006) defined the consumption, price pair (Q, P) from data of the local water utility, and they assumed a constant elasticity $\alpha = -0.45$.

$$\boldsymbol{Q = AP^{\alpha}}$$

Equation 6.6

Furthermore, following Cai et al. (2006) suggestions, this methodology was restricted to analyse the surface water consumption for urban uses in the catchment.

The input data to describe the urban water consumption was taken from the *five-years plan* of ESVAL (i.e. the local water utility) (ESVAL, 2014). The surface water consumption of this user in the first irrigation area is around 79.7 l/s (2.5 million m^3 per year – 2,500 ML/yr).

Regarding the price, ESVAL has a charging system with different types of rates: a monthly fixed fee, a non-peak fee, and a peak fee (charged between December and March). The values for 2007 are shown in Table 6.8, including the average ($461.41 CLP/$m^3$). This value was calculated assuming that consumption is similar throughout the year, thus the price can be estimated as a weighted average proportional to the amount of peak (4 out of 12) and non-peak (8 out of 12) months. Yearly values were defined using the average yearly consumption per client in the case study (222.55 m^3/yr).

Table 6.8 – ESVAL fees for urban water consumption in the case study in 2007 prices.

	Fixed ($ CLP)	Non-Peak ($ CLP/m3)	Peak ($ CLP/m3)	Total per year ($ CLP/client)	Average per year ($ CLP/m3)
Monthly Values	$ 755.75	$ 419.98	$ 422.02		
Yearly Values	$ 9,069.00	$ 419.98	$ 422.02	$ 102,688.27	$ 461.41

The *five-years* plan also shows that the average cost of supply per m^3 is $ 369 CLP. It is assumed that this figure comprises both CAPEX and OPEX, as several sections of the plan discussed how infrastructure investments and other CAPEX were included in the user fees as annualised capital costs (ACC).

Taking this into account, the net revenue per m^3 for the water utility is approximated here as the average price (see Table 6.8) minus the cost ($ 369 CLP/m^3), which is:

$$Total\ profit = \$\ 461.41\ \frac{CLP}{m^3} - \$\ 369\,\frac{CLP}{m^3} = \$\ 92.41\,\frac{CLP}{m^3}$$

The price elasticity of demand, or an approximation of it, was not found in the five-years plan, thus, this parameter was taken from the HEM of the Maipo River previously mentioned, where this value was defined as -0.45 (Cai et al., 2006). As mentioned before, the authors warn that this value should only be used for surface water sources.

The selection of this value was further discussed with experts in Australia and Chile, both of whom agreed that this was a good approximation. A summary of the values used to parameterise Equation 6.6 is included in Table 6.9. Once all other values were defined, the value of A could be calculated.

Table 6.9 – Parameters of the urban water demand model.

$P\ (CLP/ML)$	$Q\ (ML)$	α	A
$ 92,412	2513	-0.45	431,362

6.2.2.1. Results of the economic analysis of urban water demand

The water demand function for the urban user is shown in Figure 6.4. The shadow value of water for urban uses corresponds to the willingness to pay by this user in the point of observed consumption in 2007 ($ 92,412 CLP/ML), which is considerably higher than the value for agriculture ($ 6,219 CLP/ML) by roughly one order of magnitude. This was expected a priori as it is known that the willingness to pay by urban users is higher than by farmers (Medellín-Azuara, 2006, Forni et al., 2016, Young and Loomis, 2014), and the differences usually involve at least one order of magnitude.

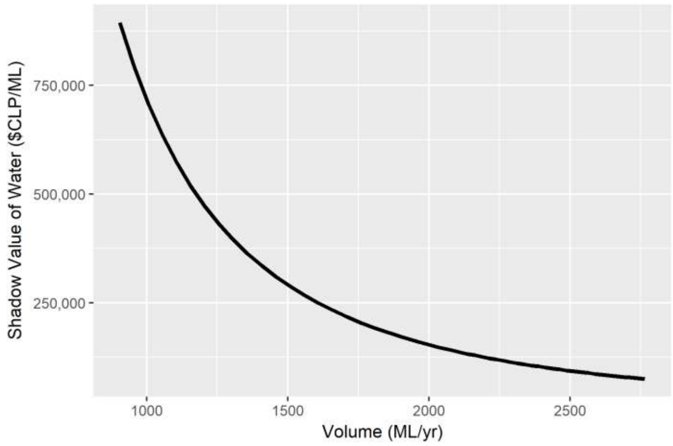

Figure 6.4 – Water demand curve for urban water.

Figure 6.5 shows the agriculture and urban curves together. In this figure it can be seen that the urban user is always willing to pay more than agricultural users to obtain additional water. It is important to note the difference in the x-axis between Figure 6.5 or Figure 6.2, and Figure 6.1 or Figure 6.4. While the x-axis of the latter two is the volume of water available in ML, in the former two it is the percentage of the observed consumption in 2007.

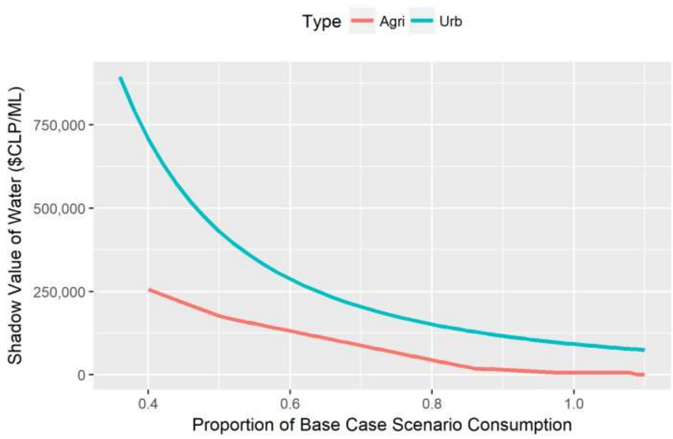

Figure 6.5 – Water demand curve for urban uses and agriculture.

By using percentages in the x-axis it is possible to scale the water demand curve, for example to downscale the analysis from the whole case study population to one client only (i.e. an average *representative* client). This would mean that the full urban consumption (100%) is not the 2.5 million m^3/yr but 222.55 m^3/yr. This does not affect the scaling of the y-axis as this is always a price per unit of volume, measuring how the WTP of the whole population or a representative client, changes as a function of available water.

This was particularly useful for this project because it facilitated monthly economic analyses of the value of water, and also enabled analysing the whole water consumption included in the WEAP water node, despite only 91% of it had economic data available. In both of these cases the x-axis of the water demand curve showed the proportion of water available relative to their normal full consumption level.

Regarding the additional metrics for urban water, water scarcity cost is 0 as the urban demand is fully covered, thus the point of current consumption is the same one as the point of full consumption. In other words, there is no area below the curve between these points, and following the previous description of this metric, this means the water scarcity cost is zero. On the other hand, defining the total value of water in urban use is more complex, and this will be discussed in the following section.

Table 6.10 – Summary of metrics for urban water demand for the observed period. Values in 2007 prices.

Metric	Unit	Value	
Shadow Value of water	$ CLP / ML	$	92,412
Water Scarcity Cost	$ CLP / yr	$	0

6.2.2.2. Limitations of the economic analysis of urban water demand

The current approach to analyse urban water takes the perspective of the producer (the water utility), as done for agriculture, and that is why the water demand curve is defined using prices net of costs. However, by defining this curve it is implicitly assumed that the water supply company is not regulated and could set higher prices for water during scarcity periods. In reality, the company is regulated and prices are controlled, and overconsumption fees are the only tool companies can use to charge higher rates during water scarce periods, but they are not as flexible as the water demand curve.

This does not mean that if future climate conditions or other phenomena increase water scarcity in the catchment, the company will be forced to operate at a loss, as they are able to review their costs every time they submit a five years plan. This means that they can adapt their fees every time they update their plan, to make sure the service continues to operate. The update of these prices, however, may not be as flexible as the water demand curve defines, however, this is not an uncommon assumption in HEMs that include urban water use.

Furthermore, to avoid very high fees (quite unrealistic due to regulations), it was attempted that the water demand curve was used from the point of 50% of total consumption only. Imposing this threshold and avoiding smaller percentages, whenever possible, was also a consequence of using a constant average cost per m^3 ($ 369 CLP/ m^3). Although this may not be a bad assumption in the vicinity of the observed consumption, the inaccuracy of this estimation may increase rapidly if very small percentages of water availability are used, as in reality the fixed costs would increase considerably relative to the variable costs in this part of the curve.

Taking this into account, the total value of water for the urban user was defined as the area under the water demand curve, but assuming that for levels of consumption below the 50% of the current one, the shadow value remained constant (see Table 6.11).

Table 6.11 – Total value of urban water use in the calibration period. Values in 2007 prices.

Metric	Unit	Value
Total value of water	$ CLP / yr	$ 795,267,193

6.2.3. Economic analysis of hydro-power demand

As opposed to agriculture and urban uses, for hydro-power it was not possible to define a water demand curve because of the complexity of the energy sector. Energy suppliers in Chile usually have contracts with the regulator, which define the prices at which they will sell the energy produced. This is somewhat similar to the case of the water utilities, however, there is a considerable difference as the energy network is connected to several producers, which makes it resilient to cases in which one supplier (e.g. the hydro-power stations in this case study) struggle to generate energy (e.g. during a dry period).

This means that defining a water demand curve for this sector is virtually impossible, as it would be necessary to take into account several producers in the grid, plus all the regulation involved. In addition, the result of this would likely be an inelastic curve (i.e. no matter the changes in water availability in the case study, the price may remain almost constant). Due to this, it is a realistic assumption to set the willingness to pay from the hydro-power company at a constant value, independent of the volume of water available (Cai et al., 2006, Satti et al., 2015).

Taking this into account, to define the value of water for hydro-power it is only required to define the price and costs of producing energy, and then analysing these with the volumes of water available to generate it. The only restrictions are the WRs from these companies and the capacity of the generators (i.e. the maximum flow that can pass through them).

These physical and legal restrictions were included, and were complemented with another one aimed at reproducing real conditions of the catchment as accurately as possible. This involved using the values of energy production between 2000 and 2017, as the target for the HEM. As mentioned in Chapter 5, these generation targets were included in the WEAP model, while the actual generation is a WEAP output. The total value of water for this user was then defined as the product of this output with the net revenue. It is important to bear in mind that as stations are located in series, the same volume of water may produce energy in several successive generators.

Furthermore, water scarcity costs were not included as there was no water curve, therefore, this would be redundant taking into account how the Total Value of Water was calculated.

The price of energy was taken from the regulator (CNE, 2018), while the cost of production was approximated from an industry average in Bezerra et al. (2012), who did a review of CAPEX and OPEX for run of river hydro-power generators in Chile and defined levelised costs (i.e. yearly OPEX plus annualised CAPEX, a concept similar to ACC). More accurate values are difficult to find as companies are not required to disclose them. Price and cost estimates are shown in Table 6.12.

Table 6.12 – Price and costs of the Hydro-power user. Values in 2007 prices.

	Unit	Value
Price	$ CLP/kWh	38.8
Cost	$ CLP/kWh	28.0
Profit	$ CLP/kWh	10.8

Taking into account the production generated in the WEAP model for 2007 and the values in Table 6.12, the total value of water for the energy user in this year is $ 7,964 Million CLP, in 2007 CLP. This methodology was easily adapted to calculate monthly values, as the WEAP model provides monthly energy generation figures, and these can be multiplied by the profit per kWh.

6.2.4. Economic analysis of mine water use

Developing insight into the analysis of the economic value of mine water use was one of the aims of this project, due to the lack of literature on the valuation of water used by resource industries (e.g. mining, oil and gas) (Young and Loomis, 2014). A priori, it was known that some of the complexities are derived from the fact that for many years, these industries had seen water resources as a relatively minor cost of operation in their large CAPEX and OPEX (even when compared with other input resources like energy). Thus, water was often taken as a fixed input that could be obtained almost at any cost, because it would not influence considerably their bottom line. On the other hand, access to energy, amounts of minerals, their concentration, and other mining or metallurgical considerations were considered the key factors determining their production function.

This has changed to some extent as water has gained more relevance and is now considered by many as a key input in mining. This is partly because of the potentially high costs that social opposition may generate for projects. However, the new relevance of water is also caused by the fact that relatively cheap sources of water (e.g. surface water and groundwater) that were frequently used in the past are being depleted, and this industry has had to invest considerable amounts of money in desalination or tailings water recycling systems.

For an illustration, farmers paid around $8,075 CLP/ML (to maintain the irrigation infrastructure) and production costs of urban water (e.g. treatment and pumping) are around $ 754,000 CLP/ML, in the case study in 2014. As opposed to this, desalinated water costs around $2,000 USD/ML ($1.14 million CLP/ML) in areas nearby the sea (Ghaffour et al., 2013, Zhou and Tol, 2005), and around $5,000 USD/ML ($2.8 million CLP/ML) (Concha et al., 2016) at high elevation mines. This illustrates the increasing costs that are making water a more relevant input to mine economics.

In this context, this project attempted to analyse mining's participation in water markets, to elucidate the value by analysing their transactions. Records between 2004 and 2014 were taken from the DGA and these were analysed after doing a basic quality control (e.g. eliminating duplicate, incomplete or misleading values[14]). Then, an exploratory analysis was undertaken following Donoso et al. (2010) and Donoso et al. (2014). Despite providing interesting results, this analysis made it clear that it would be difficult to understand mining's value of water through market information. The key findings are summarised as follows:

1. The share of mining in water markets is minor compared to agriculture, urban utilities, and even to other traders like real estate.
2. Mining participation is mostly focused in the northern regions of the country where mining is more abundant. Furthermore, due to the very different climate conditions, values change considerably as a function of the region.
3. Mining's willingness to pay is considerably higher than any other user, to the point that it is not clear if some transactions are outliers or simply were not registered properly. Figure 6.6 shows an example of how mining transactions considerably affected the average price in the Antofagasta region in 2008.

Further to these observations, some mining users also argue that to avoid further problems with communities, they prefer not to see traditional sources of water as viable options for future supply, thus there is little incentive to trade. This means that even in the context of a market with transparency and price variability issues like the Chilean one (as explained in Section 2), the uncertainty in an estimation of the value

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[14] This included checking for values that involved transactions of land as well, and deals that had zero price, which are likely to be related to gifts, or inheritance DONOSO, G., CANCINO, J., MELO, O., RODRIGUEZ, C. & CONTRERAS, H. 2010. Análisis del Mercado del Agua de Riego en Chile: una Revisión Crítica a Través del Caso de la Región de Valparaiso. PONTIFICIA UNIVERSIDAD CATÓLICA DE CHILE..

of water for mining based on trading data would be quite high. Moreover, if values from the northern regions were used, it would be required to adjust them first using econometric tools, as to account for the differences in climate conditions. Therefore, this exploratory analysis of the prices paid by mining for water was not taken forward along the lines of other water market analyses (Donoso et al., 2014, Donoso et al., 2010).

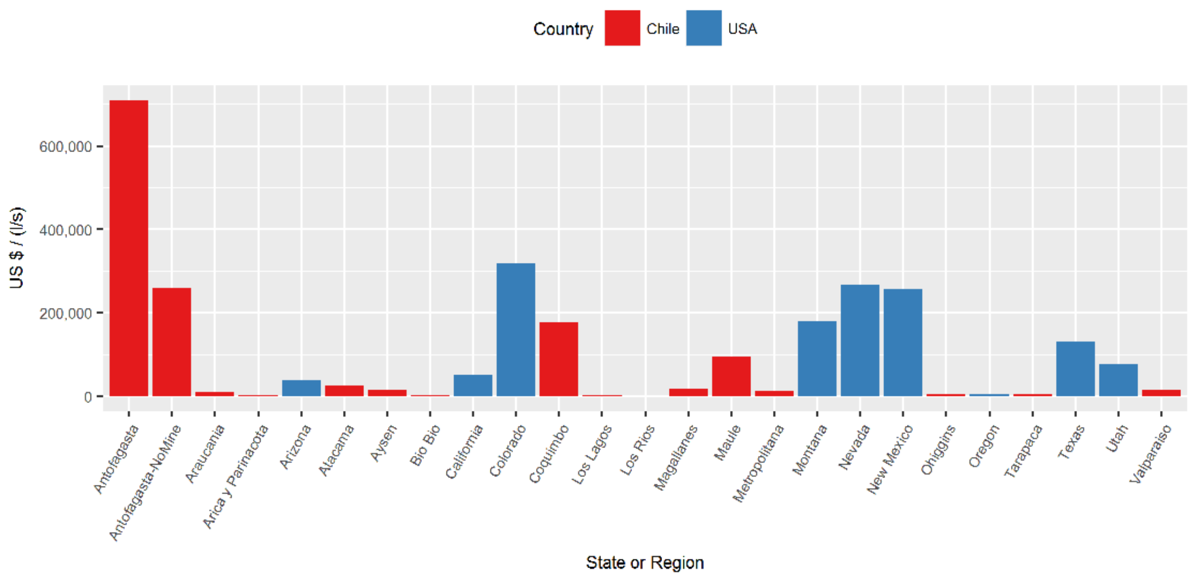

Figure 6.6 - Average price of one l/s of long-term consumptive WR by state/region in the USA and Chile in 2008. Antofagasta and Antofagasta-NoMine represent the values in the region with and without mining transactions (Bren School of Environmental Science & Management - University of California, 2010, DGA, 2015b)[15]. Taken from (Ossa-Moreno et al., 2018).

After rejecting the previous approach, the best alternative to analyse the economic value of water for mining was to apply a method similar to that used for hydro-power. It was assumed that full production (i.e. the production for 2007) was achieved during all years of the base case scenario of the HEM. If the water supplied in another scenario was less than in this case, this would entail a scarcity cost equivalent to the difference in the profits between both scenarios.

This approach does not incorporate a detailed understanding how the shadow value of water for mining changes as a function of water availability, but it allows including this user in the HEM, and comparing their degree of satisfaction through a quantitative

[15] This Figure was constructed after carefully reviewing water prices, however, it is acknowledged that these datasets have limitations, including price transparency, thus they are mainly presented for illustrative purposes (Grafton et al., 2011, Hearne and Donoso, 2014).

metric. Prices and costs of the copper concentrate in 2007 were taken from Cochilco (2017) (see Table 6.13). These are the highest quality publicly available values, although they are estimates from all operations of the company, and not only the mine inside the case study.

Table 6.13 – Price and costs of the mining user. Values in 2007 CLP.

	Unit	Value	Unit	Value
Price	US c/lb	$ 323.2	CLP/lb	$ 1,687.4
Operational Cost	US c/lb	$ 136.0	CLP/lb	$ 710.1
Total Cost	US c/lb	$ 272.0	CLP/lb	$ 1420.1
Net Revenue	US c/lb	$ 180.9	CLP/lb	$ 267.3

The cost estimate in Table 6.13 includes OPEX only, thus it was required to approximate CAPEX in a similar way as for agriculture. Capital intensity in the mining industry may fluctuate as a function of ore grades and other factors, and for this project this was defined with data from market analyses (AME, 2016). Based on this, it was assumed that the ratio of CAPEX intensity (US$/lb) to total costs (PeCAPEX) was 50%. This is larger than for agriculture as this is a more capital intensive industry. A sensitivity analysis of this value was undertaken for the mining user as well.

By using the price and cost estimates in Table 6.13 and the copper production for 2007 (218,400 Tons of copper concentrate), the total value of water for the mining user in 2007 is $ 128,710 Million CLP, in 2007 prices (the total consumption by this user in this year was assumed to be 21.58 million m^3). These calculations can be done in monthly time-steps assuming that the yearly production is evenly distributed throughout the months. Furthermore, although a water demand curve was not defined, the mining user's willingness to pay for extra units of water, whenever demand is not fully covered, is $5.96 million CLP/ML.

As mentioned in Chapter 5, copper production during the whole period of analysis of the HEM was assumed to be the same as for 2007, to follow the same limitation of the agriculture user and in order to do a fairer comparison.

6.3. Coupling methodology for the water resources and economic components

There were practical considerations for the development of the coupling methodology. First, it was desired that the exchange of data between components was fast and automatic (i.e. avoiding just one transfer of data after running one component first, and using its outputs to run the other), and preferably using only one software. It was also required that importing and exporting data was efficient, to facilitate changing model inputs and parameters, and doing data analysis of the outputs.

The second consideration was that the coupling methodology should be robust enough to allow a detailed representation of water resources and the economic values of water. This would allow going beyond the use of historical or synthetic flow values (i.e. using the WEAP model), and would also allow a detailed representation of the value of water by means of water demand curves for agriculture and urban uses.

Finally, it was also desired to use relatively easy to access tools that facilitated the replication of the model in other case studies. WEAP is a free tool if used in developing countries and it is relatively inexpensive otherwise, thus it was desired to complement it with software with similar licensing conditions.

With these requirements in mind, it was decided that the best alternative was to use a computer programming language like Python, connected to WEAP through the API (Application Programming Interface).

The steps to develop and use the HEM are described as follows, while a flowchart is shown in Figure 6.7:

1. Calibrate the water resources model in WEAP to reproduce the conditions of the catchment (see Chapter 5), and define the economic value of water for each user (see previous sections of Chapter 6).
2. Within Python define any desired changes (e.g. climate data, water demands, energy generation targets, consumption patterns, minimum flow requirements, etc.). If no changes are specified, the standard WEAP model described in Chapter 5 is used.

3. Using Python, WEAP runs the model[16] and extracts all desired outputs at monthly time-steps including:
    a. Flows at the six flow gauge locations in the catchment.
    b. Hydrological fluxes at each sub-catchment (e.g. runoff, groundwater, interflux).
    c. SWE in all sub-catchments.
    d. Water volumes provided and demand coverage to each user, including minimum flow restrictions.
4. The economic analysis of urban, hydro-power and mining users is done.
5. Yearly agriculture production is restricted by the month with the smallest demand coverage and the economic calculations are done following this restriction. Those months with a larger demand coverage than the driest one are not able to use all the water allocated by WEAP, but only up to the point of the driest month. This generates a spare volume of water than can be traded with other users.
6. A Python script analyses if any user has unfulfilled demand. If there is, water is re-distributed towards the user with the largest willingness to pay (i.e. simulating a water market), until an equilibrium point is reached[17]. The mining user is not included here, following observed behaviour which evidences that water users are reluctant to trade with them. By default there are no transactions fees, but they could be included.
7. After water is redistributed, overall economic metrics are calculated for each user and for the catchment as a whole. Inflation and exchange rates are used to present all results in real prices for a determined year. This is complemented with demand coverage metrics.

[16] In this step all users are assumed to have the same priority in WEAP, in order to replicate the ideal conditions in the case study in which everyone attempts to get as much water as their WRs allow. When water is not enough to fulfil all WRs, it is allocated proportionally. All priorities can be modified from Python.
[17] The water market explained here (e.g. the transactions between agriculture and urban uses) should not be confused with the ideal allocations of water by the PMP. As explained in Section 6.2.1, the latter takes information from current water use by the agricultural sector in the case study and optimises water allocation to maximise the economic value of water. The results from this PMP are in turn used to define water demand curves for the sector as a whole, and these curves are used to define the trades between agricultural and urban sectors.

Although the model uses previously defined water demand functions by default, it is possible to update them to allow changing economic inputs as well, while other type of restrictions (e.g. minimum coverage for a specific user required) could also be included. All this can be done before or during the coupling process, as Python scripts make sure that there is constant exchange of data between components.

The model does not require major computational requirements involving HPCs. Currently, it is run on a computer with 8G of memory, an i7 processor and 4 cores, and it takes between 2 and 5 minutes, depending on how long it takes to reach equilibrium with the shadow values of water.

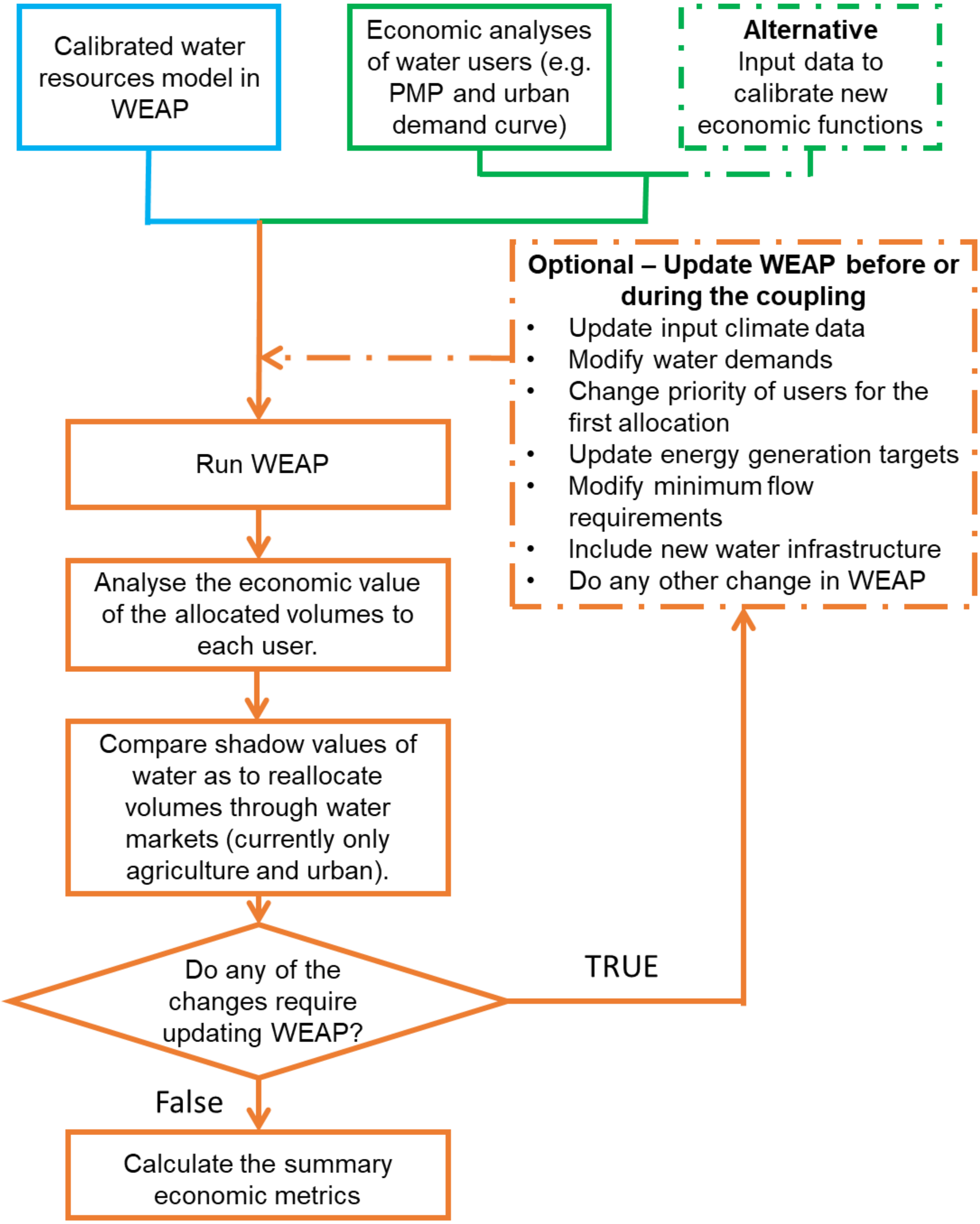

Figure 6.7 – Flowchart of the coupling methodology using WEAP's API and Python scripts.

6.4. HEM coupling results

The *Base Case Scenario* for the HEM corresponds to the period between 2000 and 2017 using the standard WEAP model (i.e. including the observed past climate conditions). The key summary metrics are presented in Table 6.14. Furthermore,

Table 6.15 shows the average demand coverage for each of the users during the whole period of analysis. It is important to remember that water scarcity cost and shadow value of water are only influenced by agriculture and urban uses.

Table 6.14 – Summary economic metrics of the base case scenario of the HEM. Values in 2017 prices.

Metric	Value
Total Value of Water	$ 5,849.1 Million USD
Total Value of Water Profit WM**	$ 5,849.2 Million USD
Total Value of Water Profit NM*	$ 1,013 Million USD
Water Scarcity Cost	$ 6.11 Million USD
Water Scarcity Cost WM**	$ 6.08 Million USD
Average Shadow Value	$ 122 USD/ML
Average Shadow Value WM**	$ 121 USD/ML

*** Total value of water without including the mining user (NM= No Mining User).**
**** Values after trading water between agriculture and urban uses (WM= Water Market).**

Table 6.15 – Demand coverage in the base case scenario of the HEM.

User	Demand Coverage (%)
Agriculture	96.1
Urban	99.7
Hydro-power	92.8
Mining	90.0
Average	94.3

In addition to the results of the Base Case Scenario, the model was checked by analysing its sensitivity to; the minimum flow requirement at the outlet (i.e. the one representing downstream users), and the ratio of CAPEX to total costs (PeCAPEX). Table 6.16 shows the economic metrics for the minimum (5 m^3/s) and maximum (10 m^3/s) flow requirements at the outlet of the catchment, while Table 6.17 shows the coverage of demand.

Table 6.16 – Summary economic metrics of the minimum and maximum flow requirements at the outlet of the catchment. Values in 2017 prices.

Metric	Minimum outlet flow requirement (5 m^3/s)	Maximum outlet flow requirement (10 m^3/s)
Total value of water	$ 5,853 Million USD	$ 5,782 Million USD
Total value of water WM	$ 5,853 Million USD	$ 5,783 Million USD
Total value of water NM	$ 1,018 Million USD	$ 998.7 Million USD
Water Scarcity Cost	$ 1.93 Million USD	$ 20.6 Million USD
Water Scarcity Cost WM	$ 1.92 Million USD	$ 20.4 Million USD
Average Shadow Value	$ 109 USD/ML	$ 157 USD/ML
Average Shadow Value WM	$ 109 USD/ML	$ 150 USD/ML

Table 6.17 – Demand coverage for the minimum (5 m^3/s) and maximum (10 m^3/s) flow requirements at the outlet of the catchment, before and after water markets.

User	Demand Coverage Minimum requirement (%)	Demand Coverage Maximum requirement (%)
Agriculture	100	87.9
Urban	100	99.0
Hydro-power	92.9	92.6
Mining	90.5	89.1

Regarding the sensitivity of the model to PeCAPEX, different percentages were tested for agriculture and mining. However, for the remainder of the calculations of this project the selected values were 26% for the former and 50% for the latter. Table 6.18 and Table 6.19 show the effect of these changes on the economic metrics. None of these parameters affected the water resources component therefore there are no changes in demand coverage.

Table 6.18 – Analysis of the sensitivity of the HEM to changes in the ratio of CAPEX to total cost for agriculture (PeCAPEX).

Metric	10%	15%	20%	26%	30%
Total value of water (in US 000,000)	$ 6,359.4	$ 6,220.2	$ 6,063.5	$ 5,849.1	$ 5,681.9
Total value of water WM (in US 000,000)	$ 6,359.4	$ 6,220.3	$ 6,063.5	$ 5,849.2	$ 5,681.9
Total value of water NM (in US 000,000)	$ 1,523.5	$ 1,384.4	$ 1,227.7	$ 1,013.3	$ 846.1
Water Scarcity Cost (in US 000,000)	$ 9.07	$ 8.29	$ 7.39	$ 6.11	$ 5.04
Water Scarcity Cost WM (in US 000,000)	$ 9.04	$ 8.26	$ 7.37	$ 6.08	$ 5.00
Average Shadow Value (in US / ML)	$ 132	$ 129	$ 126	$ 122	$ 118
Average Shadow Value WM (in US / ML)	$ 131	$ 128	$ 125	$ 121	$ 117

Table 6.19 – Analysis of the sensitivity of the HEM to changes in the ratio of CAPEX to total cost for mining (PeCAPEX).

Metric	30%	40%	45%	50%	55%
Total value of water (in US 000,000)	$ 13,189.2	$ 10,130.9	$ 8,184.6	$ 5,849.1	$ 2,994.6
Total value of water WM (in US 000,000)	$ 13,189.3	$ 10,130.9	$ 8,184.6	$ 5,849.2	$ 2,994.7
Total value of water NM (in US 000,000)	$ 1,013.3	$ 1,013.3	$ 1,013.3	$ 1,013.3	$ 1,013.3
Water Scarcity Cost (in US 000,000)	$ 6.11	$ 6.11	$ 6.11	$ 6.11	$ 6.11
Water Scarcity Cost WM (in US 000,000)	$ 6.08	$ 6.08	$ 6.08	$ 6.08	$ 6.08
Average Shadow Value (in US / ML)	$ 122	$ 122	$ 122	$ 122	$ 122

Average Shadow Value WM (in US / ML)	$	121	$	121	$	121	$	121	$	121

6.5. Discussion

A HEM model was developed after coupling water resources and economic components through Python scripts. The purpose of using a HEM with these two components was to better represent real conditions in the catchment where water is allocated through a system of water rights (e.g. where all water holders have the same priority). However, these rights can be traded in a water market in which agriculture and urban users are the most active participants, while mining and other users are not quite involved and tend to keep their rights relatively constant (See Chapter 2).

The methodology involved running the previously calibrated WEAP model, and then defining the economic value of water for all users by means of three economic metrics; Shadow Value of Water, Water Scarcity Cost and Total Value of Water. These outputs were complemented by reporting the percentages of demand coverage for each user.

By using Python scripts and WEAP, it was possible to provide *real time* feedback from both components at all time steps, without doing major simplifications of any of them. This meant that the coupling was not limited to one directional transfer of data.

The water resources model was run in monthly time-steps to take into account intra-annual variations and seasonality, was calibrated with 5 flow gauges and snow data, and was able to fulfil the demand for water to a large extent. The economic component made the best use of available data to develop water demand curves for two of the water users in the catchment, and two more simple approaches for the rest, in order to provide a more *robust* analysis than other alternatives to allocate water (Forni et al., 2016). Further alternatives such as allocation based on priorities (Esteve et al., 2015) or penalty functions (George et al., 2011) can also be implemented.

Further benefits of this approach are its *efficiency* in terms of computational requirements and processing times. In addition, as WEAP is a platform that is free in many countries for research or government purposes, and Python is an open-access programming language, the tools are not limited to a specific region (Dale et al., 2013b, Medellín-Azuara et al., 2015), but can be replicated elsewhere.

Regarding the specific results of the HEM in this project and the sensitivity analysis, it can be seen that the participation of mining in the total value of water is very large (83% in the base case scenario). This may fluctuate as a function of PeCAPEX values for mining and agriculture, but it is always high (see Table 6.18 and Table 6.19), which highlights that mining is a special user in HEMs. This is why the Total Value of Water was complemented with others metrics in order to better understand the value of water for different users. These alternative metrics could also be viewed as proxies of the water conditions and water conflicts in the catchment. For example, the higher the shadow value of water and water scarcity costs, the more likely it is that conflicts and problems will arise between water users.

Results also show that water markets enhance conditions in the catchment (e.g. increase total value of water, while reducing shadow value of water and water scarcity costs), however, improvements are relatively small. Shadow values and water scarcity costs are improved by between 0.1 and 4.5% only (see Table 6.16 and Table 6.18), while the impacts on total value of water are even smaller. This is partly because urban coverage before the trading is already quite high (for the 5 m^3/s flow requirement case it was not required to trade water in the model). In addition, and more importantly, this is because the volumes of water consumed by urban uses are relatively small compared to the rest, which means that small trades of water can rapidly fulfil urban demand with little impact on the economic metrics. If urban consumption was larger compared to agriculture, the effects of water markets may have been more evident.

It is also important to mention that the water scarcity costs for the base case scenario and the sensitivity analyses, are relatively small compared to the total value of water with and without mining (in these cases most water scarcity arises in agriculture only). There are three orders of magnitude in the difference, meaning that on a catchment scale, the foregone benefits of not having enough water to irrigate the unused land in the catchment are not very large compared to the total value derived from water in other uses.

This is a consequence of the last units of water (i.e. before land becomes the constraint) having a relatively low shadow value, as they are used for seasonal (low-value) crops that do not require securing long-term access to water and are cultivated whenever water is available only. High value crops require securing access to water during several years, thus, in an optimisation scenario they are expected to be the last to sacrifice during dry periods. This is reflected in Figure 6.2 where shadow values, and the steepness of the curve, increase as demand coverage is reduced.

Nevertheless, even though this value is small when analysing the whole catchment, it does not mean that it is insignificant for individual farmers. It may be the case that for some of them the values are considerable. Thus, analysing this metric and how it fluctuates as a function of external conditions or water management strategies, is still important if a catchment scale approach is to be taken, covering the perspectives of all water users.

In terms of the sensitivity of the model, it can be seen that the mining PeCAPEX value has a very high impact on the total value of water, with differences up to 125% compared to the default value. This highlights again the importance of using a broader set of metrics to analyse water conflicts in mining catchments, as to avoid being biased by a single metric that is strongly influenced by one user only. All other metrics were not affected by changes in this variable.

The impact of the agriculture PeCAPEX on the shadow value and water scarcity costs is not large, as this variable did not affect low-cost crops that much, and these are the ones influencing these metrics in the base case scenario. On the other hand, the total value of water for agriculture, hydro-power and urban users (without mining), is affected considerably by this variable, producing up to a 50% difference from the default value (see Table 6.18). These changes, however, are small compared to the value of water for mining, thus, they generate changes of less than 10% in the total value of water (with mining).

Regarding the sensitivity to the minimum flow requirement at the outlet of the catchment, it was found that there were not large differences in terms of total value of water with or without mining. Differences in the shadow values of water between the minimum or maximum scenarios and the default condition are larger (10% and 30% respectively). On the other hand, differences in water scarcity costs are 68% and 236%.

Once the HEM was developed and its sensitivity to key assumptions analysed, it was possible to develop insight in how this tool can be used to support water decision making in mining catchments. Three potential applications of the HEM were analysed in this PhD project, they are discussed in the next Chapter.

6.6. Closing Remarks

1. A Hydro-Economic Model (HEM) has been developed for a mining catchment and it has been calibrated to reproduce hydrological and economic observations. The model assists understanding relationships between water users in mining catchments, which, to the best knowledge of the author, has rarely been attempted through a HEM.
2. This model couples a water resources and an economic model to represent the system of water rights in the case study, and the potential trades between some of its users.
3. The coupling in the HEM was done in an efficient, robust and automatic way, through Python scripts and WEAP's API.
4. Although the Total Value of Water is calculated using information from all major users, taking a catchment scale approach, in the sense of effectively communicating the impacts on all users, was only possible by using a set of metrics. Otherwise results would have been biased by the very large CAPEX and OPEX of the mining user. These metrics are more robust (i.e. provide a wider perspective of the value of water) when considering the interests of multiple users, including producers of both high and low-value crops. These metrics could be regarded as proxies of the perceptions of users towards water conditions, and as indicators of the potential for conflicts in the catchment.
5. The economic calculations for each user follow commonly applied approaches. However, the key added value of this HEM is its application to a catchment with interactions between mining and further users, and this shows how this tool can support water decision making in these regions (see next chapter).
6. The coupling methodology is another key added value of this project as it allowed a robust connection between the water resources and the economic components, without oversimplifying either of them.
7. Further research and case studies are desirable to better understand how to integrate the value of water for mining users into HEMs. However, the high degree of confidentiality in this industry represents an obstacle for this.

8. A sensitivity analysis of the key assumptions of the HEM was done to give an idea of the uncertainty ranges in the final outputs. These results are useful to understand the model performance, but also to use as a benchmark of the changes in the scenario analysis (see Chapter 7).
9. An important assumption of the whole HEM approach, which was not mentioned previously, is the perfect foresight of the users. This is required to justify, amongst other things, the fact that an agricultural user limits his/her water consumption in each year to that available in the driest month (i.e. which defines how much "excess water" he or she should trade to optimise its revenues). This is a common assumption in similar models (Hurd and Coonrod, 2012), although some authors address the first issue by including risks factors (Fernández et al., 2016, D'Agostino et al., 2014). The inclusion of risk factors in all users could be implemented as a future improvement of the model.
10. Future refinements of this model could analyse how to include indirect economic benefits and risk factors of each water user.
11. Another benefit of this HEM is that the tools used are not limited to a geographical area, but can be replicated in other catchments (including the analysis of climate variables). Furthermore, all software used is free in developing countries.
12. The mining industry has been the focus of researchers and international organisations (e.g. The International Council on Mining and Metals - ICMM), who try to define metrics and frameworks; to assess mining's water performance and to monitor their relationships with other water users. The methodology developed here represents a step forward in this field, as it facilitates understanding the value of water catchment wide, and how this fluctuates as a function of external factors or shared infrastructure projects. Moreover, the pros and cons of the set of metrics used were discussed, including an explanation of how each one of them reflects the perspectives of specific users and specific parts of the water demand curve of agricultural users.

7. Scenario Analysis

After developing the HEM, it was analysed how this model could add value to water decision making in mining catchments. This chapter uses the metrics defined in the previous one as proxies of water conditions and conflicts in the catchment.

An analysis of scenarios was done to test how the model reacts to changes in climate conditions, and to the introduction of environmental flow requirements. The former is important taking into account that changing climate conditions pose a risk for water resources management in the region. On the other hand, the minimum environmental flow requirements were included as they are seen by many as one of the ways to improve the ecological condition of catchments like the case study in this project. This is even being debated in Chile, as part of potential amendments of the water code.

The third scenario analyses the impacts of a tailings water recycling project in the catchment. The benefits that this project will bring to the mining user have been analysed elsewhere, however, it was desired to complement them with a catchment scale approach that takes into account the potential benefits to all users. This represents one of the more practical added values of this HEM. Evidence will be provided of how this tool may support taking a catchment scale approach within a project-appraisal context.

7.1. Impacts of changes in climate conditions in the HEM

Changes in climate conditions are one of the key risks for water management worldwide, thus, this scenario explores how the HEM can be used to analyse how precipitation and temperature changes may affect water conditions in the case study. Being able to include both variables is an added value of HEMs with a detailed water resource component, as the effects of temperature changes are difficult to analyse when using historical flows observations.

Developing a climate change model of the catchment, by means of a GCM or an RCM (Buytaert et al., 2010, McGregor, 1997), was not part of the scope of this project. Therefore, a predetermined group of changes in both precipitation and temperature was used. This is commonly referred in the literature as "***Climate Response Function***" analysis (Mendelsohn and Schlesinger, 1999, Brown et al., 2012, Arnell, 2000), and it is quite useful to analyse the effects of changing climate conditions in a water resources system without a climate model. This approach takes into account a broad spectrum of climate variations, which is particularly useful taking into account the uncertainty surrounding climate change forecasts.

This analysis explored precipitation changes from 60% to 110% with 10% changes, and temperature changes from -2 to +2 °C. These values were defined taking into account the range of variability of the results of an existing climate model in the catchment (CEPAL, 2012, CONAMA and DGF, 2006). These ranges were extended in some directions for the sake of understanding how the HEM would react to these changes.

Nevertheless, temperature ranges were limited to a maximum of two degrees of change. Larger increments of temperature would entail further changes in the crops that are not currently analysed in the HEM in its current form. Future improvements of the agricultural analysis may allow modelling temperature increments beyond these ranges.

Table 7.1 shows the range of climate conditions analysed. The table also identifies which of the precipitation-temperature combinations correspond to the **A2** and **B2** scenarios of the Intergovernmental Panel on Climate Change Reports (IPCC, 2014), which were the scenarios analysed in the aforementioned climate change model for Chile (CEPAL, 2012). These results cover three different periods of time (2010-2039, 2040-2069 and 2070-2099)

Table 7.1 – Changes in climate conditions analysed during the scenario analysis, including the description of the A2 and B2 climate scenarios in the existing climate model for Chile (CONAMA and DGF, 2006).

Temperature / Precipitation	-2	-1	0	0.5	1	1.5	2	2.5*	3*
60%									
70%									
80%								B2 2070-99	A2 2070-99
90%				B2 2010-39		B2 2040-69	A2 2040-69		
100%				A2 2010-39					
110%									

* For illustration purposes only, not analysed in the model.

The changes in the input data were done using Python scripts, as described in Figure 6.7, by perturbing the WEAP input data used in Chapter 5 either through multiplication (precipitation) or addition (temperature) depending on the climate scenario.

7.1.1. Results of the scenario of changing climate conditions

The results of the analysis of the sensitivity of the model to changes in climate conditions is divided into three parts: the first will analyse the changes in modelled flows at the outlet of the five hydrological areas, and in the hydrological processes within them. The second will analyse the effects on the demand coverage of water users, and the last will cover the impacts on the economic metrics. The effects of changes in precipitation are explained first, and this is followed by those due to changes in temperature. In order to facilitate the comparison between results of different magnitude, some of them are either normalised or presented relative to benchmark values.

Figure 7.1 shows the relation between time-averaged flows at the outlet of the hydrological areas (at the location of the observation gauges) and the *Precipitation* (*P*) *factors*. Figure 7.2 shows the same results after flows are divided by the values in the precipitation benchmark case ($P\ factor\ =\ 1$). In both figures, the results of different changes in *T* were aggregated (i.e. averaged).

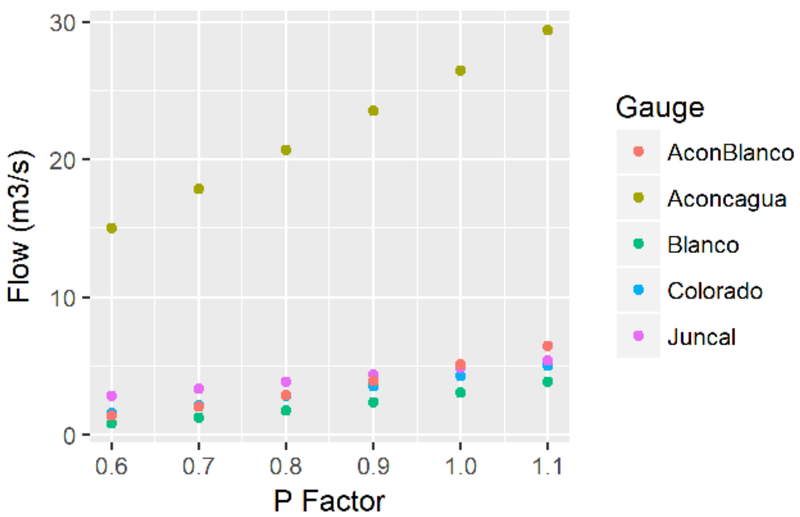

Figure 7.1 – Precipitation factor versus average flow at the five hydrological areas (aggregating all temperature changes).

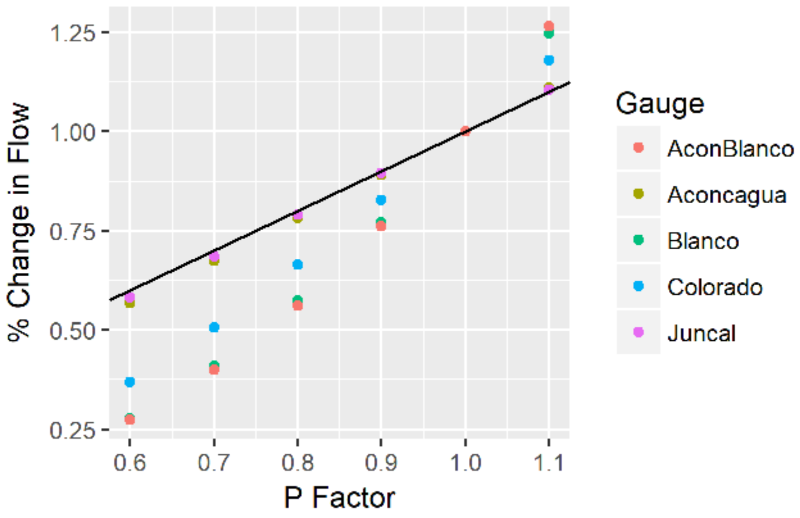

Figure 7.2- Precipitation factor vs percentage changes of the average flow (compared to the values when P Factor = 1) at the five hydrological areas (aggregating all temperature changes). The figure includes a reference line with $Slope = 1$ and $Intercept = 0$.

Figure 7.3 shows how specific hydrological variables change as a function of different *P* factors. The variables analysed are Base flow (BF), Decrease in snow (Dec_Snow), Decrease in Soil Moisture (Dec_SoilMois), Evaporation (Evap), Increase in Snow (Inc_Snow), Increase in Soil Moisture (Inc_SoilM), Interflow (InterFl), Precipitation (P) and Surface Runoff (Surf_Runoff) (see Figure 5.1 and Appendix C). Figure 7.4 shows the same relationship after flows are divided by the precipitation benchmark values. In both figures, the results of different hydrological areas and changes in *T* were averaged.

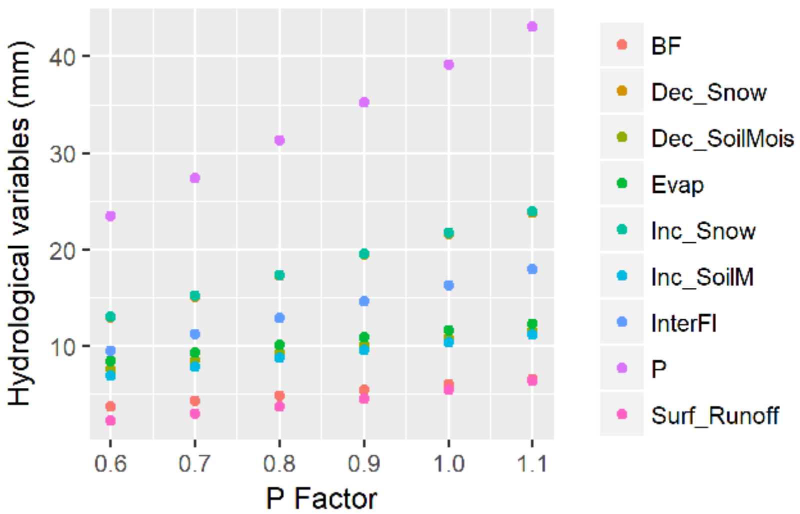

Figure 7.3 – Precipitation factor versus average hydrological variables in the catchment (aggregating over all calibration areas and temperature changes).

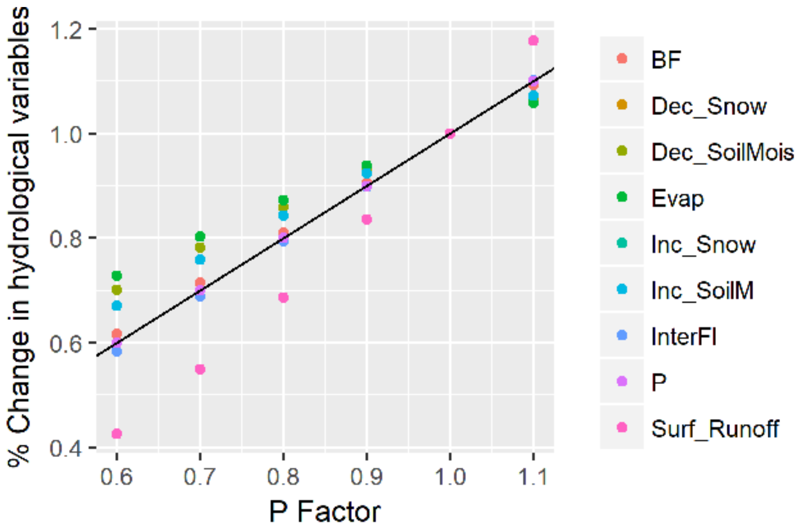

Figure 7.4 –Precipitation factor versus percentage changes of the hydrological variables in the catchment (compared to the values when P Factor = 1 and aggregating all temperature changes). The figure includes a reference line with $\boldsymbol{Slope\ =1\ and\ Intercept\ =\ 0}$.

Figure 7.5 and Figure 7.6 show how the average monthly flows and the normalised flows (which were normalised using the mean and standard deviation of the monthly results with a $P\ factor\ =\ 1$ and $T\ =0$), change as a function of P factors. This required averaging the monthly values of all hydrological areas over the 17 years period of analysis, for each combination of *P* factor and Temperature change (*T* Change). Then, all results with the same *P* factor are aggregated, so each point in the graphs represents the average results of several changes in *T*.

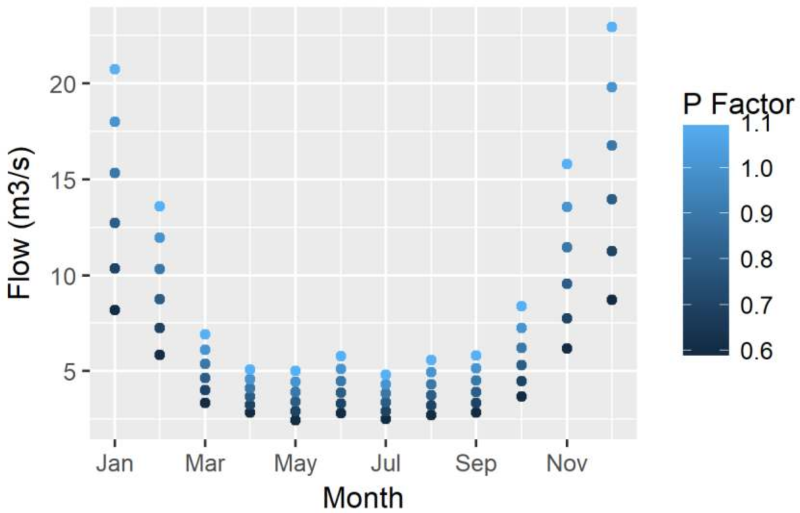

Figure 7.5 – Average monthly flows over the whole period of analysis for different P Factors (aggregating all hydrological areas and temperature changes).

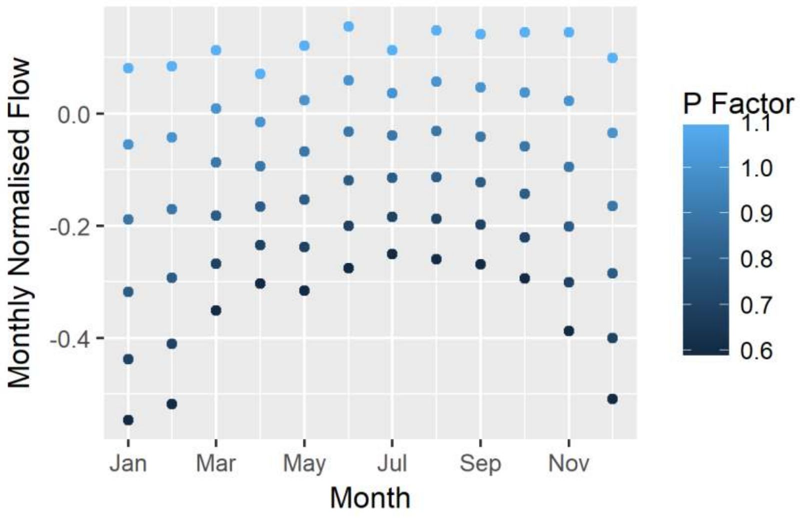

Figure 7.6 - Average monthly-normalised flows over the whole period of analysis for different P Factors (aggregating all hydrological areas and temperature changes).

Figure 7.7 and Figure 7.8 show a similar relation, but this time values are a function of the changes in temperature (*T* changes), while the aggregation is over all the *P* factors. In Figure 7.8, the $T = 0$ line is below $Y = 0$ because most *P* factors are smaller than 1, while the normalisation was done with the monthly $P\ factor\ =\ 1$ and $T\ = 0$ cases. In addition, Figure 7.9 shows how these results change as a function of the calibration areas.

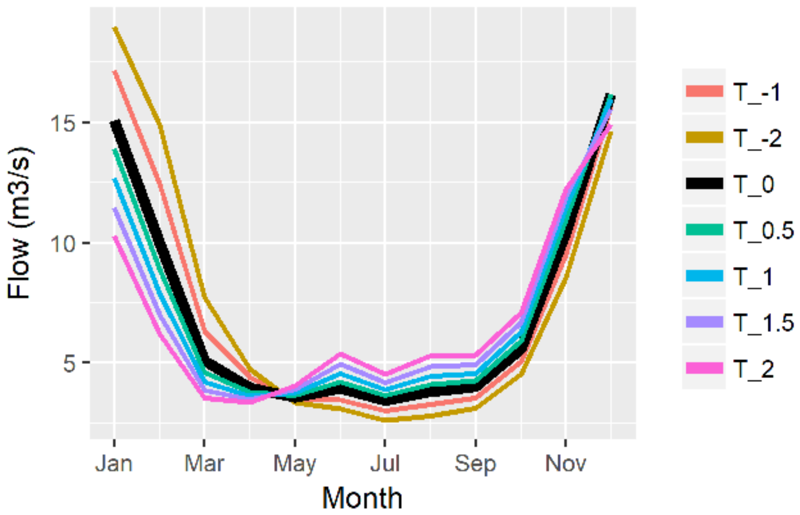

Figure 7.7 – Average monthly flows over the whole period of analysis for different temperature changes (aggregating all hydrological areas and precipitation factor changes).

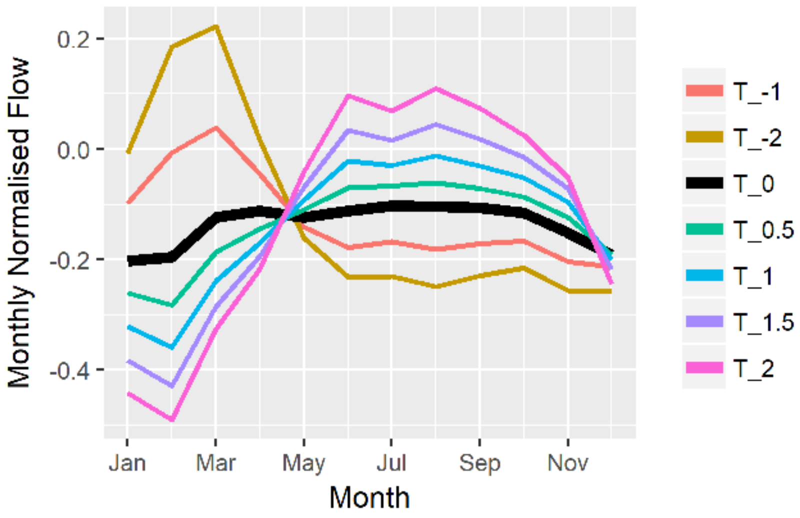

Figure 7.8 - Average monthly-normalised flows over the whole period of analysis for different temperature changes (aggregating all hydrological areas and precipitation factor changes).

Figure 7.10 shows how changes in temperature affect the average flow at each gauge. The latter are shown as a percentage change of the values in the temperature benchmark ($T\ Change\ =\ 0$), and they aggregate all precipitation factors. Figure 7.11 is similar, although this time results from different hydrological areas are aggregated as well.

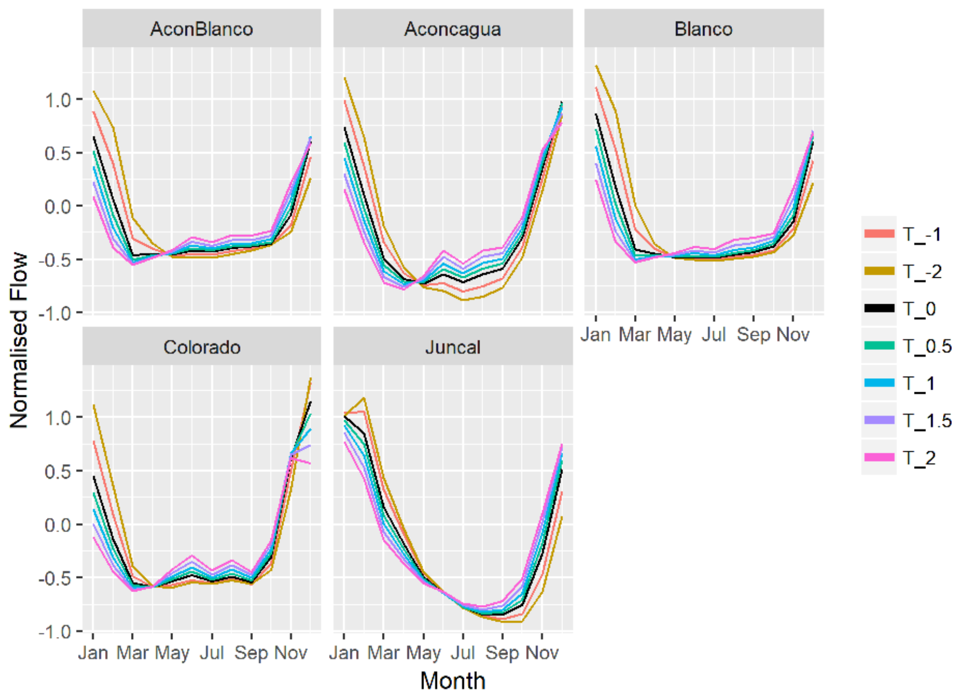

Figure 7.9 – Average monthly flows over the whole period of analysis for different temperature changes and different gauges (aggregating changes in precipitation factors). Values were normalised with the mean and standard deviation of each hydrological area to facilitate visualisation.

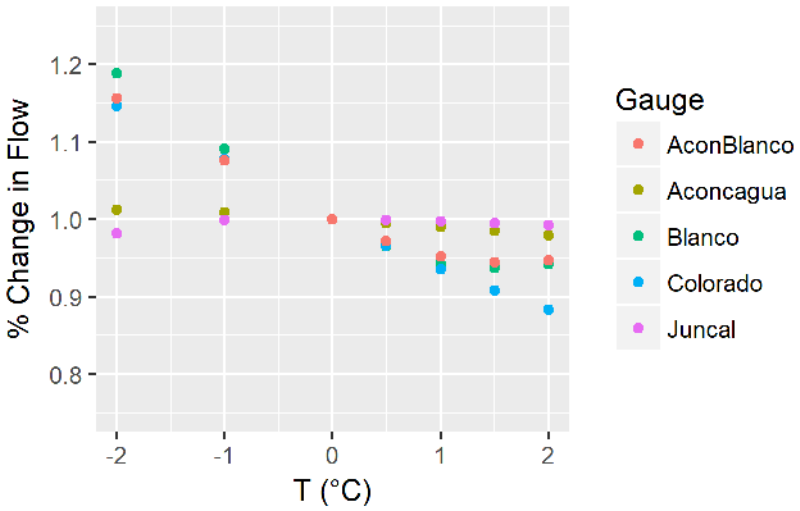

Figure 7.10 – Temperature changes vs percentage changes in the average flows for each hydrological area (aggregating changes in precipitation factors).

The second group of results analyse how the demand coverage is affected by the changes in climate conditions. Figure 7.12 shows how the demand coverage of different users is affected by *P* factors, after aggregating results with different changes in *T*. Users include Hydro-Power (Hydro), Mining (Min), Urban (Urb), Agriculture (Agr), and it also includes the coverage of the minimum flow requirement at the outlet of the catchment representing downstream demand (MinFlow). The last two overlap each other in the figure because their values are very similar.

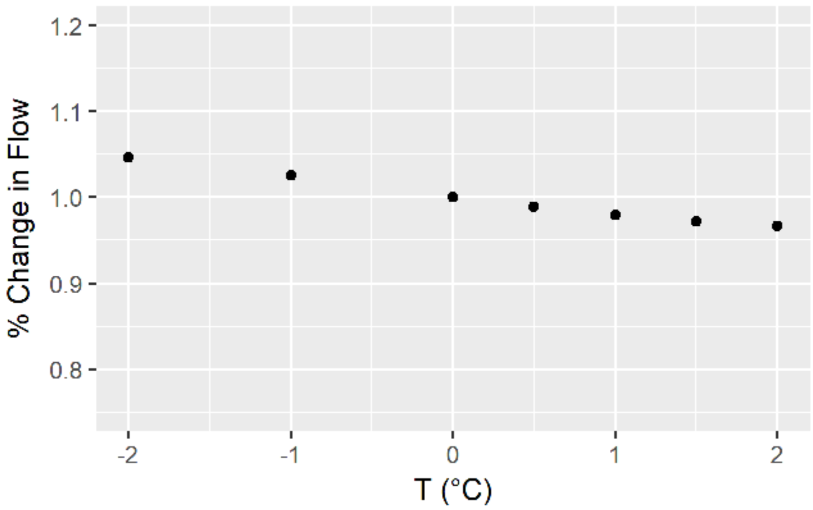

Figure 7.11 – Temperature changes vs percentage changes in the average flows (aggregating all hydrological areas and precipitation factor changes).

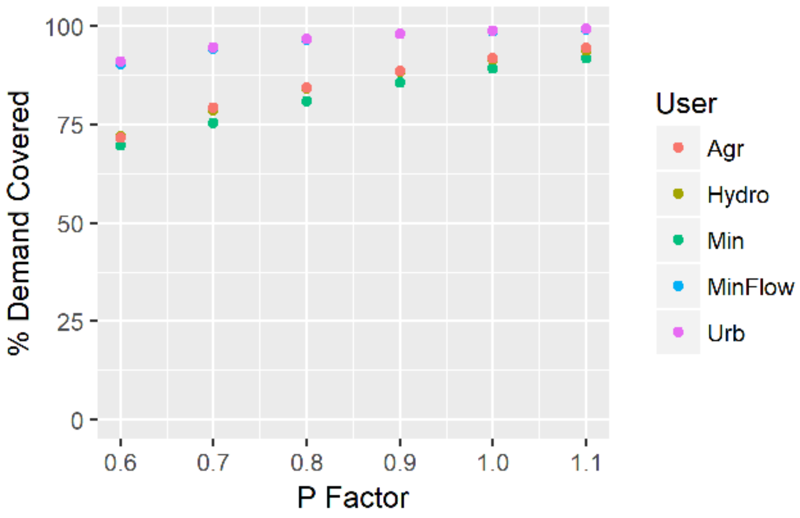

Figure 7.12 – Precipitation factor vs percentage of covered demand for different water users (aggregating all temperature changes).

Figure 7.13 shows the average monthly demand covered for each user over the 17 years period of analysis, after aggregating all *P* factor and *T* changes. Figure 7.14, on the other hand, shows the same values change as a function of different changes in *T* (aggregating *P* factors and results from all hydrological areas). Moreover, Figure 7.15 shows how different *T* values affect the demand coverage of all users, aggregating information from different months and different *P* factors.

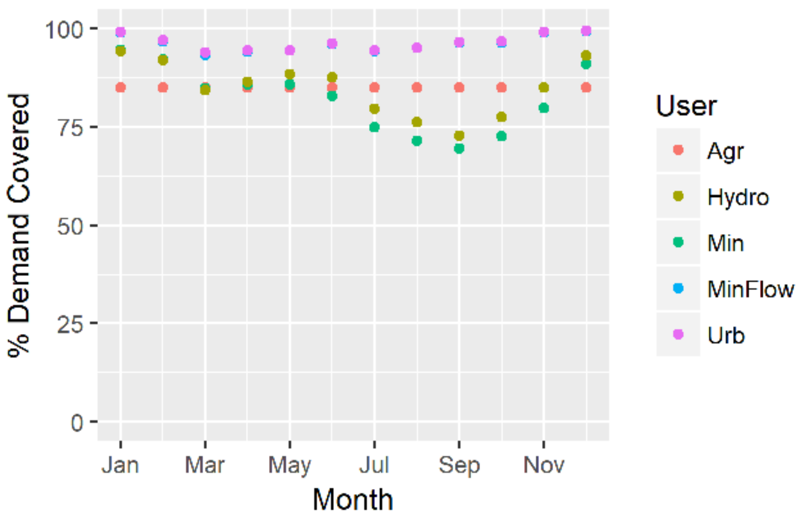

Figure 7.13 – Average monthly percentage of covered demand over the whole period of analysis for different water users (aggregating all temperature and precipitation factor changes).

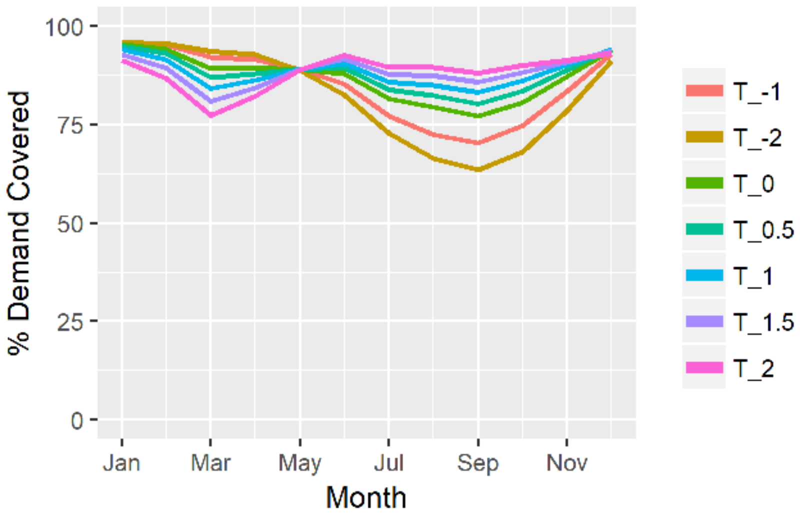

Figure 7.14 – Average monthly percentage of covered demand over the whole period of analysis for different temperature changes (aggregating results of all water users and all precipitation factor changes).

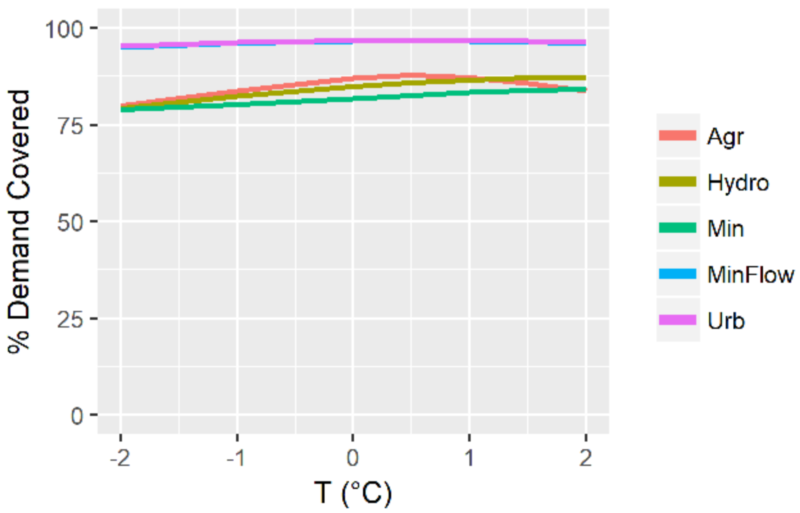

Figure 7.15 – Temperature changes vs percentage of demand covered for different water users (aggregating all precipitation factor changes).

The last group of results involves the analyses of the effects of changes in climate conditions on the economic metrics described in Chapter 6. The effects of changes in temperature on the shadow value of water, total value of water and water scarcity costs are shown in Figure 7.17, Figure 7.18 and Figure 7.19 respectively. These values aggregate the results for different *P* factors. In addition, Figure 7.16 shows the relation between different *P* factors and the shadow value of water, after aggregating results from all changes in *T*. Figure 7.20 complements this by showing how all combination of changes in precipitation and temperature affect the shadow value of water. The other economic metrics behaved similarly.

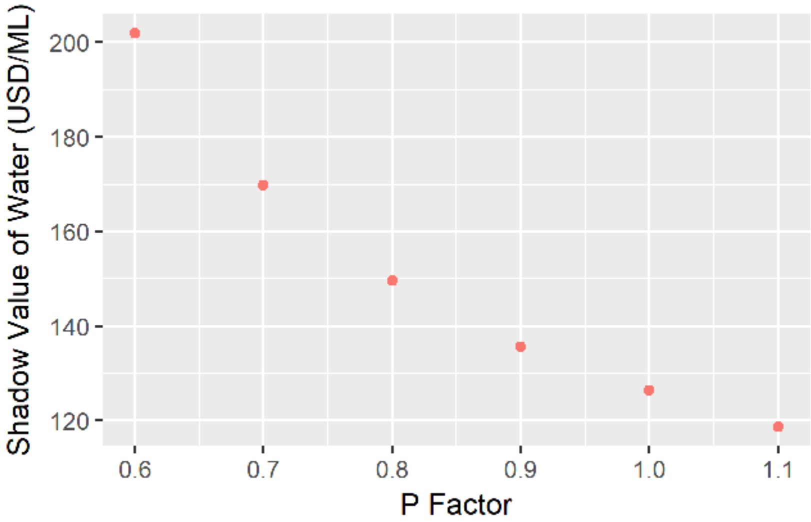

Figure 7.16 – Precipitation factor vs shadow value of water (aggregating all temperature changes).

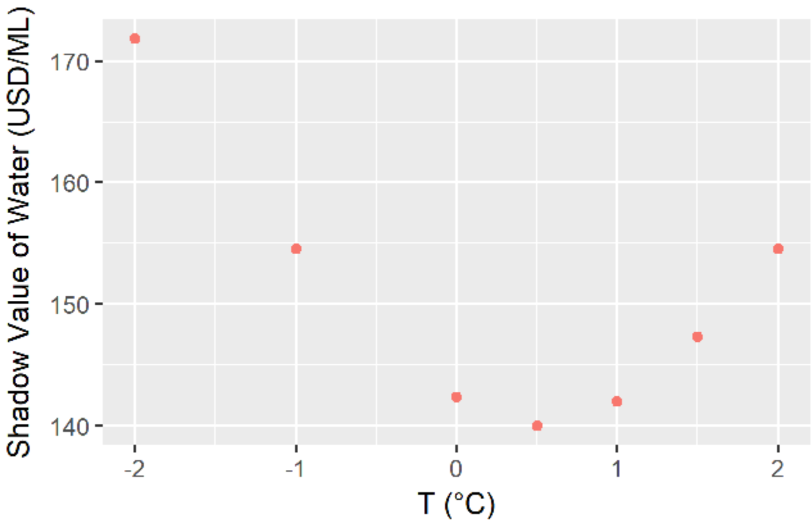

Figure 7.17 – Temperature changes vs average shadow value of water (aggregating all precipitation factor changes).

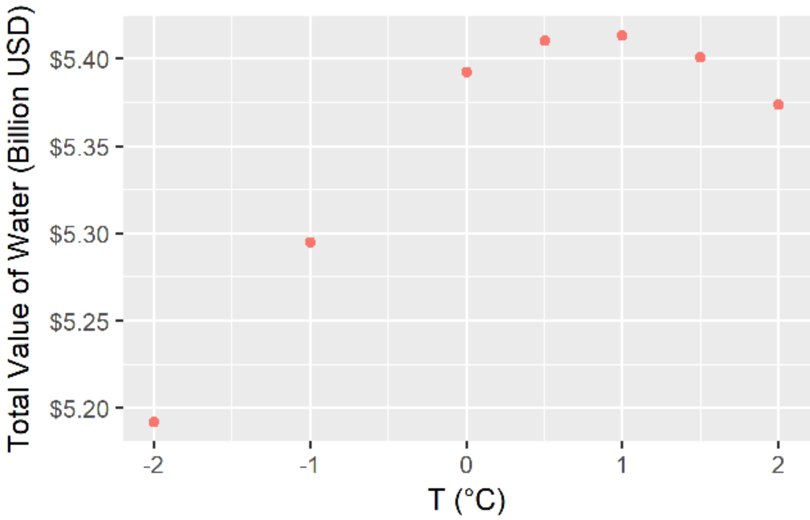

Figure 7.18 – Temperature changes vs total value of water (aggregating all precipitation factor changes).

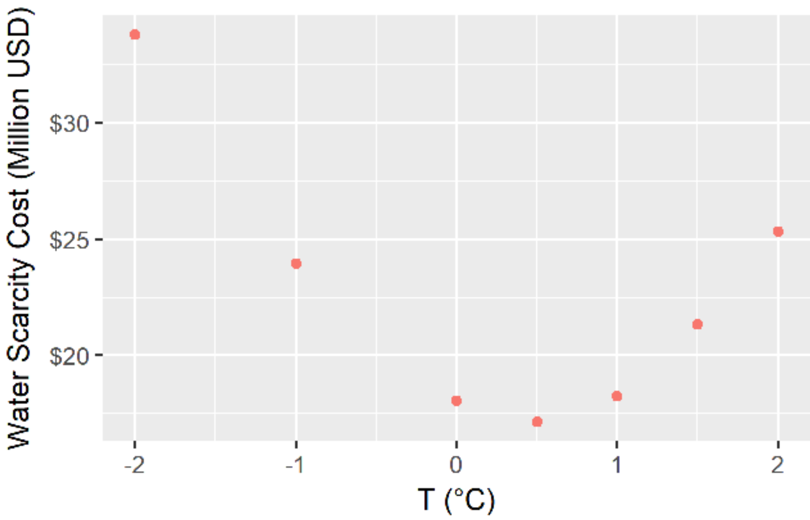

Figure 7.19 – Temperature changes vs water scarcity cost (aggregating all precipitation factor changes).

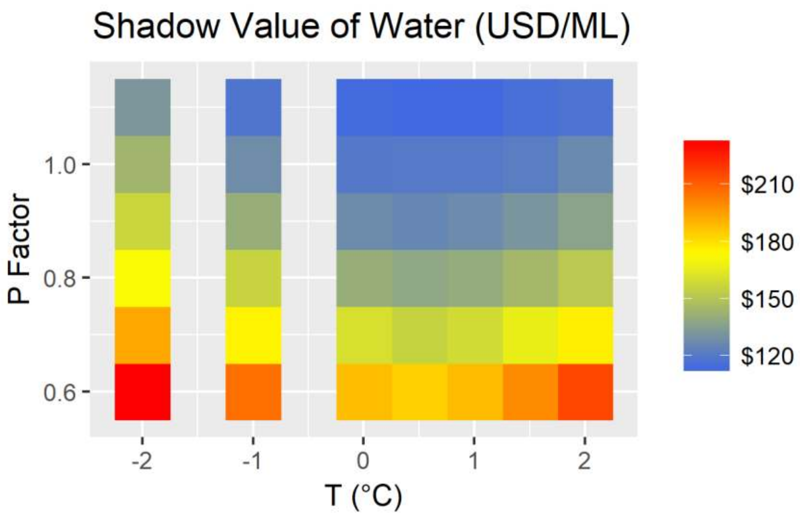

Figure 7.20 – Climate response function of the Shadow Value of Water.

7.1.2. Discussion of results

Results in Figure 7.1 show that as expected a priori, there is a strong correlation between changes in precipitation and the outlet flows in the hydrological areas of the case study.

When flows are analysed relative to the benchmark case, it can be seen that the values at the outlet of Aconcagua en Chacabuquito (Aconcagua) and Juncal change proportionally with precipitation, while the other three increase faster (see Figure 7.2). This could be caused by the fact that the latter include abstractions by the hydro-power stations or consumption by the mining company. During dry conditions users expect to obtain their normal allocations whenever possible, thus the flows in the outlet decrease faster than precipitation factors. On the other hand, during wet periods users stop consuming water after fulfilling their demand, therefore flows in the outlets increase faster than the *P* factors.

Figure 7.3 and Figure 7.4 show how different hydrological processes were affected by changes in precipitation, both in absolute terms and relative to the benchmark. Although these results are illustrative and relevant for water users, the key message here is that the inclusion of a hydrological model allowed having a detailed understanding of water fluxes and storages inside the catchment, which goes beyond knowing how output flows change.

Figure 7.5 and Figure 7.6 also show how a detailed representation of hydrological processes in a HEM (compared to the use of historical flows), allow understanding how changes in precipitation translate into flows variability. In both figures it can be seen that the largest variability is seen in the wettest months (austral summer). Further in this section it is discussed how these changes then translate to impacts on the economic metrics.

Figure 7.7 allows doing a similar analysis for temperature, as it shows the influence of this variable when defining periods of minimum and maximum flows (by changing snow melting periods). Figure 7.9 expands this by providing insight into the specific effects of temperature on each of the hydrological areas of the case study. This figure shows how impacts depend on the area of study, particularly on their elevation.

In the last two figures, it is of particular importance to note that increments in temperature have proportional effects on flows between March and November, and an inversely proportional effect in the rest of the year. Temperature decreases, on the other hand, have the opposite effect in the two periods. This is confirmed in Figure 7.8, which shows that normalised flows for increments in temperature are larger than the benchmark after mid-April, and this lasts longer than the corresponding reductions before mid-April.

Complementing the previous analysis, Figure 7.10 shows how temperature influences flows as a function of the hydrological area. It can be seen that flows in all catchments are affected in different ways by the changes in temperature. Overall, a decrease in temperature generates larger flows for the whole case study (see Figure 7.11). Based on the predictions by CONAMA and DGF (2006), only positive changes in T will be experienced, thus, in the light of the evidence of the water resources component only, any increase in temperature will be negative for the catchment.

Regarding the demand coverage for each user, Figure 7.12 shows that the percentage covered increases with P factors, and it approaches 100% asymptotically. Furthermore, Figure 7.13 shows that most users face more water scarcity during the second semester of the calendar year, which corresponds to later winter, spring and early summer in the southern hemisphere. The values for agriculture are constant, because it was assumed that this user was constrained by the driest month of the year, which tends to be during the second semester. Coverage during these months is the lowest for all users as most precipitation falls as snow, but the snow melting period only starts towards the end of the year.

Figure 7.14 shows how the monthly aggregated demand coverage of all users is affected by changes in temperature. This figure is strongly related to Figure 7.7 and Figure 7.8 as the periods of low flows in the latter, correspond to the lowest demand covered in the former, for all temperatures. Future increments in temperature will reduce the demand covered in the first part of the year, compared to the benchmark conditions, but will improve coverage during the second part, which as seen in Figure 7.13 is more critical. Decreases in temperature would generate the opposite behaviour.

Figure 7.15 is quite interesting as it shows how changes in temperature affect the overall demand coverage for each one of the users, and confirms what was discussed in the last paragraphs. In the figure, it can be seen that larger coverage for Hydro and Mining, compared to benchmark conditions, is achieved when temperature increases. The largest coverage for hydro and mining is achieved with at 2°C, while for the other three users the best scenario is achieved with a temperature increment between 0°C and 1°C.

Turning to the detail of the economic metrics, Figure 7.16 shows the relation between precipitation factors and the shadow value of water. Based on the experience of previous variables and *a priori* assumptions, the behaviour of this metric was an inverse correlation. This time, however, the points do not show a linear behaviour, which can be explained by the inclusion of non-linear functions in the economic analysis. A similar pattern was found for the other economic metrics.

Figure 7.17 analyses the variability of the shadow value of water (as explained in Chapter 6 this variable only analyses agriculture and urban water) as a function of changes in temperature (aggregating results with different precipitation factors). It can be seen that this variable has the lowest value for 0.5°C, which coincides with the behaviour of agriculture and urban uses in Figure 7.15. The same behaviour can be seen in Figure 7.19, as water scarcity cost is also determined by the conditions of agriculture and urban water.

At this point, it is clear that the improvement of these metrics due to the positive changes of temperature, is explained by the fact that increasing temperatures shifts the snow melting period from summer towards the spring. This, in turn, increases flows in the second semester of the year, which is the period with the largest rates of uncovered demand (see Figure 7.13). In this way, the negative economic impacts during the first part of the year are outweighed by the benefits in the second part.

Therefore, despite reducing the overall availability of water (see Figure 7.11), temperature increments may bring economic benefits for users. As seen in Figure 7.17 and Figure 7.19, for agriculture and urban water the peak is achieved with increments of around 0.5°. Furthermore, as the uncovered demand during spring is larger for hydro (likely to be because these users are located in higher elevation points), the improvements are larger for this user, and reach a maximum with 1 °C (see Figure 7.18).

Taking into account that the previous analysis aggregated the changes due to precipitation fluctuations, Figure 7.20 shows the *climate response function* of the shadow value of water. In other words, how the shadow value of water changes as a function of both climate variables (the other economic metrics behaved similarly). In this figure it can be seen that the lowest values (i.e. the best conditions), are found with zero or small temperature increases. However, it can also be seen that the changes due to temperature fluctuations are small, compared to the effects of the reduction of precipitation. This is confirmed after checking that in Figure 7.20, the fluctuation of values in the y-axis is larger than that in the x-axis.

Bearing in mind the predictions in the A2 and B2 climate scenarios for 2010-2039 (as reported in Table 7.1), this model suggest that the former may not have substantial effects in the catchment, while the second will have, due to the reduction in precipitation. In general, it is suggested that as long as there are no reductions in precipitation, slight temperature increments may not largely affect water users in the case study. However, if temperature increases by more than 1° C (as expected for both scenarios closer to the second half of the century) water conflicts may be exacerbated again.

It is important to highlight that it would have been difficult to get to this result without the HEM. If a purely hydrological model had been used, it would have been concluded that any increase in temperature would be negative for the catchment (see Figure 7.11). If the latter had been merged with an analysis of the demand for water only, it would have been possible to predict some improvements with the rise of temperature. However, only with the HEM it was possible to summarise this in monetised metrics that analyse all users, including the effects of potential water trades between them.

On the other hand, if a purely economic model had been used, it would have been difficult to predict the influence of temperature changes on flows, and all subsequent analyses. All this highlights the added value of a robust tool as the HEM in this project, which includes a detailed water resources component.

7.2. Environmental Flow Requirements

This section analyses the effects of including minimum Environmental Flow Requirements (EFR) in the case study. A total of 6 EFRs were analysed, each of them located downstream of a flow gauge in the catchment (see Figure 5.8 and Figure 5.9). This includes *Aconcagua en Chacabuquito* (Outlet), *Colorado en Colorado* (Colorado), *Juncal en Juncal* (Juncal), *Aconcagua en Blanco* (AconBla), *Blanco en Blanco* (Blanco) and *Blanco en Los Leones* (Leones). In addition, it was analysed the scenario of having all of them (All), and none of them (None/Baseline).

There are multiple methods to define the magnitude of the EFRs, and they range from thresholds defined using statistical analysis of historical flows, to deep ecological analyses of the streams (Acreman and Dunbar, 2004, Pastor et al., 2014). This project takes the former approach, and analyses four percentiles of historical observed flows: 10, 20, 30 and 40 (i.e. the flows that exceed 90%, 80%, 70% and 60% of the records respectively). Each month was analysed separately to take into account hydrological seasonality.

Initially, the complete historical record was analysed to define the percentiles, however, it was realised that very old measurements were done when not many users were present in the catchment, or when they consumed different volumes of water. Therefore, it was decided to analyse observations after 2000 only, as to generate thresholds that were more easily implemented in practical terms.

Some issues were found with two flow restrictions; Outlet and Leones. In the outlet this was because all water for the first irrigation area was taken in one point only. In reality, users would take water in several points, and restrictions could be defined accordingly to the flows at different points of the river. Thus for this station it was decided to define the restriction based on the simulated flows downstream of the diversion points in the base case scenario.

The Leones restriction, on the other hand, was recently installed and has a relatively short historical record (see Figure 5.10F), where most correspond to a relatively dry period. This means that the calculated percentile values may be relatively low. Despite this, it was decided to keep this restriction, as it allowed developing valuable analyses of the mining and hydro-power users. Table 7.2 shows a sample of the flow restrictions for the six locations.

Table 7.2 – Percentile 30 restriction for the six locations in the catchment (all values in m^3/s).

Month	AconBla	Outlet	Blanco	Leones	Colorado	Juncal
Jan	6.68	12.80	6.39	5.36	0.18	9.47
Feb	3.24	8.37	2.01	5.52	0.11	7.38
Mar	2.01	4.89	1.09	3.50	0.07	5.29
Apr	1.63	4.16	0.82	1.64	0.08	3.55
May	1.32	4.32	0.67	0.84	0.11	2.55
June	1.58	5.14	0.75	0.71	0.14	2.06
Jul	2.33	4.56	0.82	0.68	0.16	1.83
Aug	2.17	5.02	0.77	0.98	0.26	1.86
Sep	2.48	5.23	1.00	1.45	0.30	2.07
Oct	4.30	6.56	1.12	2.16	1.00	3.26
Nov	5.73	10.78	3.01	4.93	4.06	5.54
Dec	10.86	14.94	6.78	7.49	1.78	8.48

7.2.1. Results of the analysis of Environmental Flow Requirements

The results in this section are divided into two groups, the first analyses the effects on the demand coverage and the second one covers the effects on the economic metrics. Figure 7.21 shows the average monthly demand coverage for all users as a function of the location of the EFR, after aggregating results for all restriction percentiles.

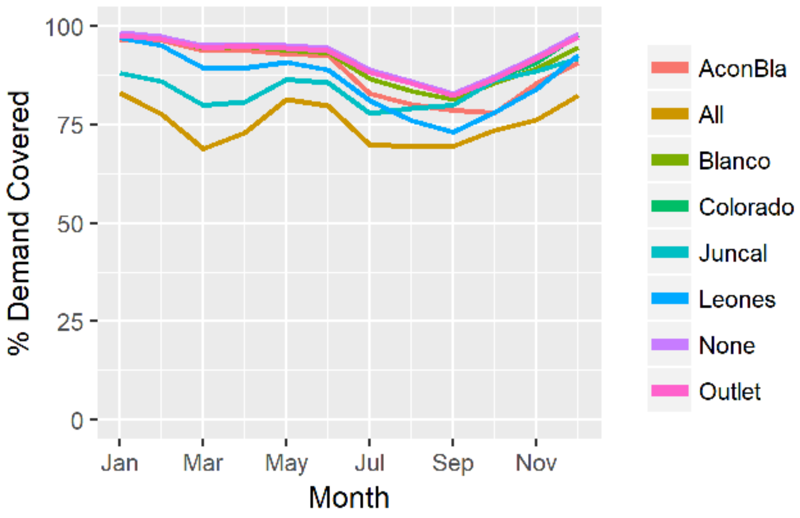

Figure 7.21 – Average monthly percentage of covered demand over the whole period of analysis for different locations of the EFR (aggregating results for all percentiles).

Figure 7.22 and Figure 7.23 show how different percentiles of flow restrictions affect the average demand covered, as a function of the location of the restriction and the type of user respectively. Figure 7.24 shows how the location of the EFR affects the percentage of demand covered as a function of the user, and also of two percentile restrictions (the smallest and the largest), plus de baseline (no restrictions).

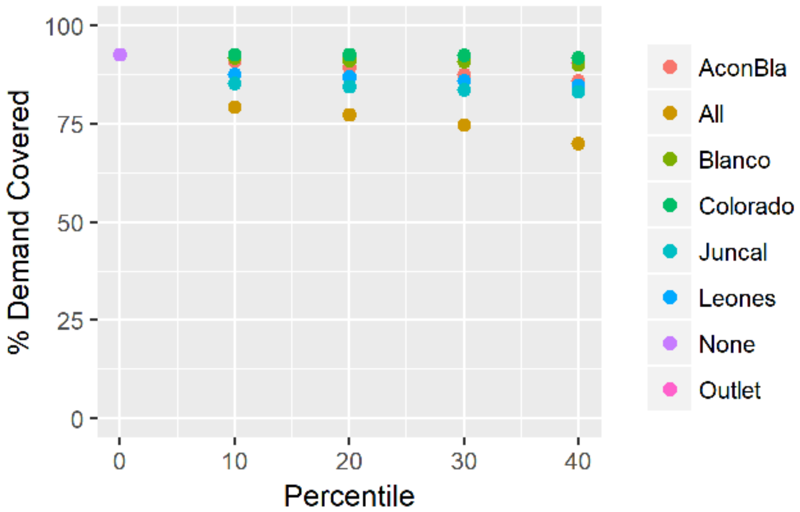

Figure 7.22 – Percentile of flows restrictions versus percentage of covered demand for different locations of the EFR.

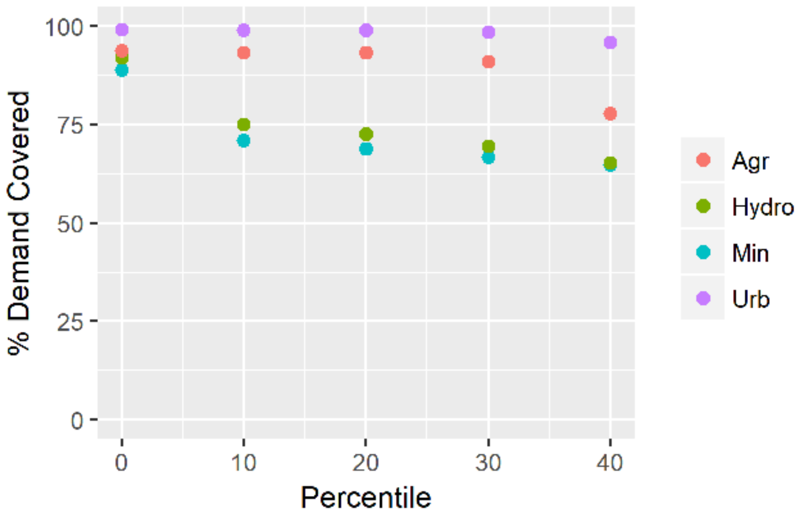

Figure 7.23 - Percentile of flows restrictions versus percentage of covered demand for different users with all the EFRs.

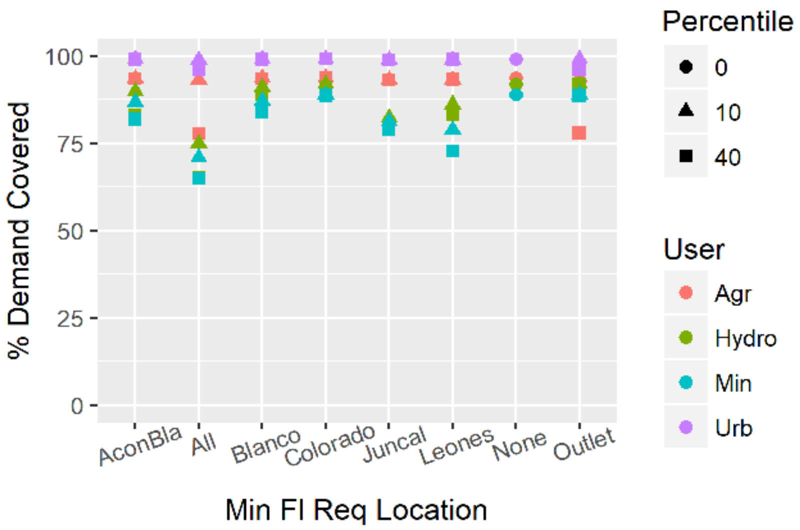

Figure 7.24 – Location of EFR versus percentage of covered demand for different users and two percentiles of flows restrictions (10 and 40) plus the baseline.

Figure 7.25 show the average monthly percentage of demand over the 17 years period of analysis, as a function of all type of users and two percentiles (10 and 40, plus the baseline).

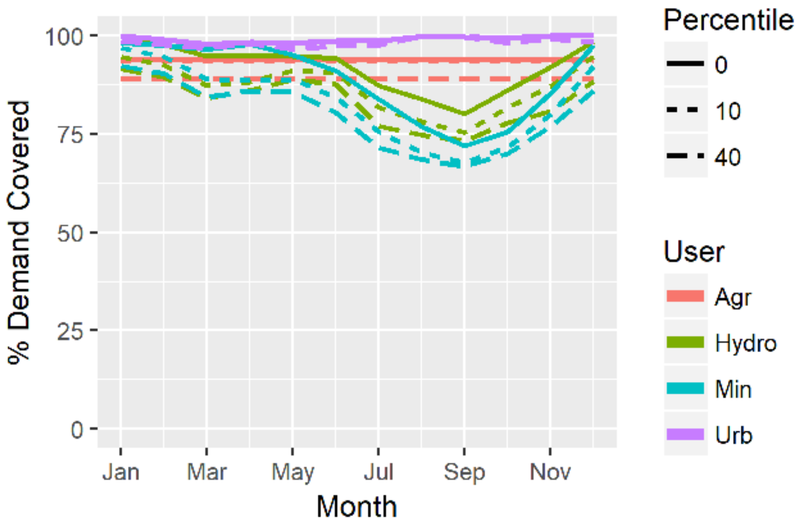

Figure 7.25 - Average monthly percentage of covered demand over the whole period of analysis for different users and two percentiles of flows restrictions (0.1 and 0.4).

Figure 7.26 is similar to Figure 7.25, although instead of percentiles it classifies results for two conditions, when all restrictions are imposed and when none is included (i.e. baseline). Other locations are not shown to facilitate visualisation of results.

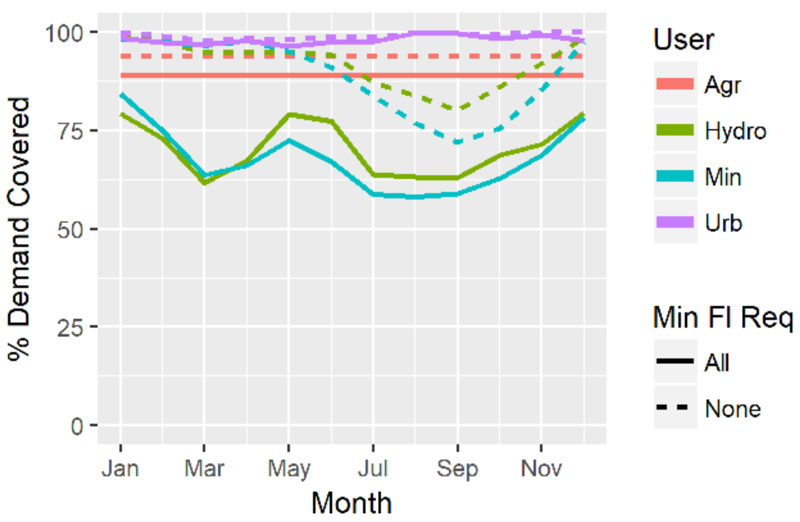

Figure 7.26 - Average monthly percentage of covered demand over the whole period of analysis for different users and two locations of flows restrictions.

Figure 7.27 shows how different percentiles of flow restrictions affect the total value of water for all users in the catchment, while Figure 7.28 shows the relation with the total value of water for agriculture, hydro and urban uses only. The Y-axis of both figures has been adjusted as to facilitate visual comparison with other figures with the same economic metric. It is important to realise that as opposed to the demand coverage analysis, for the economic metrics only three percentiles are included in the figure, as it was not possible to calculate values for 0.4 (further details of this will be given in the discussion of results).

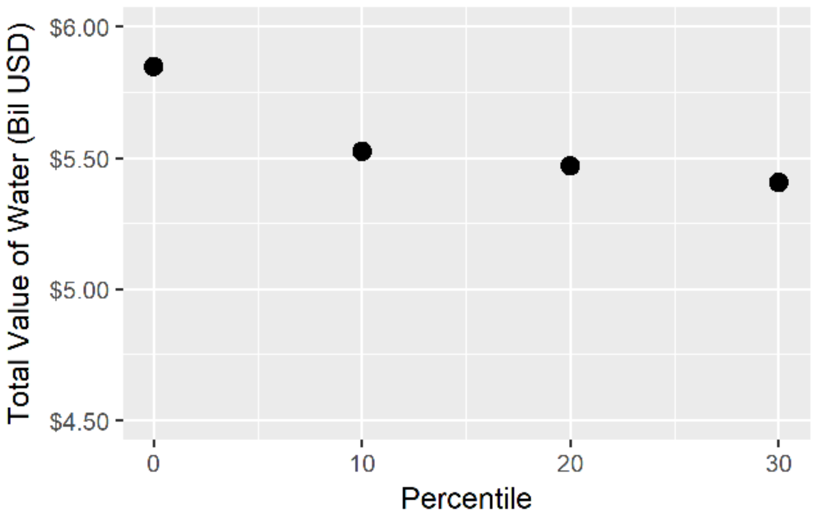

Figure 7.27 - Percentile of flows restrictions vs total value of water (aggregating all locations of flow requirements).

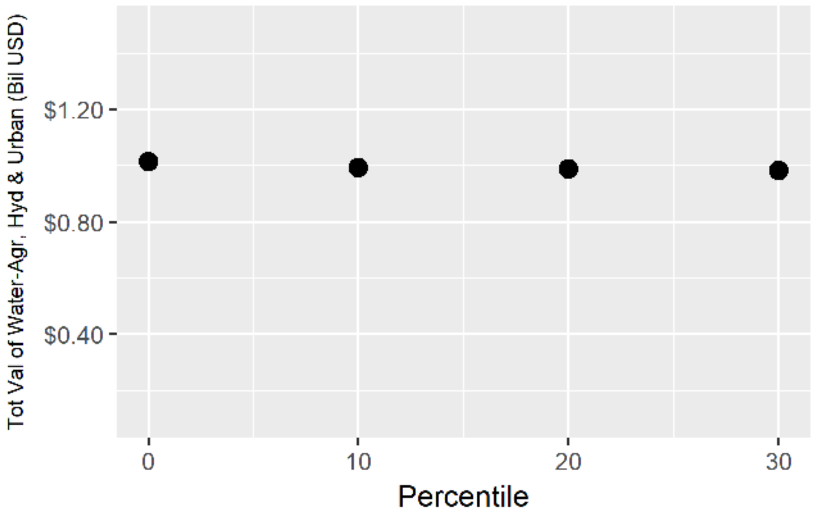

Figure 7.28 - Percentile of flows restrictions vs total value of water for agriculture, hydro and urban uses only (aggregating all locations of flow requirements). The Y axis scale was adjusted to facilitate comparisons with other figures in this section.

Figure 7.29 and Figure 7.30 show how the percentiles of flows restrictions affect the water scarcity cost and the shadow value of water respectively, and their Y axis have also been adjusted to facilitate comparisons.

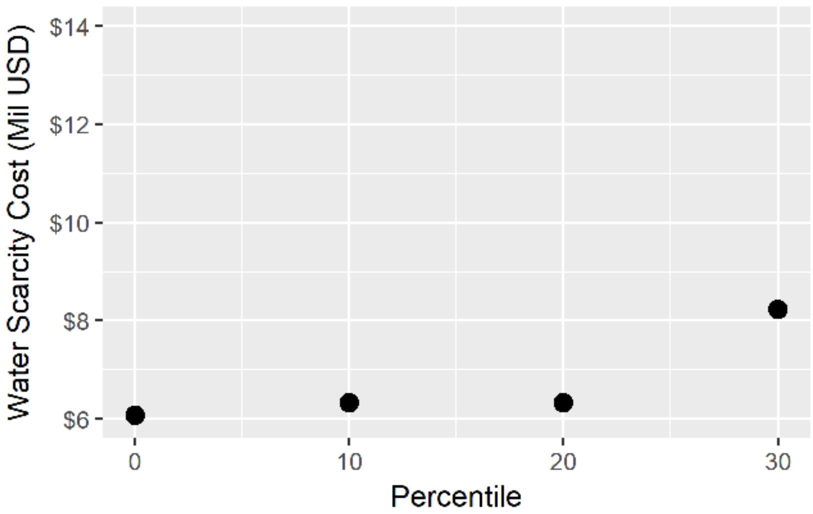

Figure 7.29 - Percentile of flows restrictions vs water scarcity cost (aggregating all locations of flow requirements). The Y axis scale was adjusted to facilitate comparisons with other figures in this section.

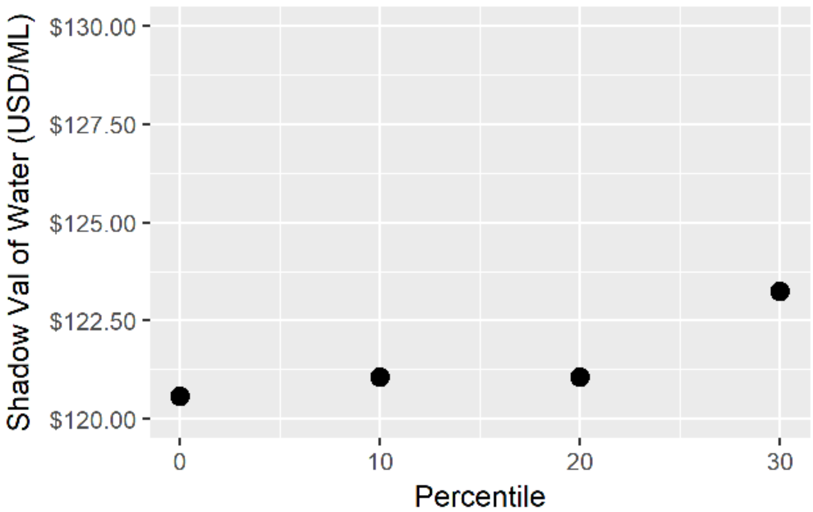

Figure 7.30 - Percentile of flows restrictions vs shadow value of water (aggregating all locations of flow requirements). The Y axis scale was adjusted to facilitate comparisons with other figures in this section.

Figure 7.31 shows how the location of the flow requirement affects the total value of water for all users, as a function of the percentiles, while Figure 7.32 shows the relation with the total value of water for agriculture, hydro and urban uses only.

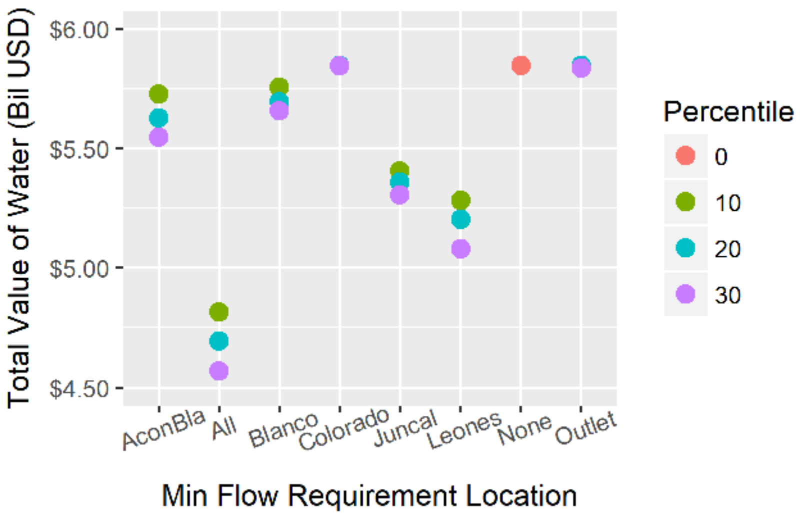

Figure 7.31 – Location of EFR vs total value of water for different percentiles of flow restrictions.

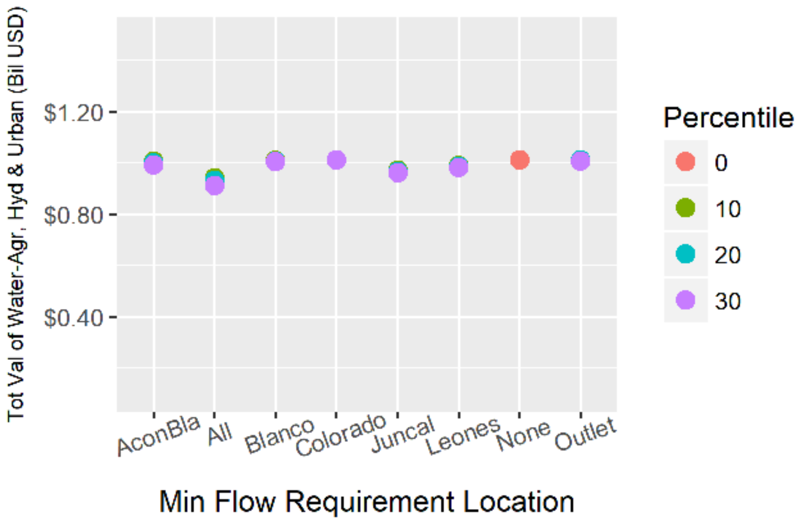

Figure 7.32 - Location of EFR vs total value of water for agriculture, hydro and urban uses only, for different percentiles of flow requirements. The Y axis scale was adjusted to facilitate comparisons with other figures in this section.

Figure 7.33 and Figure 7.34 show how the EFR at the outlet of the case study affects water scarcity cost and shadow value of water, as a function of the percentiles. These two plots do not include the other flow restrictions because they do not considerably affect agriculture and urban water, which are the users described by these economic metrics. It is important to recall that water used for hydro-power purposes is returned to the river and can be used for agriculture and urban uses, thus the latter are not affected by the flow restrictions in areas where hydro-power abstracts water.

Figure 7.33 - Location of EFR vs water scarcity cost, for different percentiles of flow requirements (only the restrictions affecting agriculture and urban uses are included).

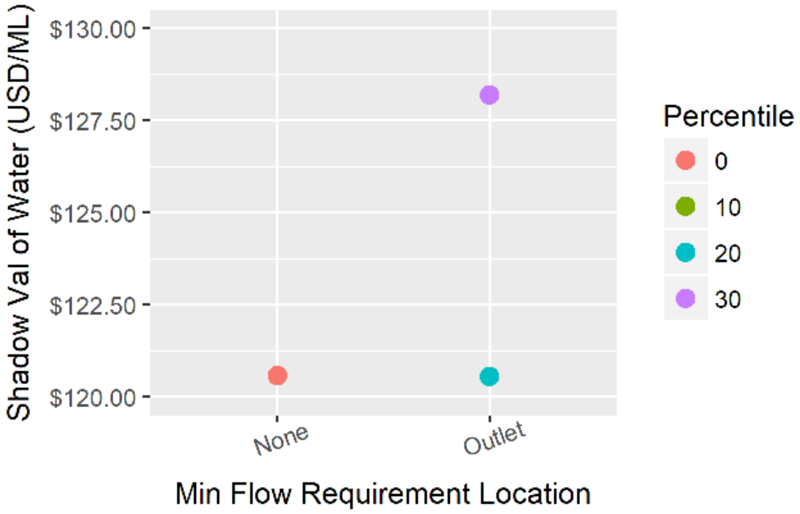

Figure 7.34 - Location of EFR vs shadow value of water, for different percentiles of flow requirements (only the restrictions affecting agriculture and urban uses are included).

Results in this section showed that many variables were not affected by EFRs, as much as by changes in climate conditions (see Section 7.1). In order to explore how both scenarios affected variables, Figure 7.35 shows the yearly coverage of agricultural demand when including the EFR in the outlet of the catchment and three different percentiles (PCTL). This is compared in the same figure with the results of three different precipitation factors.

Figure 7.35 – Yearly percentage of agricultural demand coverage for the whole period of analysis for a simulation with a temperature change of – 2°C and three P factors (0.6, 0.75 and 0.9), and a simulation with a EFR in the outlet of the catchment and three percentile restrictions (0.1, 0.3 and 0.4).

Moreover, Figure 7.36 show how the same group of conditions affected the shadow value of water during the same period (2000 – 2017), although this time the percentile 0.4 was not included as it was not possible to calculate economic values for this case.

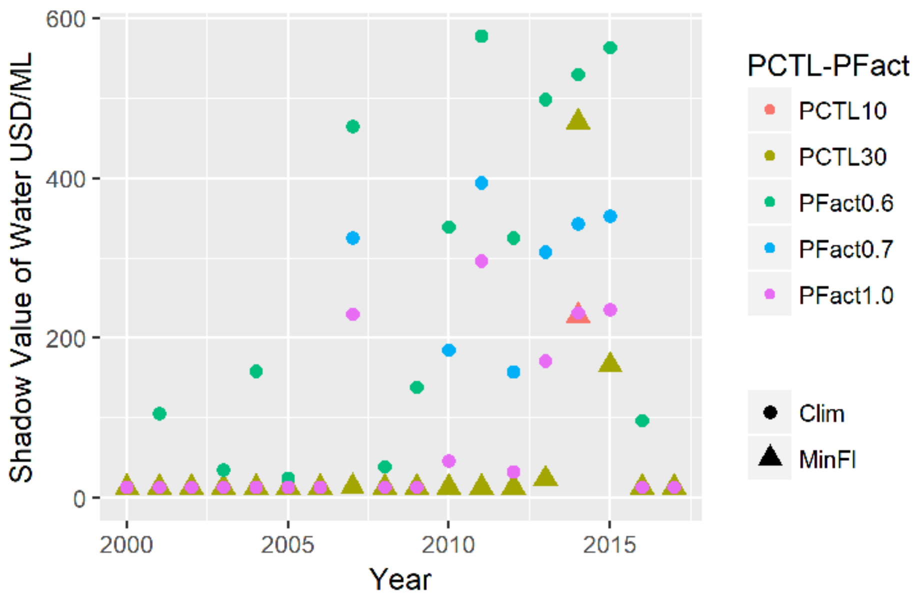

Figure 7.36 – Yearly average shadow value of water for the whole period of analysis for a simulation with a temperature change of – 2°C and three P factors (0.6, 0.75 and 0.9), and a simulation with a EFR in the outlet of the catchment and two percentile restrictions (0.1 and 0.3).

7.2.2. Discussion of Results

Regarding the overall impact of the location of flow restrictions on monthly demand coverage, Figure 7.21 shows that Juncal and Leones generate the largest impacts, although the second is known to be a relatively stringent restriction as previously explained. Furthermore, although demand coverage with most restrictions is lower in the second half of the year (similar to results in previous sections), this figure shows that the one in Juncal seems to distribute the impact more evenly throughout the year.

In terms of the effect of the different percentiles of the restrictions, as expected, there is an inverse correlation between them and the covered demand (see Figure 7.22 and Figure 7.23). However, the incremental differences between percentiles (see Figure 7.22, Figure 7.23 and Figure 7.25) are not as large as the ones seen for changes in temperature and precipitation (see Figure 7.12 and Figure 7.15). Indeed, there are flow restrictions that have very small impacts (e.g. those at Colorado and Blanco). This may be because the flows (and the associated restrictions) are rather small, there are few demand nodes immediately upstream of them, or because they are downstream of the convergence of multiple streams, which may facilitate a more resilient response to EFRs (e.g. AconBlanco).

The location of the flow restrictions affect users in different ways. Juncal station for instance, despite being located in an upstream point has larger observed values than Blanco, AconBlanco (i.e. in several but not all months) and Leones, and this affects the main abstraction point for Hornitos and Juncal hydro-power generators, which are just upstream of the restriction. This is why this restriction has such large impacts (see Figure 7.24).

Results also show that hydro-power and mining often bear larger economic impacts with the flow restrictions, agriculture is only impacted when a relatively large restriction (Percentile 40) is in place, while the urban sector is barely affected (Figure 7.24). The differences between agriculture and urban use arise mostly because of the assumption that the yearly value of the former is constrained by the month with the minimum coverage in each year.

Regarding the users that each EFRs specifically affects, it can be seen that the one in the outlet mainly influences agriculture, while those in Leones, Blanco, AconBlanco and Juncal affect hydro-power. Mining is affected by Leones, Blanco and AconBlanco, as expected, but it is also affected by Juncal (see Figure 7.24). After analysing the latter, it was found that due to the restriction on the abstraction of water by hydro-power, with the flow requirement in Juncal, WEAP reduces the demand allocated to the mine project as to alleviate the water scarcity for hydro.

This behaviour is caused by the way WEAP algorithms were set, and it raises the question if a restriction should be beared by those with water rights upstream of it only, which looks like the status quo, or if partnerships should be created in the catchment as to alleviate the burdens of the restriction. This also raises a warning that the results of this type of models should be interpreted in light of real life restrictions.

Before analysing the economic metrics, it is important to mention that calculations were limited to a maximum 30 percentile restriction in flows, after evidencing that using 40 at the outlet would generate a demand coverage for agriculture near 0% in one year. As explained in Chapter 6, such small values were avoided for agriculture and urban uses, as the assumptions used were only logical for larger consumptions. This meant that values smaller than 50% were avoided as much as possible, while demands coverages of less than 30% would trigger errors in the algorithms.

Turning to the detail of the economic metrics, the losses in total value of water due to changes in the magnitude of the EFRs, come mostly from mining use. The other three uses, although affected, experience smaller changes that are almost imperceptible when using a range in the Y axis scale that is similar to the one in the previous plot (compare Figure 7.27 and Figure 7.28).

Water scarcity cost and shadow value of water, which are key descriptors of the impacts on agriculture and urban uses, fluctuate as a function of the percentiles of the flow restrictions and their location (see Figure 7.29, Figure 7.30, Figure 7.33 and Figure 7.34). However, these changes are small compared to the ones seen in the analysis of climate conditions (see Section 7.1.1).

Results also show that changes due to different percentiles are smaller than those arising as a consequence of different locations. This suggests that deciding the magnitude of the restriction on flows may not be as important as defining its location.

Taking into account that the inclusion of EFRs seemed to have very small impacts on agriculture and urban uses, but at the same time it was not possible to calculate economic values for percentiles beyond 30, it was decided to explore results in a year by year basis. Up to now, results in this chapter aggregated the whole period of analysis (2000 - 2017) for each run of the model, even in those cases in which monthly values were presented.

The yearly comparison between scenarios showed that there were differences in the way agriculture and urban use were affected. While the changes in climate conditions would impact demand coverage throughout the period of analysis (several although not all of the years), the inclusion of EFRs would only affect values in very dry years (see Figure 7.35 and Figure 7.36). These figures show that during the driest years of the period of analysis (2011-2015), the changes of climate conditions and the inclusion of EFRs have a similar impact on the analysed metrics, nevertheless, the rest of the years behave differently.

This meant that the changes in climate conditions managed to affect the aggregated metrics, while the inclusion of EFRs barely influenced values, as the impacts in a few years were averaged with the unaffected ones, as to generate a small overall impact. This suggests that the methods used to define the magnitudes of EFRs should be flexible. This could involve a set of frequent restrictions that benefit the environment in most years, with less tight restrictions during very dry periods that do not impose an unbearable burden to users.

These outcomes could have changed if flow restrictions had been set using the whole set of historical observations (i.e. as opposed to using records from 2000 only as in Table 7.2). However, this would have entailed further challenges as very old observations were made when conditions in the catchment were quite different. This highlights the relevance of the selection of the historical period to develop the statistical analysis that defines flow restrictions.

An alternative to this statistical approach would be to use more robust analyses (Acreman and Dunbar, 2004, Pastor et al., 2014), like setting the requirements on the basis of an ecological analysis for the streams. This approach, although desirable to have a tailored solution for the environment, may face practical problems during the implementation due to the challenge of studying all streams in such a detail, and making sure users agree with the restrictions.

7.3. Tailings Water Recycling Project

The mining project located in the case study has its main Tailing Storage Facility (TSF) or Tailings Dam[18] outside the Aconcagua catchment, in an area that is part of the Maipo River in a much lower altitude than the mine and processing plant (see Figure 7.37). The company has previously analysed the feasibility of developing the infrastructure, to pump back the water that accumulates in this dam. The aim of this was to increase the supply of water to the processing plant, as part of a project that expected to increase the production capacity of the mine. This expansion project was put on hold, and is being updated by the company, but the TSF is still seen as a potential source of water if the copper production capacity of the mine is increased.

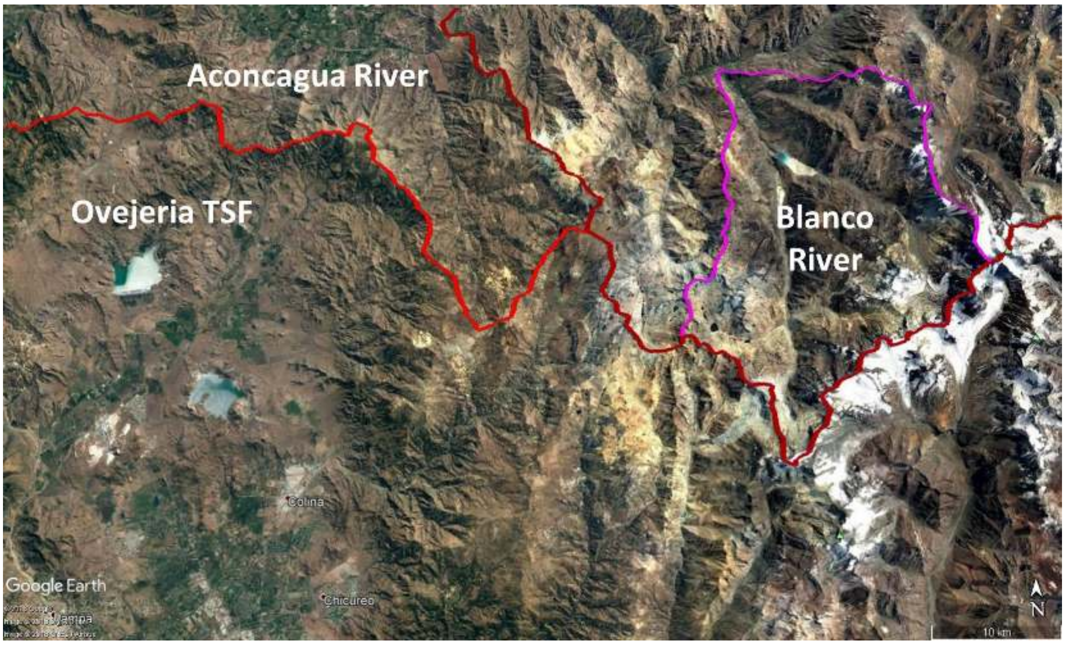

Figure 7.37 - Location of Ovejeria Tailings Storage Facility.

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[18] Tailings are a slurry containing the mining waste after processing the economically desirable minerals. This slurry tends to have high contents of water that are frequently the main loss in the system. This water is lost through evaporation or seepage, although the latter is usually undesirable due to the environmental impacts associated. Many mining projects around the world now see Tailings Water (TW) as an alternative source of water. This, however, requires investing in pumping systems and eventually in treatment facilities, although the water quality requirements for mineral processing are not high compared to potable or agricultural standards.

As well as being considered as an alternative source of water for a potential expansion, there has been some research to analyse how this water could be used to help the mine facing droughts in the catchment (Correa-Ibanez et al., 2017, Correa Ibanez, 2015). This analysis, however, was only focused on the direct economic benefits that this source could bring to the mine project.

Thus, it was desired to analyse how a catchment-scale approach could provide insight, into the benefits that the same infrastructure project could be brought to the whole catchment. This was done by using the HEM developed in this project to analyse the tailings water recycling project. The information regarding the capacity and costs of this, was taken from Correa Ibanez (2015), is summarised in Table 7.3.

Table 7.3 - Characteristics of the tailings water recycling project. Values in 2017 prices.

Variable		Value
Flow recycled from TSF (m3/s)		0.25
CAPEX in 2017 prices (Millions USD)	$	69.15
OPEX in 2017 prices (Millions USD per year)	$	2.19
Lifespan - Assumed from data available (yrs.)		25
Annualised Cost in 2017 prices (Millions USD)	$	8.67
Interest rate %		8
Total Net Present Cost (Millions USD)		**$92.6**

The inclusion of the recycling infrastructure in WEAP was done by adding an *"Other Supply"* node, which provides the system with an extra constant supply of 0.25 m^3/s (7.9 million m^3 per year, around 36% of the assumed yearly consumption of the mining user). This object was connected directly to the mine project, and it was assumed that this source would be the first choice of the project, which in several months would reduce its requirements from the river. This, in turn, makes some water available, which can be used by downstream users, which represent the shared benefits from the project. In other words, the priority for the use of the recycled water is the mine project, but eventually the benefits are received by downstream users.

It is important to remember that in the first scenario of this Chapter, it was assumed that the coverage of mining's demand for water in the base case was enough to allow full production during the whole period, even if WEAP had not allocated 100% of the demand during all years. Taking this into account, this scenario assumes that the demand for water target with the additional source of water is the same as in the base case scenario (see Chapter 6).

7.3.1. Results of the inclusion of recycled Tailings Water

Figure 7.38 is similar to Figure 7.12, as it shows the improvements in percentage demand coverage as a function of precipitation factors, for all users in the model, with tailings water recycling. Figure 7.39 is related to Figure 7.13 and illustrates the intra-annual improvements in demand coverage for each user in the catchment after including the TSF recycling, after aggregating temperature and precipitation changes. Figure 7.40, on the other hand, shows the improvements on percentage demand coverage as a function of changes in temperature.

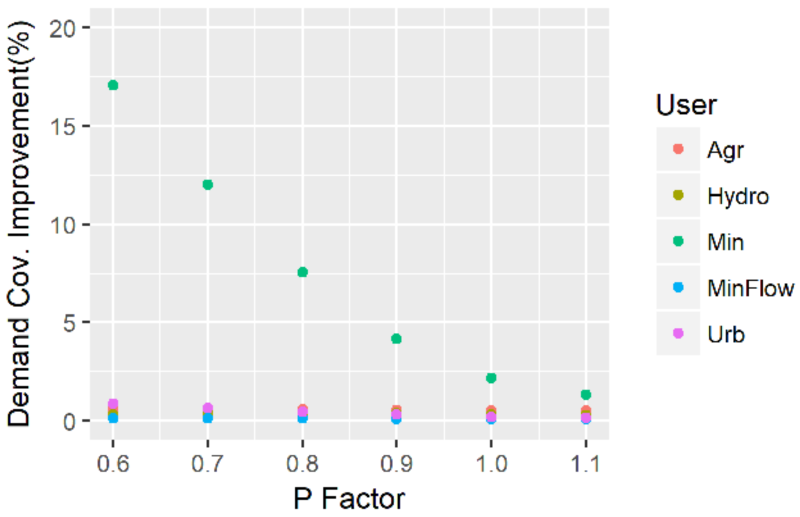

Figure 7.38 - Precipitation factor versus percentage of demand coverage improvement for different water users after including the tailings water recycling (aggregating all temperature changes).

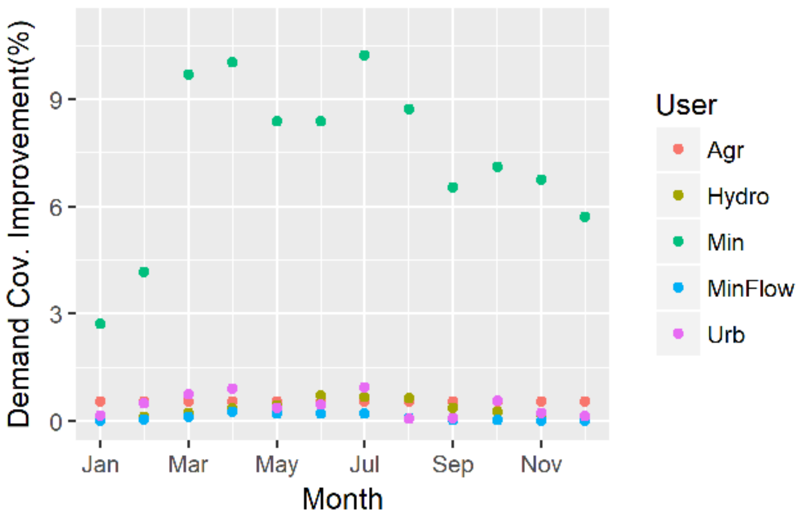

Figure 7.39 - Average monthly percentage improvement of demand coverage over the whole period of analysis for different water users after including the tailings water recycling (aggregating all temperature and precipitation factor changes).

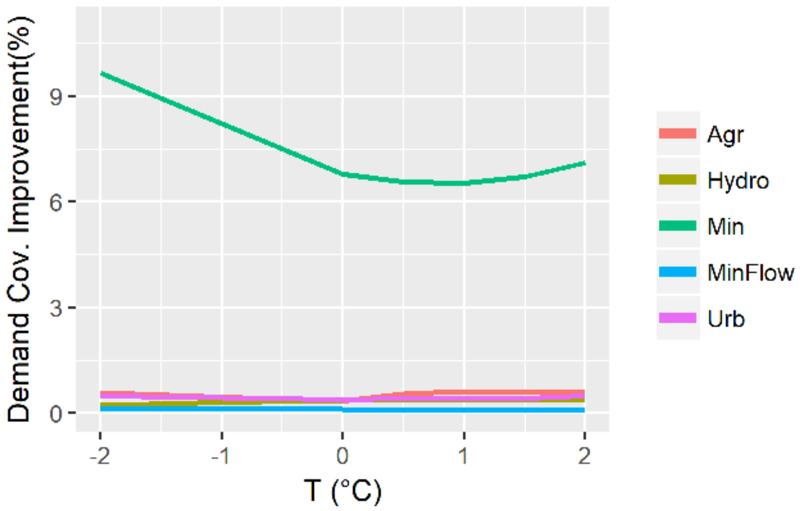

Figure 7.40 - Temperature changes vs percentage improvement of demand coverage for different water users after including the tailings water recycling (aggregating all precipitation factor changes).

Figure 7.41, Figure 7.42, Figure 7.43 and Figure 7.44 show respectively how; shadow value of water, total value of water, water scarcity cost, and total value of water for hydro, agriculture and urban uses fluctuate, as a function of temperature changes. All these figures also show the way results change with and without tailings water recycling.

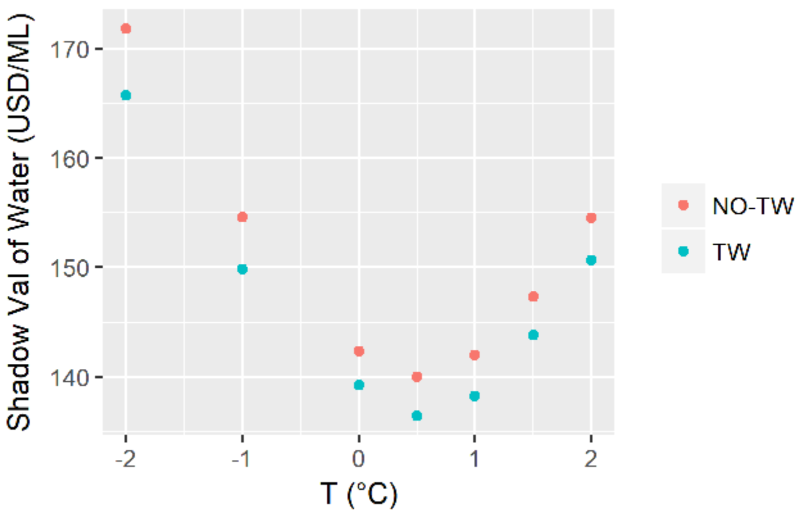

Figure 7.41 - Temperature changes vs average shadow value of water with (TW) and without (NO-TW) tailings water recycling (aggregating all precipitation factor changes).

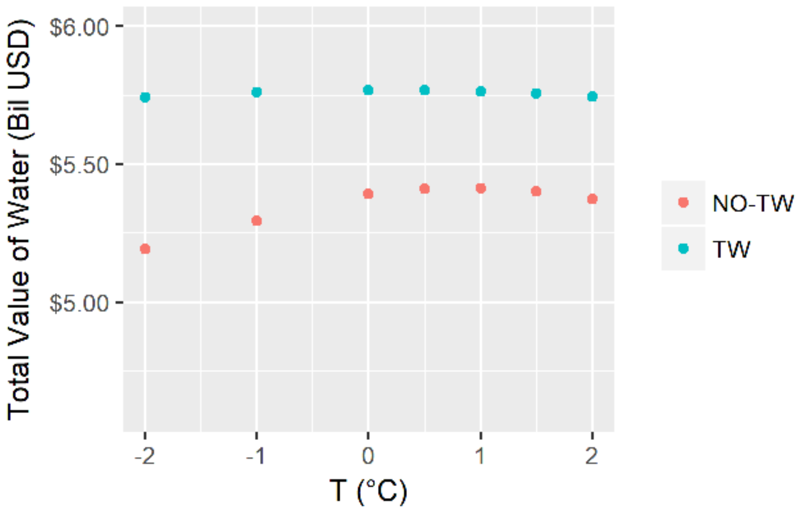

Figure 7.42 - Temperature changes vs total value of water with (TW) and without (NO-TW) tailings water recycling (aggregating all precipitation factor changes).

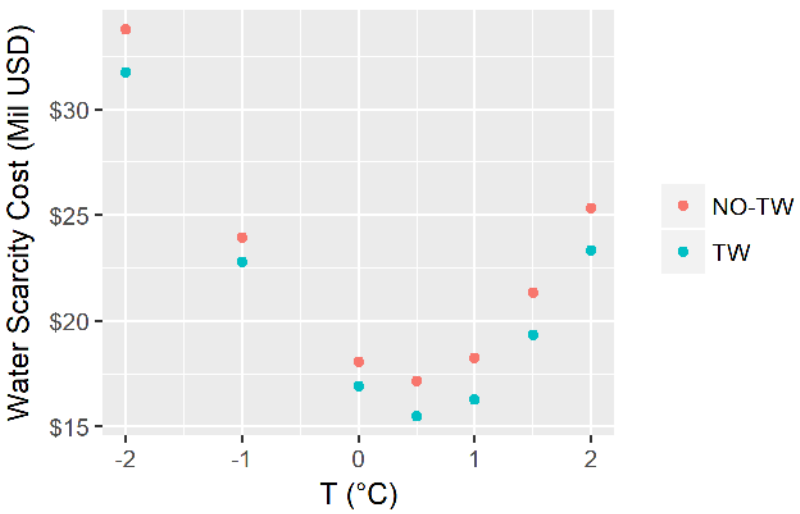

Figure 7.43 - Temperature changes vs water scarcity cost with (TW) and without tailings (NO-TW) water recycling (aggregating all precipitation factor changes).

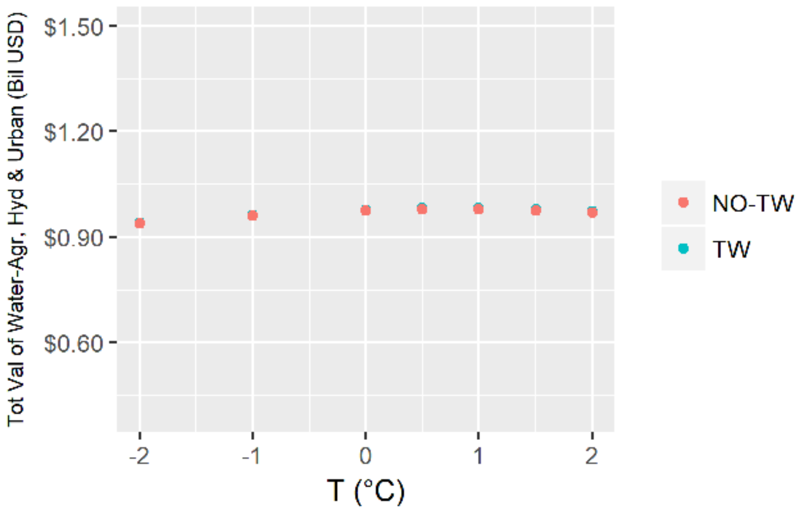

Figure 7.44 - Temperature changes vs total value of water for agriculture, hydro and urban uses, with (TW) and without (NO-TW) tailings water recycling (aggregating all precipitation factor changes). The Y axis of this figure have been adjusted as to facilitate the comparison with Figure 7.42.

Figure 7.45, Figure 7.46, Figure 7.47 and Figure 7.48 show respectively how; shadow value of water, total value of water, water scarcity cost, and total value of water for hydro, agriculture and urban uses fluctuate, as a function of the precipitation factors, with and without tailings water recycling.

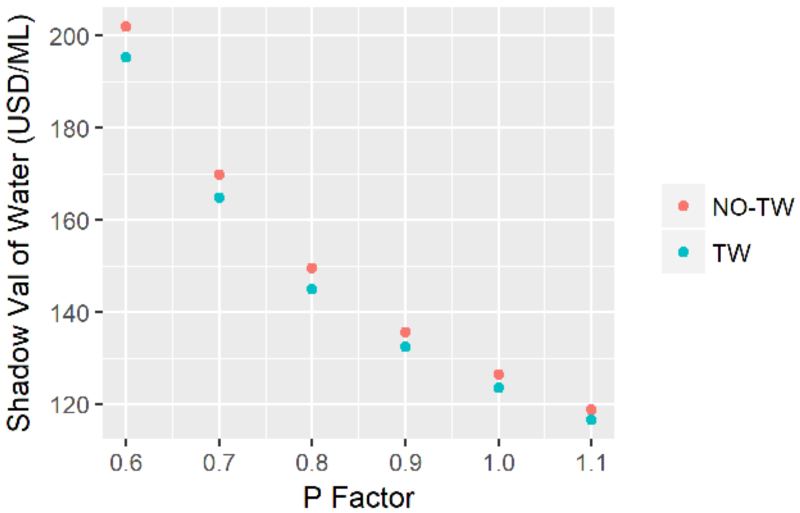

Figure 7.45 – P factors vs average shadow value of water with (TW) and without (NO-TW) tailings water recycling (aggregating all precipitation factor changes).

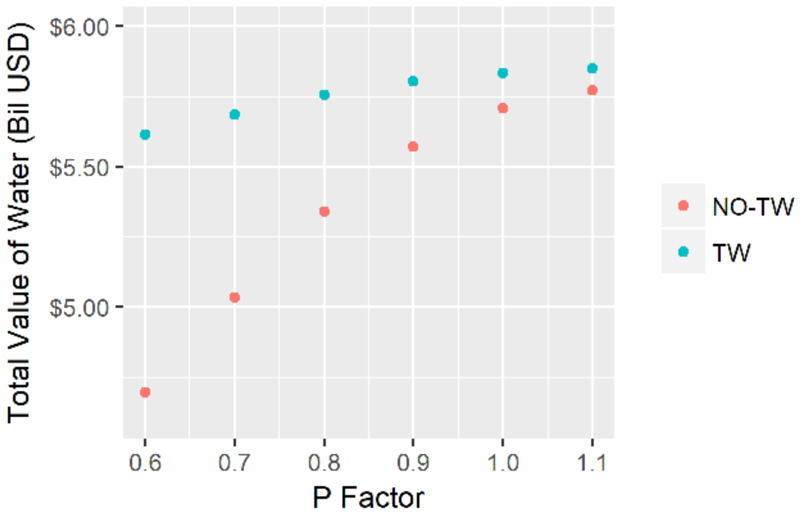

Figure 7.46 – P factors vs total value of water with (TW) and without (NO-TW) tailings water recycling (aggregating all precipitation factor changes).

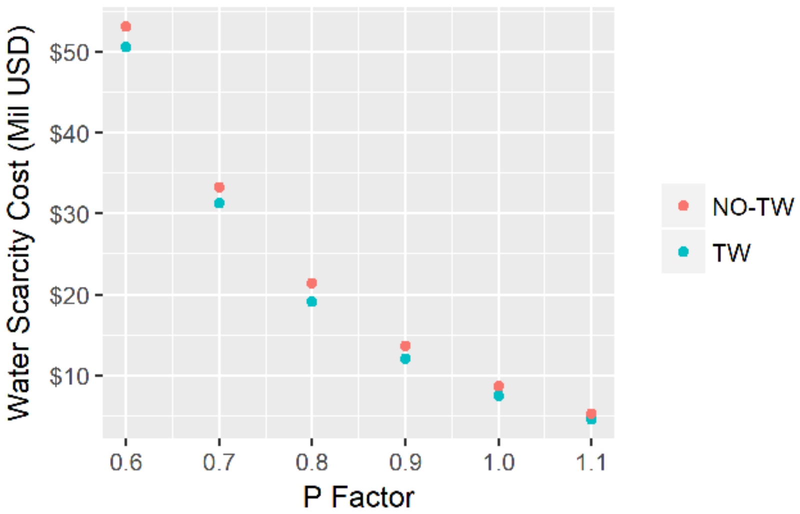

Figure 7.47 – P factors vs water scarcity cost with (TW) and without (NO-TW) tailings water recycling (aggregating all precipitation factor changes).

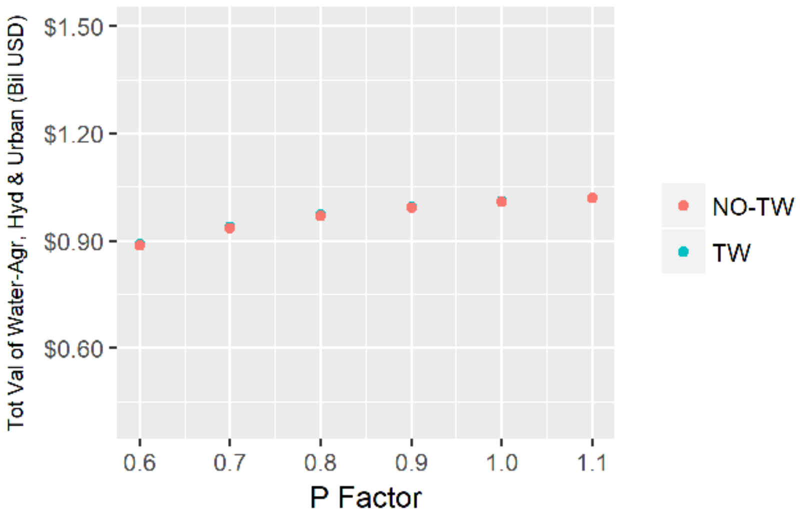

Figure 7.48 – P factors vs total value of water for agriculture, hydro and urban uses, with (TW) and without tailings (NO-TW) water recycling (aggregating all precipitation factor changes). The Y axis of this figure have been adjusted as to facilitate the comparison with Figure 7.45.

In order to better understand the differences generated after including the tailings water recycling, it was decided to average the economic metrics for the climate conditions analysed. Table 7.4 show the average values for all the climate combinations in Table 7.1, while Table 7.5 shows the average results for those combinations that matched the forecasts of the A2 and B2 climate scenarios, in the climate model for Chile. In both tables the differences between the values with and without including tailings water recycling are calculated.

Table 7.4 – Summary of catchment-scale economic metrics of the benefits of the tailings water recycling project, for all climate conditions tested.

Name	NO-TW	TW	Difference
Shadow Value of Water (USD/ML)	$150	$146	-$4
Total Value of Water - Hydro, Agr and Urban (in US 000,000)	$968.37	$971.0	$2.6
Total Value of Water (in US 000,000)	$5,353.8	$5,756.8	$403
Water Scarcity Cost (in US 000,000)	$22.55	$20.8	-$1.8

Table 7.5 - Summary of catchment-scale economic metrics of the benefits of the tailings water recycling project, for the climate conditions forecasted by CONAMA in the A2 and B2 scenarios only.

Name	NO-TW	TW	Difference
Shadow Value of Water (USD/ML)	$129	$126	-$3

Total Value of Water - Hydro, Agr and Urban (in US 000,000)	$1,004.6	$1,007.1	$2.5
Total Value of Water (in US 000,000)	$5,694.89	$5,816.6	$122
Water Scarcity Cost (in US 000,000)	$10.7	$9.3	-$1.4

7.3.2. Discussion of results

The last scenario in this Chapter investigated the benefits of including the tailings water recycling project in the catchment. The results showed that this alternative source of water considerably improves the conditions of the mine, throughout all combinations of climate conditions (see Figure 7.38, Figure 7.39 and Figure 7.40), and in all seasons of the year. Nevertheless, the benefits for other users are almost imperceptible in the figures. This is partly because the mining user had the priority to consume this water. However, it is also because the flow made available with the TSF recycling is relatively small compared to the volumes required by agriculture or hydro-power, thus it is not enough to considerably improve conditions of other users.

The latter is confirmed with the economic metrics that analyse the mining user, which clearly show an improvement over all precipitation and temperature conditions (see Figure 7.42 and Figure 7.46), to the point that this user becomes quite resilient to all changes in climate conditions. Furthermore, results also show that once this alternative source of water is included, the maximum total value of water for all users (over al precipitation conditions) is achieved with a 0.5°C temperature change, although all other changes show small decreases only. This means that this metric, and the mining user who is related to it, becomes quite resilient to any changes in climate conditions.

On the other hand, the rest of the economic metrics show perceptible, but very small improvements with the inclusion of tailings water, which confirms the results found with the demand coverage.

In terms of the numeric results, particularly the total value of water, it can be seen that the benefits of recycling tailings water outweigh the net present costs (see Table 7.3), both for all climate conditions tested and for those in the CONAMA analysis only. This is of course quite important, as if the difference was negative, it would be difficult to justify the development of this infrastructure.

Regarding the benefits to other users, it can be seen that the differences in the metrics after including the TSF recycling are small. In relative terms with respect to the no TW case, they are 2% for shadow value of water, 0.25% for total value and 13 % for water scarcity cost. This confirms that the shared benefits of this project are small, mainly because of the two reasons mentioned before.

It could be argued that this would change if the priorities were modified, and the tailings water was shared evenly between mining and other users. However, this is an unlikely scenario as the water belongs to the mine company, and they expect to be the key beneficiary. Furthermore, it would be difficult for the project to be economically feasible when the mining benefits are not accrued. In addition, the direct use of tailings water by other users would require further treatments, which would reduce the financial feasibility of the project even more.

7.4. Closing remarks

The first part of this Chapter involved a *climate response function* analysis, which showed examples of the insights that a HEM with a detailed description of the water resources component can provide, when compared to a HEM that uses historical observations of flows only. Amongst the specific results of this case study, the analysis of temperature changes stands out as it suggested that users would not be largely affected, or they would even be slightly better off, with a small rise of temperature in the catchment, despite the forecasted overall decrease in average flows. On the other hand, a decrease in precipitation will negatively affect everyone.

Results also evidenced the methodological advantages of using a HEM, as opposed to separate models for hydrological processes, demand for water and economic analyses. By means of the HEM it was possible to describe water conditions and conflicts in the catchment with monetised metrics, which can be integrated into decision making frameworks. It is acknowledged that several social issues may not be covered with these values, thus they represent a great complement to qualitative analyses to find holistic solutions that reduce water conflicts in mining regions.

This section has also provided evidence supporting the use of multiple metrics to understand the conditions of all water users in a mining catchment (i.e. taking a catchment scale approach). This avoids using the total value of water or similar variables alone, as they may be biased towards the mining user. This highlights some of the special characteristics of mine water users, which should be taken into account when analysing them through HEMs.

Despite the magnitude of the alternative metrics used here were small compared to the total value of water, they helped capturing the conditions of the other sectors involved, thus should not be ignored.

HEMs in mining regions could be aimed to optimise the total value of water, while including constraints in the other metrics to safeguard the interests of other users (e.g. setting a minimum shadow value or water scarcity cost for the period of analysis). Alternatively, the economic information provided by the alternative metrics could be used to negotiate compensation schemes beyond water markets, between the mine and other users. This is what this project defines as taking a catchment-scale approach to analyse water conflicts within a mining region.

The second scenario showed how this HEM can provide valuable insights into the economic impacts of EFRs. A relatively simple statistical methodology was used to calculate the magnitude of the EFRs, as the main focus was to understand how this type of model can be used in this context. Results showed how the selection of the exact location of EFRs may be equally, o more important, than defining their magnitude. Moreover, it was shown how the latter may affect water users in a different way than the changes in climate conditions, highlighting the importance of setting flexible EFRs for dry periods.

When using historical observations to define the EFRs, it is also important to define the period of data in which the statistical analysis will be done. This project used a recent record (2000-2018), in order to take into account the hydrological conditions that are already affected by current users. Including very old measurements with the same percentiles used here may generate extremely strict restrictions that would be difficult to achieve in reality. An alternative is to set restrictions based on a detailed ecological analysis of each stream, but this entails the challenge of repeating a detailed assessment over a large area, which for very large catchments may not be practical and difficult to agree upon.

The HEM also proved to be a useful methodology to analyse the shared benefits of water resources infrastructure in the case study, allowing understanding how an additional source of water would benefit each user in the catchment. Results suggest that this specific TSF project is not a very useful alternative for the users beyond the mine site, in terms of the economic value of extra water released to the catchment. However, this may not be the case for other catchments or other projects, or under alternative allocation strategies for the extra water, all of which can be analysed with this HEM.

Finally, it is important to comment on the potential impact of the uncertainty of model parameters and design, on the results in this section. First of all, it should be noted that although the PeCAPEX for mining may generate relevant changes in the total value of water (see Table 6.19), it is unlikely that any conclusion may be affected by this factor, because in any circumstance, the value of water for mining is considerably larger than the rest.

Regarding the PeCAPEX for agriculture, and particularly the flow requirement at the outlet of the catchment, both features have a substantial impact on the shadow value of water and the water scarcity cost. This may affect the magnitudes of results in this Chapter (i.e. the scale of plots like Figure 7.17), however, the overall shape of these figures is more related to the hydrology. In other words, the conclusions related to the impacts of the increments of temperature are unlikely to be affected, but the exact amount of money involved in the improvements could change.

The PeCAPEX for agriculture could also modify the differences between TW and NO-TW values in the TSF recycling analysis, but not even with the lowest value would the magnitude of economic returns from water use in agriculture would compete with those in mining. Thus, the overall conclusion still stands.

8. Discussion

This project has developed a Hydro-Economic Model (HEM) of the upper Aconcauga River in central Chile. This HEM includes a water resources component developed in WEAP, where hydrological processes are analysed and where water is allocated through a scheme of priorities, in order to reproduce the water rights system in the catchment. This is complemented with an economic model that analyses the value of water for different users, and re-distributes water towards the user obtaining the largest value until an equilibrium is reached (i.e. an economic optimisation of the value of water). The mining user was not included in this market as in reality this user rarely participates in the market, and it is usually restricted to use the volumes it obtains based on its water rights (i.e. which is modelled through the WEAP component of the HEM).

This project has also defined a set of metrics that describe the conditions of water resources in the catchment. The strengths and weaknesses of each of these metrics have been explained, with the principal observation that, despite being easy to calculate the *Total Value of Water* is biased to the favour of the mining user. This is a consequence of the large sums of money involved in this industry (revenues, OPEX and CAPEX), and highlights that this user should receive special attention when included in HEMs, otherwise results may ignore the other water users in the catchment.

On the other hand, the *Total Value of Water without mining*, the *Shadow Value of Water* and the *Water Scarcity Cost* focus on alternative users, and each one of them provides a view from a different angle (for agriculture they are even able to distinguish between different types of crops). The water scarcity cost in the case study is several orders of magnitude smaller than the *Total Value of Water*, but the fact that it is small for the whole catchment does not mean that it is insignificant for individual farmers or crops. This highlights the importance of monitoring this metric to understand how it changes with external factors and water management strategies.

When working together, this set of metrics is more likely to provide a holistic impression of all water users' perceptions (i.e. concerns), which in this project is understood as taking a catchment-scale approach. It is understood that these metrics may not capture all the impressions from water users, but taking into account they are based on actual data from users, it is assumed that they are good proxies. For example, the Shadow Value of Water for agriculture may not represent the exact underlying valuation of water by farmers, but it can be assumed the higher this value (inside a water demand curve), the more difficult conditions for farmers.

It is not suggested, however, that thresholds can be easily set with these metrics, to define a value beyond which social tensions will become problematic (e.g. other water users will protest against the mining company). However, it is logical to suggest that if an external factor generates a negative change in any of them, this will exacerbate conflicts for access to water resources in the catchment. Therefore, by analysing the fluctuation of these metrics it is possible to monitor water conditions, analyse allocation strategies and estimate the effects of water resources management strategies across the whole catchment (e.g. infrastructure projects, compensation schemes, amongst others).

This does not mean that these metrics should replace all non-monetisable or non-quantifiable information, particularly the qualitative analyses of social interactions between mining companies and communities. The results of this HEM are seen more as a complement, rather than a substitute of other analyses. The proposal here is that informed applications of suitably developed HEM in mining regions, can usefully assist decision making processes in developing more informed decisions.

When compared to alternatives (e.g. purely hydrological or purely economic analyses), the value of this HEM is that it merges information from multiple disciplines, and provides a summary through a single set of monetised metrics that can be relatively easily understood by decision makers. For example, if the models had been used separately they would have arrived to a different conclusion regarding the effects of the rise of temperature, or results would not have been monetised, or simply they would not have been able to analyse these changes (see Section 7.1).

Regarding the more tangible implications for this case study, it can be seen that the HEM provided valuable insights into the potential effects of changes in climate conditions in the catchment. A priori, it was known that a reduction in precipitation would entail negative consequences for all users, and this was confirmed with the results. It was less clear what would happen in terms of changes in temperature. It was illustrative to see that small increases in temperature may not have a major negative impact, and may even benefit users (see Figure 7.17, Figure 7.18 and Figure 7.19), due to the time-shifting of the snow melting towards a period where there is currently higher water scarcity (this is for comparison of cases with the same precipitation rate). This contrasts with the overall reduction in flows shown in Figure 7.11 as a consequence of these temperature increments.

When the effects of both climate variables were merged following the predicted changes of the A2 (+0.5°C), and B2 (+0.5°C and 10% reduction in precipitation) climate scenarios. It was found that for the 2010-2039 period, the former may not considerably impact users, as it mainly involves a slight increase in temperature, while the other one will likely exacerbate conflicts as it predicts a reduction in precipitation as well (see the climate response function for the shadow value of water in Figure 7.20).

For the 2040-2069 period, both scenarios predict a decrease in precipitation compared to current conditions, and they also forecast increases of temperature beyond 1 °C (B2 +1.5 °C and A2 +2.0 °C), which is the threshold for temperature changes becoming a major issue. This means that water conditions in the catchment will worsen considerably.

These results suggest that if future conditions follow the A2 scenario, users in the catchment will have some time to adapt to more extreme conditions, as the transition will be smoothed thanks to the delayed decrease in precipitation, and the small impacts of the slight increments of temperature. On the other hand, the decrease in precipitation in the B2 scenario means that users will need to adapt rapidly to these climate conditions. In both cases, by the second half of the century the catchment will have to be adapted to more severe weather conditions.

The second scenario in this project looked at Environmental Flow Requirements (EFRs), which are increasingly been discussed in Chile (Carey, 2017) and worldwide (Pastor et al., 2014). Within the local context, there has been a long debate about amending the water code. This includes discussing the refinement of the calculation of EFRs, and the definition of the water rights that should be affected (Carey, 2017, Biblioteca del Congreso Nacional and Morales Peillard, 2016). Although they may not be popular amongst users, EFRs could be a potential path to improve the ecological condition of rivers like the Aconcagua.

This project defined EFRs using a monthly statistical analysis, which defined the restrictions based on four different percentiles or probabilities of exceedance. Results showed that defining the location was as relevant as defining the magnitude of the restrictions (see Figure 7.27 and Figure 7.31), in this case study.

In addition, results underscored the importance of carefully selecting the historical records time for analysis, if a statistical approach is used to define the EFRs. In this case study, water users have largely modified the natural environment in the last two or three decades, and this means that very old flow observations are large compared to current values and even the shape of the hydrograph could have been altered. If old values are included in the definition of the restrictions, they may end up being quite strict during dry periods, to the point that they are impractical to apply.

Furthermore, this project showed relevant differences in the way EFRs affect users, as opposed to the changes in climate conditions. While the latter continuously restricts the volumes of water available to users in a relatively homogeneous way, the former may not have any noticeable effect in most years, but during dry periods it could have very large impacts (see Figure 7.35). This calls for analysing ways of having flexible restrictions that do not pose an unbearable burden to users in dry years, but still allocate water to the environment during wet and average periods.

A step forward on this subject would be to compare these results with those from alternative methods to define EFRs. It was mentioned previously that one of the preferred options from an environmental point of view, is to develop detailed analyses of each stream and define the restrictions based on them. The main drawback of this approach is the complexity inherent in repeating such detailed analyses across the whole catchment. A mid-point could involve doing ecological analyses in a small number of key hydrological locations (e.g. the outlet), and complementing this with the statistical appraisal of historical data.

A further step forward would be to analyse options to develop the policies required to establish the EFRs, amongst others, including the negotiations with existing users. An approach to this would be that the government or an independent organisation bought water rights from users, and then used the purchased rights to improve environmental conditions. This would be similar to the model used by the *Commonwealth Environmental Water Holder* in Australia, which is a federal agency part of the Department of the Environment and Energy, which holds water rights in the Murray Darling Basin for environmental purposes. This, however, would still require defining EFRs using any of the aforementioned methods.

The third scenario analysed was of particular interest for this project, as it allowed addressing a challenge of the mining industry that has been highlighted several times in this document: Promoting water stewardship in the areas where they operate, and calculating the benefits to other users that would follow from different approaches to water stewardship by mining companies.

The HEM in this project was used to calculate the shared benefits of a tailings water recycling system, which would potentially be built by the mining company. The results suggest that this specific scheme would not generate any large benefits to users outside mining (a 2% reduction in the shadow value of water, a 0.25% increase in the total value of water for alternative users and 13 % reduction of the water scarcity cost). The main reason for this was that the priority for using the recycled water was given to the mining user, in order to fulfil the assumed deficit as a consequence of the changes in climate conditions. Another reason was that the additional flow supplied was not very large compared to the magnitudes required by agriculture or hydro-power.

If the first issue was addressed, and a higher priority was given to other users, it is likely that the project would not be economically feasible, as the mine would be unable to meet its requirements during extremely dry years, which is when most economic benefits for this user arise. Other users would be unable to generate economic benefits in the same order of magnitude using these volumes of water. This can be seen by noting that the shadow values of water for agriculture and urban uses (see Figure 6.5), even in the driest conditions and despite being in 2007 prices, are low compared to the annualised costs of the project (see Table 7.3). In addition, being the water property of the mining company this option does not sound very logical.

The second issue makes it evident that to effectively support users that consume large volumes of water (e.g. agriculture), it is required that the additional supply is in the same order of magnitude, otherwise it may only be possible to make an impact on smaller consumers like the urban sector.

Nevertheless, if the extra water supply was not used to alleviate all users but specific farmers (e.g. the ones closer to the project), the relative impacts may have been larger. This may require refining the economic analysis of agriculture, by distinguishing agricultural users by their geographical area and re-running the Positive Mathematical Programming model. All of this can be easily implemented in this HEM.

Under any circumstances, the share of water would always involve the good will from the company and their desire to share benefits at a free or reduced rate, as no other user has the capacity of paying for the costs of the project (see Table 7.3). The added value of the HEM here is the ability to approximate the benefits provided to other users, and to assess which users would find the additional water most beneficial, as a function of different hydrologic and economic conditions.

It is important to remember that when the mining company has analysed this project, it has been with the objective of supporting a future mine expansion, and the associated increase of minerals processing. However, even with this scope, this model could be used to understand how other water users in the catchment could be benefited with the new infrastructure.

9. Summary and Conclusions

This PhD project aimed to analyse how an integrated hydrologic and economic approach, implemented by means of a Hydro-Economic Model (HEM), could help to quantitatively analyse water conflicts and the potential for improving water resources management in mining regions. HEMs are multidisciplinary tools that have been used to address current and future challenges of water management, usually focused on agriculture, urban uses and environmental flow requirements. This involves taking a catchment-scale approach, which means analysing all water users in the area of interest and identifying system-wide promising water management alternatives.

This methodology can be used to help water decision makers testing policies, building synergies, analysing the benefits of new infrastructure, forecasting the impacts of changes in climate conditions and supporting independent observers monitoring water conditions, amongst others. Nevertheless, despite being a relevant user of water in many catchments worldwide, mining has not been widely included in HEMs.

This contrasts with an increasing interest by researchers, companies, and international organisations (e.g. the Minerals Council of Australia – MCA and the International Council of Mining & Metals - ICMM), to help the mining industry improve their long-term water performance. This includes discussions on how to link the value of water to regional sustainability of mining areas, how to use sustainability frameworks in the mining water context, and how to evaluate the shared benefits of mine water management and infrastructure, amongst others. The latter is relevant as sharing the benefits of new sources of water (e.g. seawater or tailings water), should be the new paradigm if this industry wants to improve its relations with communities, and preserve their social licence to operate.

Qualitative analyses by means of frameworks or methodologies have been used to address these issues, however, there have been fewer examples of how to complement them with quantitative results. The main objective of this project was to include mining water usage in a HEM with appropriately detailed portrayals of water resources and economic components, and to understand how the outputs of this HEM could contribute to improve water resources management, and to monitor current and future water conflicts in mining regions, while taking a catchment scale approach.

The first step of this research was a literature review on Hydro-Economic Modelling in order to:

1. Analyse the applicability of HEMs concepts in mining areas.
2. Identify the key challenges of implementing HEMs in mining regions.
3. Learn from existing models to define the design features of the HEM in this project.
4. Define a roadmap for the rest of the PhD project.

Based on the findings of the literature review, the PhD was divided in four stages:

- An assessment of some interpolation methods and of the usage of alternative sources of climate data, in order to address the challenge of implementing HEMs in mining regions with few or no input data of adequate quality.
- Development of a water resources model of the case study in order to make sure that the HEM would incorporate a relatively detailed representation of this component, as opposed to using historical flow observations or synthetic values derived from them.
- Development of the HEM after merging the water resources and economic components, by means of a coupling methodology that was flexible and robust. The latter meant that the coupling had to allow a relatively detailed analysis of both components, data exchange between them, support easy and flexible modifications to input data, it also had to be fast, and interactions between components should be automatic. Furthermore, it was desired to use software that allowed the model to be replicated in other catchments at a low cost.
- Implementation of three potential applications of the HEM in a mining region, including analyses of the effects of changes in climate conditions, the inclusion of environmental flow requirements (EFRs), and the valuation of shared benefits of a tailings water recycling project.

9.1. Key findings

The key findings explained in this sub-section answer the research question and address the objectives of this PhD project. Findings are reported here in the same order as they were outlined in Chapter 1.

First, the literature review highlighted the importance of using more than one metric in HEMs of mining regions, amongst others, to address the substantial gap between the sums of money involved in this industry and those in alternative users. Throughout this project, the *Total Value of Water* was used acknowledging that it was biased towards the mining user. This metric could not be ignored as it allowed understanding the value of water for mining. However, to take a catchment scale approach, the *Total Value of Water without mining*, the *Shadow Value of Water* and the *Water Scarcity Cost* (the last two for agriculture and urban uses only), were also used. These metrics were used together, as proxies of the conditions of water resources available to different users, and of the potential for water conflicts.

This project also found that by using an easy to replicate analysis of climate observations, supported by global gridded datasets of temperature and precipitation, it was possible to obtain estimations of these variables in the case study of acceptable quality. It was also possible to analyse under what circumstances the CHIRPS satellite product represents a potential alternative to estimate precipitation in the case study. This may be quite useful when thinking about implementing HEMs in remote mining regions, where there are no climate observations of adequate quality.

Using the climate data generated in this project, a water resources model for the case study was successfully calibrated and validated in WEAP. Internal consistency was checked by accompanying the comparison of flow observations, with reviews of snow water equivalents and energy demand values. This component was complemented with economic analyses of the value of water for each user in the catchment.

The coupling methodology developed involved using WEAP and Python scripts. This is one of the main methodological contributions of this project as it was possible to merge the water resources and economic components, after allowing multiple interactions between them and without major simplifications in any of them (e.g. using historical flow observations in the water resources component). By using a robust programming language like Python it was possible to easily modify input data, do data mining of results and use the existing modules available, amongst others, to do Monte Carlo sampling to calibrate the water resources model.

The outputs of the base case scenario of the HEM summarise the conditions of all users during the 17 years analysed (2000-2017). The HEM provides a monetised indication of the value of water during this period, and represents a benchmark that allows comparison among scenarios, to analyse how multiple factors may mitigate or exacerbate water conflicts in the region.

This research shows how a detailed representation of water resources in a HEM provides a wide range of useful results. The most important one for this case study was that small increases in temperature may not have a significant negative effect, or may even benefit, water users in the catchment (when comparing cases with the same precipitation rate) due to the shifting in the timing of the snow-melting period, despite the predicted overall reduction of flows. Valuable conclusions like this one would not be found if a simplification of this component (e.g. using historical flows) was used. Furthermore, as expected a priori, it was found that any reduction in average precipitation would negatively affect all users.

With the scenario analysis, this research showed the added value of a HEM, when compared to separate analysis of hydrology, demand for water and economics. Regarding the EFRs, in this case study it was found that defining the location of the EFR was as important as the selection of its magnitude. Further relevant issues with EFRs were flagged, including the importance of defining flexible restrictions for very dry periods, and the careful selection the historical period of observations when using statistical methods to define EFRs.

Finally, this project showed how HEMs could be used to quantify the shared benefits of new water infrastructure in mining regions. It is known that this industry has the financial capacity to invest in large infrastructure projects that increase water supply, and some of these benefits could potentially be shared with other users. For this to happen, however, it may be desirable to quantify these benefits in order to facilitate decision making around them. In this case study the shared benefits of a proposed tailings water recycling scheme were not large, however, this may not always be the case thus the methodology may be useful to identify regions and schemes where relevant synergies between users may be achieved.

9.2. Contributions to knowledge

At the beginning of this project it was hypothesised that HEMs could be adapted to mining regions, in order to provide valuable insight to water decision makers as done in other types of catchments. This project accepted this hypothesis after developing a HEM in the case study, and defining a set of metrics that can be used to take a catchment-scale approach to monitor water resources conditions of all users in the region analysed.

In addition to this, this project has contributed to knowledge in the following ways:

- It has developed a methodology that can be used to facilitate the estimation of input climate variables of HEMs, which is of particular interest for remote regions with poor climate observation networks. This project showed the advantages of this approach in the case study, when compared to more commonly used alternatives, like inverse distance or lapse rates. Moreover, it was described under what conditions it was useful to use a satellite product like CHIRPS in this catchment.
- It has shown the value of including a detailed representation (i.e. a hydrological model) of water resources in HEMs, as opposed to more simple representations (i.e. historical flows). It also showed the advantages of using a HEM, as opposed of separate multi-disciplinary analyses.
- It has developed a robust, but flexible, coupling methodology, which may outperform alternatives by allowing the inclusion of a detailed representation of both components in the HEM and multiple data exchange between them, amongst others. This approach may be easily replicated elsewhere, as it is not constrained to a geographical region, while the software used is easy and inexpensive to access.
- It has shown three potential applications of HEMs in mining regions, including the analysis of changes in climate conditions, introduction of EFRs, and the valuation of the shared benefits of mine water infrastructure. The specific results of this case study also provided interesting insight into water resources in this catchment.

9.3. Limitations and future research

Despite attempts to obtain the best available data, there were limitations with this. This included, although is not limited to, restricted climate data in the mountain areas, use of just one agricultural census and lack of CAPEX estimates for agriculture, lack of knowledge of the exact location and amounts of water abstracted or consumed in the upper-most parts of the river, and lack of detailed estimates of costs of the mining and hydro-power users.

This was addressed, to some extent, by analysing the sensitivity of the model to some of these limitations. Although results do fluctuate, it was found that the sensitivities tested were unlikely to invalidate the conclusions. Future refinements of this model could include improved and updated datasets, to address the rest of the data limitations and to develop insight of the sensitivity of results.

The simplification of the downstream water use (i.e. the minimum flow requirement in the outlet of the case study) allowed developing the model in the case study within the time period of this PhD. However, the merger with the existing groundwater models in the irrigated area would be a step forward, as it would provide a more detailed representation of the flow of water between the are analysed in this project and the aquifer.

It is also important to mention that the analysis of changing climate conditions was based on summarised data taken from the literature, but a next step should be to analyse temperature and precipitation outputs from regional climate models (RCMs). This would allow a better understanding of the transition of climate, and the associated impacts on the catchment over the next 20-50 years.

Future models should also attempt to analyse the methodologies used in Chile to define the EFRs. This project used a simple approach to analyse EFRs through the HEM, but other alternatives used in Chile or in other countries could be implemented in the future.

The economic depth of all economic analyses in this project involved direct benefits only, although it was acknowledged that input-output models could be included to analyse indirect benefits as well. Generally, the latter are not analysed in HEMs, however, it would be interesting to implement this to understand how macroeconomic features like employment and royalty payments, amongst others, affect the comparison between mining and other users.

The inclusion of risk factors in the economic analysis of agriculture, and even in that of other water users, could help address the assumptions of perfect foresight, and could also help analyse the risk perceptions from users. This would involve the refinement of the economic functions used to describe water users (e.g. an extra variable in the PMP with the quadratic cost function). A refinement of these economic calculations may in turn improve the accuracy of the results of the water trades between users.

Another relevant assumption of the economic component was that users cooperate in order to optimise the use of water. This was assumed when modelling the water markets between agriculture and urban users, and was also indirectly assumed when using the results of the PMP, which are an ideal allocation of resources following the maximisation of economic value. In reality, it has been seen in similar regions that some farmers are reluctant to trade water rights beyond the same irrigation channel, which means that the trades with the urban user and the ideal allocation of water following the results of the PMP would be limited. Future versions of the model could compare scenarios of cooperation and no cooperation, as to define how this assumption may affect the results.

From the beginning of this project it has been acknowledged that water decision making is not purely undertaken based on the results of models, like the one here, but also with several other factors in mind. From this perspective, the metrics used in this project are not thought to be absolute descriptors of the water resources conditions in the catchment, but proxies that can help inform the perceptions of users in the catchment towards water allocation and potential water scarcity. These values should complement further qualitative analyses, rather than replacing them, with the aim of driving more informed decision making. For example, these metrics cannot predict whether or not strong opposition and social protest will arise against a mining project, yet they can provide insight into how multiple factors may mitigate or exacerbate conflicts for access to water resources.

It would be desirable that future HEMs in mining regions included closure and rehabilitation costs of the mine site, and an economic estimation of system-wide environmental impacts from all users. As previously discussed, this has been simplified during this project as there is a lot of uncertainty defining a reliable estimate of these costs, and comparing future cash flows with present values. There are entire fields of research focusing on these topics, and it would take a whole PhD project to approximate these costs in such projects. Furthermore, many of these outputs may have considerable ranges of fluctuation depending on the assumptions used, which makes it difficult to use them for practical purposes in their current form.

9.4. Closing remark

Being an industry with potentially high negative impacts on the environment, but at the same time a provider of key resources to our modern society, mining has the challenge of continuing operating while improving their environmental performance and interactions with other water users. Water is one of the key concerns in this discussion, and the Hydro-Economic Modelling approach here represents an effort to reconcile the mine water requirements with the broader necessities from other users in catchments, and the environment.

Despite the multiple assumptions and limitations previously described, these models have the potential to develop multi-disciplinary insights into how to manage the tradeoffs between allocating water to mining, and the well-being of other users in the catchment. By including an analysis of hydrological processes in the catchment, it was possible to understand the physical behaviour of water. The economic component complemented this by including an analysis of the demand side.

The results from this research expect to foster the design, development and application of tools that support more informed water decision making in mining regions. Future refinements should aim to include refined input data and reduce the uncertainty of selected quantitative elements, while including feedback from stakeholders in mining regions, in order to generate the type of outputs that can drive positive socio-economic and environmentally sustainable change in these areas.

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11. Appendixes

A. Literature review journal paper

The Hydro-economics of Mining

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Abstract

Joint research between economists and hydrologists increasingly contributes to optimising the economic value gained from water, while safeguarding its social and environmental values. The application of hydro-economic analysis to mining regions, however, is limited. This paper examines why this is the case and how to confront it. The paper focuses on identifying and describing features of large-scale mines and mine regions that are challenging to analyse such as: magnitude of capital involved, time-scale and remoteness of projects, inherent environmental risks, and strong negative perceptions about mining's impacts on water. These characteristics may limit the applicability of established hydro-economic concepts and methods, thus risk-based metrics are discussed as complementary tools. We also contend that further research and development in water-related ecosystem services should be a priority, in order to better quantify trade-offs between the economic benefits of water use by mining and competing users, including environmental flows. Case studies of mining regions in Chile, Madagascar and Sweden are summarised to illustrate some of the issues raised. While data limitations are an obstacle, new and extended case studies are required to explore how the challenges may be addressed.

1. Introduction

Collaborative approaches between hydrologists and economists have the potential for optimising the instrumental value of water without irreparable ecological harm. This approach has been termed “hydro-economics” (Brouwer and Hofkes, 2008) and has particular salience in mining regions. On one hand, the mining industry must manage water-related economic risks associated with water scarcity, floods, pollution and community conflicts, amongst others. On the other hand, due to the large volumes of water consumed and discharged, the mining industry is a major investor in, and manager of, water infrastructure. Efficient fulfilment of these water management roles requires good understanding of the links between water management options and their economic costs and benefits. Furthermore, these links are of substantial interest to governments and other water stakeholders, when developing views about allocations of land and water to mining projects.

The term ‘hydro-economics’ may be defined as the discipline of understanding the current and potential economic value of water, using hydrologic, economic and social perspectives (Brouwer and Hofkes, 2008, Harou et al., 2009). A hydro-economic model (HEM) is the formalisation of that understanding, generally built into a numerical tool supporting quantitative scenario analysis and/or optimisation. The field of hydro-economics has increasing prominence, partly due to the relatively new emphasis placed on water as an economic good (United Nations, 1992, Seyam et al., 2003), and partly due to the increasing need for governments and industry to improve water management and promote transparent decision making (WBCSD, 2013, Canadian Council of Ministers of the Environment, 2010). The field aims to give water users and managers objective information for use in decision-making frameworks.

Although hydro-economics is a well-established discipline, there are few reviews or applications that address the important technical and conceptual challenges of applying hydro-economic techniques to mining applications. We identify the major challenges as follows:

- The high revenues from large-scale mining, and high capital and operational costs involved, mean that water supply is often a relatively minor, and typically, fixed cost. However, mining’s presence in catchments or in water markets may make water unaffordable for some alternative users.

- Due to hydrological variability and topography (i.e. some mines are below the groundwater table), many mines alternate between periods of water scarcity and water excess.
- The longevity of large-scale mine projects and consequent economic and hydrological uncertainties also requires a risk-based approach to hydro-economic analysis.
- The importance of large-scale fresh water consumption efficiency improvements.
- Increasing scrutiny of the mining industry's social and environmental performance increases the relevance of quantifying the social value of water and ecosystem services impacts.

In summary, it is the scale of investments and revenues from mining, the large spatial and temporal extent of large-scale mining projects, and the particular social and environmental perceptions and risks, which make hydro-economic analysis of mining regions special. While some of these features apply to other sectors, they are arguably more common and prominent in large-scale mining regions. Yet, to date, the mining industry and mining regions have scarcely been addressed in the hydro-economic literature. This review paper analyses this gap, and its objectives are:

- To establish and describe the features of large-scale mining that pose special challenges for hydro-economic analysis.
- To review the applicability of established economic and hydro-economic concepts and metrics, in light of the challenges.
- To present a view on the way forward for addressing these challenges to enable transparent economic assessments of water management options for mines and mining regions, covering both industry and societal interests.

This review paper first develops the argument that regions with mining projects are special in the hydro-economic context, and discusses the applicability of commonly-used economic concepts and metrics. Then, it reviews the components of HEMs, and lists some considerations when including mine water users in them. Finally, it presents case studies that illustrate some of the challenges described, and suggests pathways to address them. We restrict our analysis to regulated, large-scale mining. While artisanal and small-scale mining are also relevant in many regions, they present a separate set of challenges, which we do not explore in detail here. We also focus on the direct economic benefits of mining, and only briefly mention the indirect ones.

2. Why mining is a special case

Mines vary greatly in terms of geological features, as well as hydrological and socio-economic settings. However, for a typical large-scale mine, main water uses include:

separating minerals from the waste; dust suppression; cleaning equipment; drinking water and sanitary supplies; and for conveying tailings and concentrate (SMI-MCA, 2014). A detailed review of mine water usage and the risks that a mine project poses for regional water resources, summarised in Figure 1, can be found in Younger and Wolkersdorfer (2004) and Department of Resources Energy and Tourism - Australian Government (2008). This section will focus on describing the characteristics of mining that create special challenges when including these uses in hydro-economic analysis.

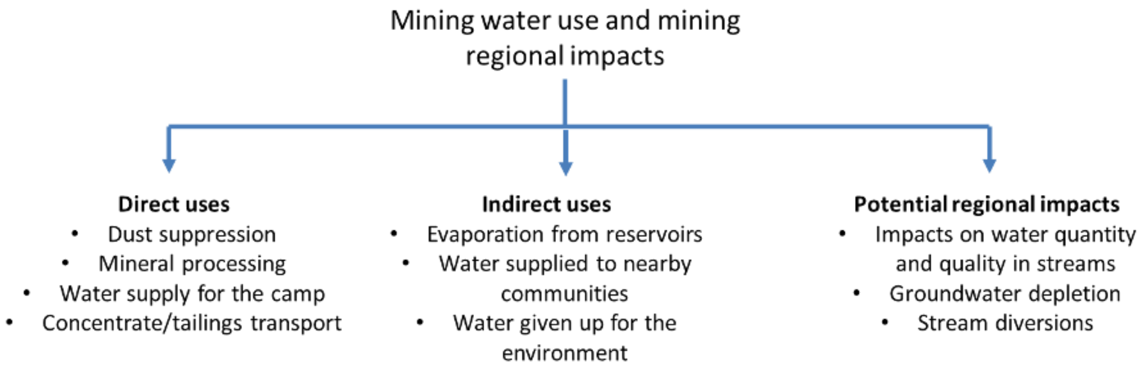


Figure 1. Overview of mine water uses and regional impacts.

The high revenues from and costs of mining

Average revenues per unit volume of water abstracted in the mining industry tend to be high compared to its main competitor for water, agriculture (Moran et al., 2008). Typical revenues for copper and gold mining operations are shown in **Table 1**. Information on production costs per mine site is rarely publicly available; thus, it is difficult to estimate net revenues per unit of water abstracted.

Table 1 - Estimations of revenue per m^3 of water consumed in the production of copper and gold, based on 2013 data.

Mineral	Source	Method	Revenue per m^3 of Water Consumed (US \$/m^3)	Range of Values (US \$/m^3)
Copper	(Northey et al., 2014)[19]	Pyrometallurgy	\$80.36	

[19] Based on the process modelling in Northey et al. (2014) along with average copper and gold prices in 2013 prior to the decline in metal prices that started in 2014.

Gold	(Northey et al., 2014)[1]	Hydrometallurgy	$105.22	
	Own Calculations[20]	Both	$78.80	$70.1 - 94.61
	(Northey et al., 2014)[1]	Non-refractory	$182.98	
	(Northey et al., 2014)[1]	Refractory	$157.86	
	Own Calculations[2]	Both	$271.39	$38.73[21] - 709.23

Similarly, **Figure 2** shows the Gross Value Added (GVA) values per unit water consumption for major water-consuming sectors of the Australian economy between 2008 and 2014. This figure shows that mining and mining-related activities (e.g. manufacturing of metals) provide high economic value to Australia in terms of GVA per unit water input. This is not unique to Australia. Mining and agriculture in Chile contributed around 8% and 4% respectively to the country's Gross Domestic Product (GDP) in 2005, while consuming around 8% and 73% of water consumptive rights (World Bank, 2011). Such comparisons are potentially powerful in terms of influencing water policy, which raises the question of what complementary metrics are needed to provide a broader view of hydro-economic performance, which will be addressed in Section 3.

[20] Based on production data published by governments and company sustainability reports for a sample of large-scale mines in Peru, Papua New Guinea, Turkey, Chile, China and USA, along with average copper and gold prices. Only mines with clear information about volumes of minerals produced and water abstracted in 2013 were included. Reports with lumped information from several mines or several countries were excluded.

[21] The lower bound is from a mine site in PNG, whose relatively wet tropical climate does not require mines to improve efficiency in consumption. This shows the influence of local conditions in the value of water.

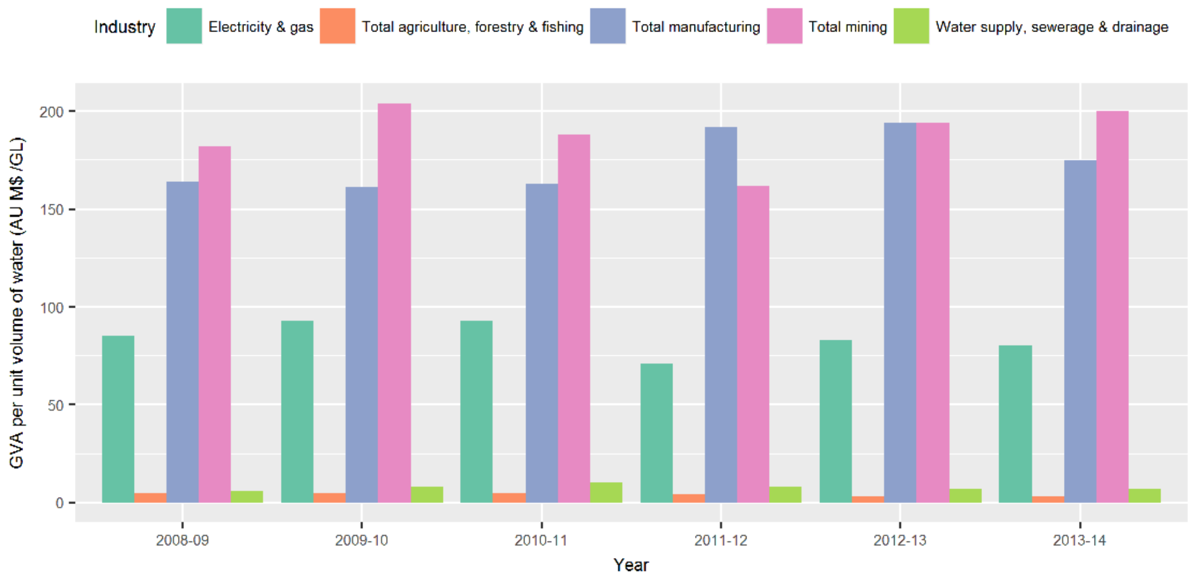


Figure 2. Gross Value Added (GVA) per unit water usage to the Australian economy between 2008 and 2014 (Australian Bureau of Statistics, 2015).

The high revenues at stake, and the high capital investment and operational costs involved, also mean that compromising water demand in times of water shortage is not regarded as an option during mine planning. Furthermore, as water costs represent a small fraction of total capital and operational costs, mines may be willing to pay sums of money often unaffordable for other users to ensure they have a reliable source of water under any demand scenario (Young and Loomis, 2014). This suggests that water may be seen as a fixed, rather than a variable input, for the mining industry.

Water excess and discharge

Most mine projects face the challenge of avoiding water deficit while minimising excess. A possible switch from input water being an asset to being a liability for the mining operation is illustrated in **Figure 3**. Before point (1), the figure shows that available water is not enough to allow production, thus its value is either 0 or negative, in cases where operational costs are still incurred in its management. Between points (1) and (2), production is possible in the mine site and the value of water may increase linearly (dashed line) or in a discrete way (points), depending on whether mine production can respond to incremental increases in available water.

Mine water surplus is shown in the figure beyond point (2), and this occurs when groundwater inflows, surface water runoff into the mine site, and precipitation into the mine site exceed the consumptive demand and storage capacity. The excess water may leave the site in a regulated manner, usually involving treatment to improve its quality, or through unregulated spillages and diffuse runoff or seepage. In the worst case mines may be forced to stop operations due to floods, or face regulatory penalties and reputational damage due to unregulated discharges (Barrett et al., 2014, Gao et al., 2014).

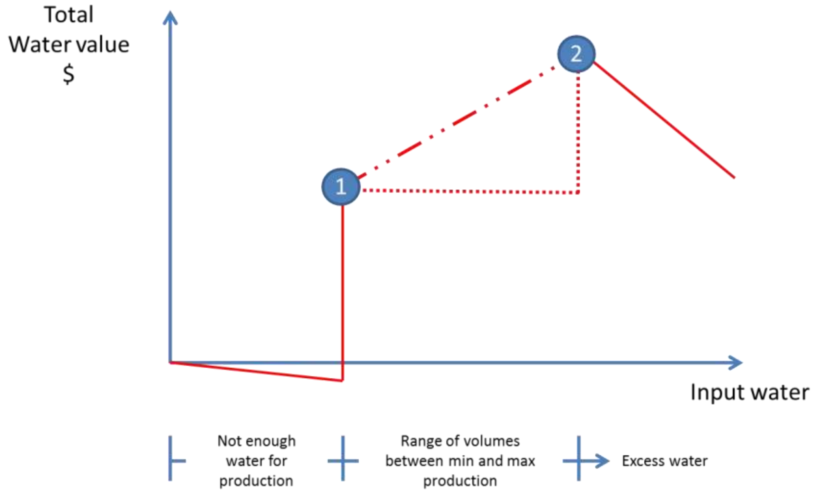


Figure 3. Example of the possible dynamics of the total value of water on a mine site.

These discharges may have large spatial and temporal impacts (Younger, 1997, Kossoff et al., 2012), and examples of this exist worldwide (Amezaga et al., 2010, Veiga and Hinton, 2002, Salvarredy-Aranguren et al., 2008, Lovingood et al., 2004, Rojas and Vandecasteele, 2007, Nazarro, 2008, Younger et al., 2005).

Problems involving tailings water, acid mine drainage, mercury and cyanide, have received special attention due to their complex interactions with the environment and potential toxicity (Oyarzún et al., 2012, Dold, 2014, Salvarredy-Aranguren et al., 2008). However sediments, salts, hydrocarbons and radio-active materials may also be sources of risks (Younger and Wolkersdorfer, 2004). Therefore, while managing water excess is a challenge across many sectors, the physico-chemical risks associated and the scrutiny of mining discharges mean that management costs can be especially large for mining.

It is important to mention that water scarcity and surplus, and quality of discharges, should be analysed relative to local conditions (Moran, 2006). The same abstraction of water, or discharge of pollutants, could have very different effects in a dry and in a wet catchment. Metrics which can account for local conditions would help to standardise the assessment of water-related risks for mines.

The longevity of mine projects and potentially perpetual impacts on water resources

The operational life of a mine is often beyond 50 years, and may be preceded by decades of exploration and planning, and then may be proceeded by years of rehabilitation and post-closure management. The long life means that the economic valuation of a mine project must involve projections of commodity demand and prices, and operational costs, which include the costs of securing a water supply. Thus, hydrological predictions over a time-scale of 50-plus years are often needed. The uncertainty in long-term forecasting of water supply, as well as other components of costs and revenues suggests that hydro-economic analyses should account for uncertainty and variability, and be risk-based (Li et al., 2008, Correa et al., 2016).

Furthermore, water-related problems are the most common environmental impacts when closing mines (Laurence, 2011); and pollution impacts can last for decades or centuries due to the gradual physical and chemical weathering of rocks that are exposed to water and atmosphere (Younger, 1997, Lovingood et al., 2004). The problem can continue until pollutant sources have been confined during mine closure or land rehabilitation phases, or until they are exhausted (Younger, 1997, Northey et al., 2014, Rojas and Vandecasteele, 2007).

Although adopting best practice guidelines for managing waste-rock and tailings effectively reduces risks (European Commission, 2009, The Mining Association of Canada, 2011), uncertainties in long-term climate, hydrology and performance of mitigation strategies (Kuipers et al., 2006), mean that residual risks always exist, including the potential for catastrophic impacts (e.g. tailings dam failures) (Amezaga et al., 2010, Salvarredy-Aranguren et al., 2008). This has led to calls for costs of recovery from pollution events and costs of long-term pollution management to be integrated into risk-based economic metrics (Kim and Kaluarachchi, 2016, Farber et al., 2002, Evans et al., 2006, Esteve et al., 2015).

Water efficiency and alternative sources of water

Mines in water-stressed regions invest considerable resources in water-efficient processes, reduction of water losses and seeking alternative sources of water (seawater or brackish groundwater). The water efficiency gains realised by these efforts tend to be large ‘step-changes’ rather than gradual changes (ICMM, 2012, Espejo et al., 2016). These efforts contribute to the high economic value of fresh water for mining, as water is expected to pass several times through the production process (Gunson et al., 2012).

Furthermore, as many water efficiency measures are energy-intensive processes (e.g. desalination), water costs and risks may be transferred to energy costs and risks. Thus, analysing energy cost and carbon emissions may become necessary from both cost-benefit and sustainability perspectives (Woodley et al., 2014, Nguyen et al., 2014, Northey et al., 2014, Simpson et al., 2014, Rivera et al., 2016).

Social and environmental performance

Water-related conflicts between mine projects, communities, environmental groups and other land and water stakeholders, arising from actual or perceived impacts, have the potential to diminish the success of mine projects (Kemp et al., 2010, Franks et al., 2014, Rivera et al., 2016). This suggests that from a mining company perspective, hydro-economic analysis should include broad considerations of how a project is perceived to protect and augment regional water resources compared to other users. This may include analysing how investments in water supplies for communities, without the project obtaining any direct economic benefits (Quintero et al., 2009), may influence the social license to operate (Franks et al., 2014).

3. Applicability of economic evaluation metrics and concepts

Economic valuation of water should ideally include all benefits that are accrued from it, net of all costs incurred (WBCSD, 2013, Morgan and Orr, 2015). The value may be higher than prices paid (e.g. to pump, treat or trade), as in many places water is free, subsidised or commercialised below its full value (Damigos, 2006, Kochhar et al., 2015). Lange (1998), for example, found that water subsidies for mining in Namibia are around 19% of their operating costs, and it is argued that this type of subsidies have adverse impacts in the environment (Clinch et al., 2002, OECD, 2003).

The selection of an economic value metric is affected by multiple factors (e.g. temporal and spatial scales, and whether a private or social point of view is taken) (Harou et al., 2009, Young and Loomis, 2014, Brouwer and Hofkes, 2008, Seyam et al., 2003, Medellín-Azuara, 2006). The specific metric to be used may change depending on the scope of the analysis. This section examines the applicability of selected economic metrics and concepts to appraise the economic value of water.

Revenues per volume of water consumed

The average revenue per volume of water consumed (as in **Table 1**), could be used to show that the economic value of using water in mining is higher than for alternative users (e.g. agriculture). An alternative metric, although more difficult to calculate, would be average revenues net of costs, hopefully including capital expenditure related to water use, to take into account the different capital structures of users in the analysis. This could be achieved through deductive methods (George et al., 2011, Davidson et al., 2010), which involve a “construction of empirical and behavioural models, from which specific parameters or shadow prices are deduced” (Young and Loomis, 2014).

An independent observer or government may be more interested in defining region-wide benefits offered by mining per unit volume of water consumed, during the whole life of the mine. These would include estimations of closure/rehabilitation costs, as well as other production costs. This could be achieved, for example, by extending Net Present Value (NPV) calculations to include social and environmental economic values.

From a government perspective, it may also be important to analyse how much of the revenues generated by mining stay in the national and local economies (Fleming and Measham, 2014, Black et al., 2005), and what their effects on national and local economies are (Khan, 1999, Petkova et al., 2009). In addition, governments may be interested in the number of jobs, and especially the number of low-skilled jobs (i.e. those that are more likely to employ lower income citizens), that will be generated by projects. The latter are macro-economic features that are not usually included in HEMs, but may be relevant to government officials analysing HEMs’ results.

Marginal Productivity

An alternative to average values (e.g. revenue per volume of water consumed) are metrics of marginal value such as marginal productivity. This metric describes the change in production due to a unit change in one input, assuming that all other quantities are kept constant (Farber et al., 2002, Varian, 2010). Marginal productivity can be complemented with the market price of the output, to define the economic value of marginal productivity (i.e. marginal revenue product or value marginal product) (Young and Loomis, 2014). This indicates the revenue or net revenue obtained by the sale of the additional units of output produced with the additional unit of input.

This metric is useful for optimisation purposes, when maximising the regional economic value of water, by allocating it to the uses with the greatest marginal revenue product until equilibrium is reached. Marginal analysis, however, assumes that users see water as a variable input, and thus they can adjust their production processes accordingly (Young and Loomis, 2014). Agriculture within well-developed water markets and some industries may be able to adapt (Grafton et al., 2012, Wheeler et al., 2014, Dupont and Renzetti, 2001), but for mining this would depend on the design of the processing plant, which tends to be the largest consumer of water in the mine. Typically, mine production cannot adapt smoothly to changes in water supply, and large processing units may be taken off-line when water supply drops below critical levels.

Willingness to pay and ecosystem services

In addition to the previously described methods to define the value of water from a producer's point of view, approaches to defining users' willingness to pay are useful to approximately monetise mining's impacts on environmental flows. Young and Loomis (2014) give a detailed description of the most common methods, which can be divided in three groups. Revealed references approaches derive values from the observation of the behaviour of users in existing markets for related economic goods (e.g. Hedonic Pricing, Travel Cost Methods and Damage Cost Methods).

Stated preference approaches rely on direct answers from users to constructed surveys which elicit water users' willingness to pay for the benefits which water provides to them (e.g. Contingent Valuation Method and Choice Modelling). A third approach, benefit transfer, uses values derived for case studies at other locations or settings. These methods can be complemented with Ecosystem Services frameworks (Millennium Ecosystem Assessment, 2005, DEFRA, 2007), to support the understanding of how environmental flows provide services to humans and hence the indirect economic impact of water use by mines.

In mining regions, while there is recognition of the need to quantify these values, only preliminary applications of willingness to pay have been undertaken (BSR, 2015). Damigos (2006) applied them to determine the loss of environmental value due to three mine projects. He concluded that willingness to pay methods produced rough, but useful estimates of social and environmental liabilities of the mines. However, the alternative methods gave differences of up to two orders of magnitude, highlighting the importance of doing sensitivity analyses, and of clearly communicating analytical assumptions.

Li et al. (2011) and Bai et al. (2011) evaluated the ecosystem services losses resulting from coal operations in the Mentougou region of China, and found that over the past 50 years, the loss of ecosystem services outweighs the value of the coal resources. These findings are consistent with a more recent study of coal mining in Colombia (Cardoso, 2015). However, these estimates are susceptible to assumptions, as guidelines for quantifying the ecosystem service impacts of mining and other industries are not well developed (Hamilton, 2013).

An alternative approach is using pre-determined environmental standards (e.g. fixed through political agreements or international requirements). This approach does not directly define the intrinsic value of the environment, but does an indirect approximation, by determining the required investments to achieve the standards (Baresel et al., 2006, Younger and Wolkersdorfer, 2004, Hasler et al., 2014) or the cost of opportunity to alternative uses of water (Medellín-Azuara, 2006). This approach, however, can be criticised because the environmental standards may be defined subjectively, without detailed/scientific assessments of the services they can provide.

Risk-based metrics

Beyond the financial risks of mining projects, frequently related to the magnitude of capital and operational expenditure required (Bertisen and Davis, 2008), water-related risks may also strongly impact projects. The latter group includes risks associated to unforeseen extreme flooding or drought, large-scale water-related accidents (e.g. tailings dam failures), uncertainty regarding mine closure and rehabilitation efficiency (Kahn et al., 2001, Kuipers et al., 2006), and poor relations with local communities. This means that risk-based approaches, involving the analysis of the probability of a range of possible scenarios and their impact in the project (Younger et al., 2005), are particularly useful when analysing the mining industry, and should ideally be included in HEMs.

Water markets

Within the spectrum of economic metrics and concepts related to HEMs, water markets stand out as important. They can be used to understand the economic value that users get from water, but they can also be included in models to explore how the redistribution of water amongst competing users can achieve an optimal allocation.

'Water market' is a generic term describing a system under which users buy and sell the right to access water (Grafton et al., 2011). They are expected to foster the flow of water towards more profitable uses, particularly during water scarcity (i.e. from low-value agriculture towards high-value agriculture, mining or industry (Young and Loomis, 2014, Donoso, 2015)), arguably distributing water more efficiently than government allocation systems (Thobanl, 1997).

Water markets may provide observed evidence of the economic value of water to different users, and allow examination of how these values vary under changing economic and hydrologic conditions. **Figure 4** shows regional differences in average trading prices of consumptive long-term entitlements/rights in several states/regions of the USA and Chile, and illustrates the spatial differences in water prices, which are strongly correlated to economic and hydrologic conditions. The very high value of water in Antofagasta region in Chile is a consequence of a single purchase from a mining company (compare the values with and without the mine transaction in **Figure 4**), probably reflecting mining's long-term water security needs and risk aversion.

Grafton et al. (2011), however, found that price transparency is low in most water markets, which means that observed prices may not be representative of users' underlying valuations of water. Hearne and Donoso (2014) confirmed this for Chile and mentioned that the lack of publicly available market data is a cause of price dispersion. Furthermore, while in some cases, mainly in agriculture, water markets have achieved their aim (Hansen et al., 2014, Donoso, 2015, Grafton et al., 2011, Young and Loomis, 2014, Rivera et al., 2016), in many regions obstructions have prevailed (Tisdell and Ward, 2003).

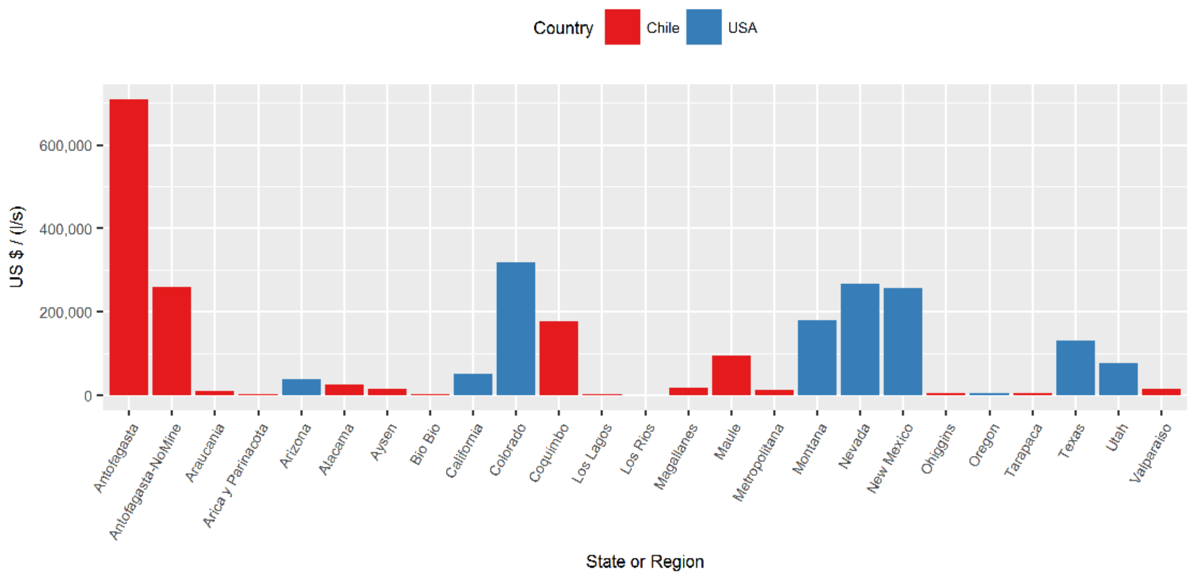


Figure 4. Average price of one l/s of long-term consumptive water entitlement by state/region in the USA and Chile in 2008. Antofagasta and Antofagasta-NoMine represent the values in the region with and without the referenced mining transaction (Bren School of Environmental Science & Management - University of California, 2010, DGA, 2015b)[22].

Mining participation in water markets

The mining industry has been a relatively minor participant in most water markets, even in the most developed ones (e.g. Chile, Australia and western USA) compared to agricultural or urban water users (MCA, 2009, National Water Commission, 2014). One reason for this is the design of the markets (i.e. institutional foundations), which defines key aspects such as the users who are allowed to trade and the initial allocations (Hearne and Donoso, 2014, Grafton et al., 2011, MCA, 2009). In Australia, the Minerals Council of Australia has stated that mining has faced more obstacles to

[22] This Figure was constructed after carefully reviewing water prices, however, it is acknowledged that these datasets have limitations, including price transparency, thus they are mainly presented for illustrative purposes (Grafton et al., 2011, Hearne and Donoso, 2014).

trade than anyone else, due to cultural perceptions against mining and limited development of markets in some mining regions (MCA, 2009).

Water quality-related markets have also been used to trade emission allowances, with the aim of optimising the use of streams to dilute and disperse contaminated wastewater and runoff. The Hunter River Salinity Trading Scheme in Australia is an example where mining is a principal player in a salts emission market (Department of Environment and Conservation NSW, 2003). There is also a potential to use water markets to assign value to low quality water (Barrett et al., 2010), including worked water, contaminated runoff and tailings water. These markets could be fostered amongst users who do not necessarily require high quality water (Kunz and Moran, 2014, Barrett et al., 2010), and they would allow using resources that are currently seen as waste (Petritz et al., 2009, Dale et al., 2013a).

It is important to recognise that there are mixed views on water markets, and in mining's participation in them. Although stakeholders generally agree that criteria beyond economic efficiency (e.g. social equity) should be taken into account when implementing water trading (MCA, 2009, National Water Commission, 2014), there are cases where trading water like a commodity is seen to have benefited mining companies at the expense of low-income and vulnerable communities (e.g. low-value agriculture farmers) (Babidge, 2016, Perreault, 2013).

4. Hydro-economic modelling in mining regions

Characteristics of hydro-economic models

Hydro-economic modelling combines hydrologic and economic approaches to understand, predict and optimise the value of water in a catchment (**see Figure 5**), promoting an efficient allocation of water amongst competing uses. The hydrologic component describes the time and space dynamics of water storage and transfer, while the economy component describes the economic value of water. The method used to couple the two components determines how their interactions are modelled (i.e. availability of water influences users' behaviour, while economic activities modify the storage and transfer of water). **Figure 5** illustrates an example of how inputs, components, outputs and external factors can be related in a hydro-economic model.

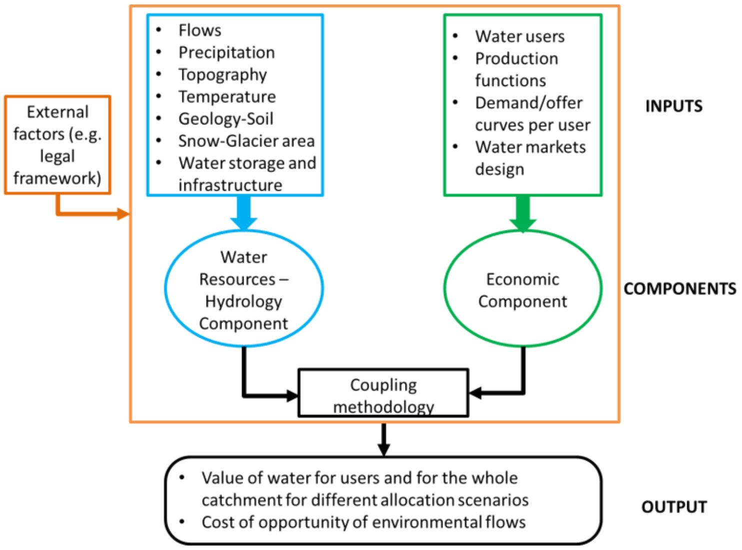


Figure 5 – Schematic representation of a hydro-economic model including inputs, components and outputs.

A comprehensive review of HEMs, including examples, can be found in Harou et al. (2009) and Bekchanov et al. (2015), while detailed examples of implementations can be found in Cai et al. (2006) and Medellín-Azuara (2006).

Table 2 summarises the key features of HEMs and comments on how these features influence the applicability of HEMs to mining regions, based on the discussion in **Section 2** and **Section 3** of this paper. This table, does not suggest a specific approach to analyse catchments with mining projects, but highlights criteria that should be taken into account when developing a model in these regions. Some of these points will be further discussed in the case study section of this paper.

Table 2 - Considerations for the development of a hydro-economic model in a catchment with mining projects

Modelling consideration	Alternatives	Examples	Potential importance when developing HEMs in a mining region
Simulation or optimisation	Simulation models that answer "what are the effects in the output due to changes in one or some inputs" (i.e. "what if" questions).	George et al. (2011), Graveline et al. (2014)	*Normal* This is entirely a function of the scope of the model. Simulation models are easy to implement, but optimisation models can be robust tools to define the ideal allocation of resources. A mid-point is optimising some components of the model only. This is a common consideration of all HEMs and is not specially challenging for mining catchments.
	Optimisation-based models that answer "what are the best" set of inputs to achieve the optimal output.	Harou et al. (2010), Satti et al. (2015)	
Time resolution	Fine (e.g. daily or monthly) to better model hydrological variability and seasonality.	Ringler and Cai (2006), Kite (2001)	*Normal* The mine water demand tends to be constant throughout the year, thus yearly time-steps would be acceptable. However, the supply changes as a function of climate seasonality, which requires monthly or smaller time-steps. This is a common consideration across HEM applications.
	Coarse (e.g. yearly) to fit production patterns and their associated economic value.	Fernández et al. (2016), Kim and Kaluarachchi (2016)	
Space resolution	Models can represent key catchment features as nodes connected by links.	Medellín-Azuara (2006), Esteve et al. (2015)	*High* Models aggregating several catchments may dilute mine water consumption by the larger demand by agriculture, and may not be suitable for analysing demands and supply in the vicinity of the mine. Distributed analyses allow a spatially detailed analysis of runoff, groundwater flows and transport of pollutants, which are key
	Using pixels to develop a distributed analysis.	Hasler et al. (2014), Dale et al. (2013b)	

	Models can aggregate the entire river in a node to do a macro-scale analysis.	Kim and Kaluarachchi (2016)	hydrological processes determining available water, risks of drought and flood, and mine environmental impacts, but may be very complex to develop. Node-link models simplify the calculations of water supply by aggregating sub-catchments in nodes, but allow representing mine water demand as a distributed model may do, in one or multiple (e.g. pit, tailings dam and processing plant) nodes.
Time frame	Analysis undertaken for past climate conditions.	Harou et al. (2010)	*Very High* The longevity of mine projects and of mine environmental impacts mean that if the HEM is used for understanding the net economic values of mining, it should involve long time-horizons. HEMs analysing existing projects or past conditions should try to involve the long-term costs or at least discuss their impacts in the catchment.
	Analysis undertaken for future conditions (e.g. short/medium term simulations or long-term planning approaches).	Lee et al. (2011), Hurd and Coonrod (2012)	
Space frame	Analysis of sub-catchments or whole catchments.	Cai et al. (2006)	*High* If very large regions are analysed in the HEM mine water demand may be eclipsed by agricultural demand. Thus, if a detailed scrutiny of social and environmental performance of mining is required, an analysis of only the sub-catchments most influenced by the project would be desirable (i.e. those affected by the mine, tailings storage facility, and processing plant).
	Analysis of larger regions (e.g. countries or group of countries).	Hasler et al. (2014), Ringler and Cai (2006)	
Economic depth	Direct impacts on particular users in the local environment only.	Qureshi et al. (2013)	*Very High*

	Direct and Indirect effects of water management in the whole economy of a country or region.	van Heerden et al. (2008), Medellín-Azuara et al. (2015)	Due to the high revenues from and costs of mining, a detailed analysis of the direct effects of mining is important. However, due to the scrutiny of social performance and the potential environmental impacts of mining, including projects' indirect costs and benefits affecting macro-economic variables may be desirable for certain users, and this is particularly relevant when the mining industry is involved in HEMs.
Integration	Hydrology and economic components can be run separately and results retrofitted to each other (compartment approach).	George et al. (2011), Medellín-Azuara et al. (2015)	*Normal* Although in principle holistic models represent powerful tools, in practice they require assumptions and simplifications about interactions between the two systems that may create uncertainty and make it difficult to interpret model outputs. The modeller has to identify a balance between the level of coupling used and keeping the model practical to use. This, however is a common consideration in using HEMs, and is not unique for applications to mining regions.
	The components can be coupled and run together so that the interlinking is internal to the model (holistic approach).	Cai et al. (2006), Cai (2008)	
Uncertainty analysis	Models can be run with deterministic inputs and parameters.	Satti et al. (2015)	*High* Due to the relevance of risk-based approaches, HEMs applied to mining regions should involve uncertainty analysis of some kind, to allow understanding how sensitive the results of the model are to changes in key inputs (e.g. prices of commodities or climate conditions). More detailed risk-metrics could also be helpful to better represent mining risk perceptions, as done for other water users
	Inputs and parameters can be specified as a range of values or probability distribution functions so that results have an associated range of variability.	Kim and Kaluarachchi (2016), Jeuland and Whittington (2014)	

			(Fernández et al., 2016, Petsakos and Rozakis, 2015, Younger et al., 2005).
Static or dynamic	Static models give a snap-shot in time, excluding the potential future impacts of current decisions	Hasler et al. (2014)	*Normal* Although the snap-shot type of model may support the understanding of multiple factors in the catchment, analyses of several years are more illustrative of the dynamics of the value of water, including the effect of several continuous dry/wet years. This, however, is a consideration for most HEMs and not only for those with mining users.
	Models can represent changes in hydrologic and/or economic conditions over time, and delayed effects of decisions.	Lee et al. (2011)	
Economic functions/tools used	Functions based on average values (i.e. values do not change as a function of water availability)	Satti et al. (2015)	*Very High* This is one of the key questions faced when including mining in HEMs and there is a lack of literature providing guidance. Use of average or marginal values should be defined after understanding if water should be seen as a fixed or variable input in the mining production process. Willingness to pay calculations should be included where it is possible and relevant to analyse environmental and social impacts of mining.
	Marginal values used based on continuous demand or production functions	Cai et al. (2006)	
	Willingness to pay calculations	Damigos (2006)	
Water Markets	Water markets are included in the HEM	Cai et al. (2006), Medellín-Azuara (2006)	*High* Although currently the participation of the mining industry in water markets is not large, the potential economic value of trading raw, worked and tailings water should be explored, as this represents an alternative to reduce water stress in mining regions.
	Water markets are omitted from the HEM	George et al. (2011)	

Affecting all the issues raised in Table 2, is the general issue of data support for developing and evaluating HEMs. This may be especially important in mining regions, as the location of mineral deposits often leads to mines being in hydrologically extreme and poorly accessible areas (e.g. high-altitude mountains and deserts) where observed climate data are sparse (McIntyre et al., 2016) and high quality modelled data-sets are not available (Jeffrey et al., 2001, Jones et al., 2009). Furthermore, in some regions climate is complex due to the interaction between weather systems and steep topography (Ragettli et al., 2014). This means that developing hydrological models with high temporal and spatial resolutions (see **Table 2**), is often not possible, and the modeller is forced to spatially and temporally aggregate the available data more than would usually be considered appropriate in hydrological modelling (van Heerden et al., 2008, Davidson et al., 2010, Harou et al., 2009).

Lack of economic input data may also be a challenge, particularly relating to confidentiality of data for individual mining projects. Using industry average values may be the only alternative, however, some projects may operate far from these averages. Data limitations on both sides – hydrologic and economic – emphasise the case for conducting uncertainty management using formalised, best practice principles (Refsgaard et al., 2007).

Also, affecting the long-term approach to analyse the mining industry is the challenge of predicting changes in climate conditions (Barrett et al., 2014, Gao et al., 2014), especially in mountain areas (Barnett et al., 2005). General Circulation Models coupled with Regional Climate Models, or other climate downscaling approaches, could be used to predict these changes (Kigobe et al., 2011), however, their performance is still far from satisfactory (Buytaert et al., 2010).

5. Case studies of hydro-economics applications in mining regions

Although mine water use in HEMs has not received as much attention as agriculture, urban uses and environmental flows, in terms of number of case studies and detail of models (Harou et al., 2009, Bekchanov et al., 2015), there are some examples worth highlighting. In this section three of these are reviewed, including a brief summary of the models, and an analysis of the extent to which they successfully address the special challenges of mining regions (as reviewed in Section 2 of this paper), and how the considerations in **Table 2** have been included.

5.1 Aconcagua River Catchment

The first example is the Aconcagua River in central Chile, a catchment with increasing competition for water between agriculture, urban development, hydro-electricity and mining (Aitken et al., 2016). A large-scale copper mine, which produced 224.3 kMT of copper in 2015, is located in the headwaters, at around 3,500 m above sea level. Downstream, the central valley supports intensive agriculture including fruits, fodder, legumes and cereals crops, while several urban areas are located throughout the catchment. All water rights have been allocated, thus a relatively active water market exists in the catchment (Hearne and Donoso, 2014), although mine participation in the water market is infrequent (Figueroa San Martin, 2016).

Correa-Ibanez et al. (2017) calibrated a hydrological model for the sub-catchment where the mine project is located, analysed the impacts of future climate conditions through three climate scenarios, and did an economic assessment of alternatives for securing future water supply for the mine. The compartment approach was taken, and it was assumed that the economic model output did not affect any relevant aspects of the hydrology. The hydrological component was a lumped model of the sub-catchment, which was run continuously with monthly time-steps during the calibration and long-term future scenario periods. Flows were aggregated by years in the scenario period to run the economic calculations.

This model is a good example of the merging of water resources and economic calculations for the purpose of cost-benefit analysis from a mine project planning perspective, including analysis of the impacts of long-term future climate conditions. Reviewing how the paper addresses the special challenges of mining regions highlights the following:

1. Regarding the high revenues from and costs of mining: The economic assessment involved capital and operational expenditure of the alternatives for future water supply, and an estimation of the average value of water based on the costs of lost production. However, the selection of the alternative was taken using a *no water risk logic*, which illustrates the characteristic of mining that water demand is seen as a fixed input to be met at any cost.
2. Regarding water efficiency and new sources of water: The solution identified as optimal was recycling water from the tailings dam, which is a resource that was previously not exploited. The study therefore illustrated the opportunities for mines to free up regional water resources, and thus economic opportunities, by finding new and potentially low quality sources of water that meet mine needs.

3. Regarding social and environmental performance: The authors did not analyse the benefits or impacts of the water supply alternatives on other water users or environmental flows, but they acknowledged that quantifying these would affect the business cases for the alternative options. This calls for greater attention to integrating social and environmental metrics into hydro-economic models of mine regions in order to respond to the close scrutiny placed on mine water use.
4. Regarding the modelling of water scarcity and excess: The authors highlight the uncertainty in current and future climate conditions as a constraint, in particular limiting the accuracy of drought estimation (the key source of risk for the mine site). The study recognises these limitations and recommends that sensitivity of results to input uncertainty is examined more deeply.

5.2 The Ankeniheny–Zahamena Corridor

The second example is the Ankeniheny–Zahamena Corridor in Madagascar. The World Bank's Wealth Accounting and the Valuation of Ecosystem Services global partnership (Portela et al., 2012), used this region as an example of how to measure return on investment of water consumption for development alternatives, including large-scale mining (cobalt and nickel).

Annual water supply estimates for the catchments of analysis were generated using the Artificial Intelligence for Ecosystem Services (ARIES) model (Bagstad et al., 2011), in yearly time-steps (Portela et al., 2012). The economic component was defined separately using Cobb-Douglass production functions, in order to define the economic value of marginal productivity of agriculture, mining, tourism and hydro-electricity sectors. Furthermore, the project analysed two ecosystem services; carbon storage and sequestration, and sediment retention, although the later was not monetised.

This is one of few examples of including the mining water use in a regional ecosystem service analysis, setting a pathway for holistic approaches to hydro-economic analysis of mine regions. However, the study also illustrates major difficulties in doing so, related to the special challenges of mining:

1. Regarding the analysis of revenues and costs: A production function for mine water use was employed, however the study does not comment on the applicability of marginal analysis to this mine site. Also, from the report is not possible to determine the sufficiency of the data for selecting the Cobb-Douglas function. Regarding their

results, **Table 3** shows that nickel mining, and to a lesser extent cobalt mining and residential electricity use, generate the highest economic value of marginal productivity from water. However, it is not clear if costs were subtracted from the prices of the output when defining the economic value of marginal productivity.

Table 3 - Economic results of the Madagascar's Ankeniheny–Zahamena Corridor analysis (adapted from Portela et al. (2012)).

Economic sector	Economic value of marginal productivity (2012 USD / m3)
Cobalt Mining	7,541
Nickel Mining	11,906
Rice Agriculture	469
Luxury segment tourism	50
Residential electricity use	6,980
Industrial electricity use	680

2. Regarding social and environmental performance, and the longevity of mine projects and potentially perpetual impacts on water resources: The study attempts to address these challenges by analysing water supply as an ecosystem service related to other ecosystem services. However it does not clearly overcome the challenges of implementation, for example it was not able to monetise the values related to sediment retention, and their relationship with water supply. Furthermore, the other ecosystem service, carbon storage and sequestration, did not analyse potential links to water supply (e.g. carbon footprint of the energy required to manage water resources). While this study provides a valuable template for advances in mine region hydro-economics, the assumptions limit the robustness of results in **Table 3**.
3. Regarding water efficiency and new sources of water: As Madagascar is a relatively wet country, water efficiency measures seem not to be as relevant as in drier contexts (e.g. Chile). Thus, the study did not mention nor analyse alternative sources of water like tailings water recycling or desalination. In addition, the report does not clearly differentiate "water use" and "water consumption", which are important concepts in

the mining context, where high recycling and re-use ratios mean that metrics such as those in Table 3 are sensitive to exact definitions.

5.3 Mine rehabilitation in the Dal River Catchment

The last example is slightly different from the previous two as the hydrological component is not focused on water supply, but on the abatement of pollution from a post-operational mine site. Baresel et al. (2003) present a case study of a region in Sweden where closed mines are responsible for zinc, copper and cadmium loads to the river. The authors explained that the hydrologic component assessed the capacity of different rehabilitation techniques to reduce pollution in the receiving streams. The economic component, on the other hand, did not calculate the economic value of mine water, but the cost to implement each one of the abatement technologies.

The coupled model was used to minimise the cost of achieving different pollutant reduction targets, presenting a good example of the application of HEMs in optimisation mode, to the long-term economic liability aspect of mining. There are several features to highlight relating to the special challenges of mining:

1. As the model is focused on mine land rehabilitation, it does not analyse revenues and costs from the industry, but the costs of addressing environmental impacts in the short and long run.
2. Regarding water excess and discharge, and the longevity of mine projects: The model is focused on the problem of water discharge from the mine site and the associated liability in the long term, therefore directly addressing this challenge. Together with the ecosystem service approach of the previous case study, it provides a complement of water supply analyses for developing a holistic, life-of-mine calculation of the net value of mining.
3. Regarding social and environmental performance: While the HEM directly addresses environmental impacts, it does not define functions describing the intrinsic value of the environment that may be used to optimise the net value of abatement options, rather it uses a series of predetermined water quality standards. However, authors included different standards, to address the problems of subjectiveness when defining one only.
4. Regarding data availability issues: The authors considered different levels of performance of each pollution abatement measure, to take into account the lack of data regarding their effectiveness. Furthermore, they also include different

implementation costs of wetlands, as the costs of this abatement measure were deemed very uncertain. This explicit treatment of uncertainty is consistent with good modelling practice to address risks.

6. Conclusions

This paper has presented the case that large-scale mines pose special challenges for hydro-economic analysis, and assessed the applicability of some commonly used hydro-economic metrics and concepts. While various conclusions might be drawn from the discussion, here we focus on those we consider to be the primary outcomes.

The magnitude of revenues and costs of large-scale mining means that it is often difficult to compare the economic contributions of mining with those from other sectors. Furthermore, the lack of information on how the mine production process responds to changes in water availability hinders the definition of economic functions (e.g. water demand curves) for mining.

Environmental risks associated with mining (e.g. acid mine drainage and accidental emissions) may be mitigated by good environmental regulation and mine water management planning. Nevertheless, experience shows that there are substantial residual risks that should be encompassed in net economic benefit calculations, particularly the long-term impacts of mining. This requires research in environmental science, but also monitoring closed and rehabilitated projects, in order to learn from their efficiency and the magnitude of costs involved.

Events such as commodity price fluctuation, tailings dam failures, floods and droughts, and water-related protests against mining projects, highlight the relevance of taking risk-based approaches when including mining in hydro-economic models. This may be addressed by including uncertainty in medium to long-term projections of hydrology and commodity markets, and by including risk frameworks that help address unlikely events that considerably affect the expected net economic benefit of projects.

The lack of data is an issue for hydro-economic models of all kind, however, this may be particularly challenging for mining regions, as minerals are often located in remote areas with few long-term climate observations, and this industry tends to be quite confidential with its project-level economic and financial data.

Finally, at present, there are few hydro-economic case studies described in sufficient depth and supported by sufficient databases, thus the development of more examples is important to foster improved analysis of hydro-economics in mining regions. Further case studies should aim to:

- Improve the functions describing the economic value of water for mine users, based on a better understanding of the use of water in their production process, and their perception of water as a fixed or variable input.
- Appraise the impacts of mining projects on environmental and social values of water at a catchment scale, with emphasis on the long-term.
- Analyse the sensitivity of model results to changes in input variables and apply risk-based approaches to deal with the various uncertainties in model inputs.
- Include indirect economic benefits on different water user groups, as macro-economic features, such as employment and contribution to the local and national economies, tend to be arguments in the debate over new mine projects.
- Analyse the trading of raw and worked water, as this may alleviate water stress in catchments with mining projects.

B. Information of the Climate Gauges Used in Chapter 4

	Station	Elevation	Long	Lat	Variable	Dates available	% of Missing Gaps in P and T in the 5 year period
1	05200007-6	1202	-70.68	-32.42	P	All period	0
2	05403006-1	1313	-70.36	-32.92	P	All period	1.67
3	05410002-7	954	-70.51	-32.85	P	All period	5
4	05410005-1	642	-70.74	-32.76	P	All period	3.33
5	05410006-K	1078	-70.47	-32.86	P	All period	0
6	05410007-8	830	-70.6	-32.83	P	All period	0
7	05410008-6	650	-70.72	-32.75	P	All period	0
8	05414001-0	1193	-70.58	-32.5	P	All period	23.33
9	05414004-5	1209	-70.58	-32.5	P	All period	5
10	05414005-3	943	-70.7	-32.57	P	All period	0
11	05415004-0	1023	-70.6	-32.68	P	All period	1.67
12	05422002-2	835	-70.82	-32.93	P	All period	1.67
13	05732001-K	575	-70.8	-33.09	P	All period	1.67
14	05732002-8	597	-70.77	-33.08	P	All period	5
15	05733006-6	973	-70.75	-32.95	P	All period	0
16	05733010-4	809	-70.81	-32.95	P	All period	1.67
17	Los Bronces	3423	-70.29	-33.15	P	All period	0
18	330019	654	-70.55	-33.45	T	All period	44.58
19	330020	529	-70.68	-33.45	T	All period	0.16
20	330021	481	-70.79	-33.39	T	All period	1.04
21	AWS1	3088	-70.11	-32.99	T	Summer 08-09	96.11
22	AWS2	2785	-70.11	-32.97	T	Summer 08-09	96.11
23	AWS3	3269	-70.1	-33	T	Summer 08-09	96.66
24	Angela	3573	-70.27	-33.08	T and RH	All period	1.81
25	Barroso	3776	-70.23	-33.11	T and RH	All period	4.05
26	Hornitos	2214	-70.15	-32.87	T and RH	From Sept/12	80.01
27	Lagunitas	2922	-70.25	-33.08	P, T and RH	All period	0
28	MachuPichu	4080	-70.26	-33.17	T and RH	All period	2.35
29	Saladillo	1585	-70.28	-32.93	T and RH	From Dec/11	66.32
30	TLog1	3254	-70.1	-33	T	Summer 08-09	96.22
31	TLog10	3004	-70.11	-32.99	T	Summer 08-09	96.22
32	TLog11	2968	-70.11	-32.98	T	Summer 08-09	96.22
33	TLog12	2911	-70.11	-32.98	T	Summer 08-09	96.22
34	TLog2	3269	-70.1	-33	T	Summer 08-09	96.22
35	TLog3	3269	-70.1	-33	T	Summer 08-09	96.22
36	TLog4	3212	-70.1	-33	T	Summer 08-09	96.22
37	TLog5	3153	-70.11	-32.99	T	Summer 08-09	96.22
38	TLog6	3081	-70.11	-32.99	T	Summer 08-09	96.22
39	TLog7	3094	-70.11	-32.99	T	Summer 08-09	96.22
40	TLog8	3092	-70.11	-32.99	T	Summer 08-09	96.22
41	TLog9	3070	-70.11	-32.99	T	Summer 08-09	96.22

C. Hydrological Model Details

This appendix textually reproduces the description of the Soil Moisture Method, the hydrological model used in this project, which is available in the WEAP user guide in Page 198 (Sieber and Purkey, 2015).

"*This one dimensional, 2-compartment (or "bucket") soil moisture accounting scheme is based on empirical functions that describe evapotranspiration, surface runoff, sub-surface runoff (i.e., interflow), and deep percolation for a watershed unit (see Figure 1). This method allows for the characterization of land use and/or soil type impacts to these processes. The deep percolation within the watershed unit can be transmitted to a surface water body as baseflow or directly to groundwater storage if the appropriate link is made between the watershed unit node and a groundwater node.*

A watershed unit can be divided into N fractional areas representing different land uses/soil types, and a water balance is computed for each fractional area, j of N. Climate is assumed uniform over each sub-catchment, and the water balance is given as,

$$Rd_j \frac{dz_{1,j}}{dt} = P_e(t) - PET(t)k_{c,j}(t)\left(\frac{5z_{1,j} - 2z^2{}_{1,j}}{3}\right) - P_e(t)z_{1,j}^{RRF_j} - f_j k_{s,j} z^2{}_{1,j} - (1 - f_j)k_{s,j} z^2{}_{1,j}$$

Equation 11.1

where $z_{1,j} = [1,0]$ is the relative storage given as a fraction of the total effective storage of the root zone, (mm) for land cover fraction, j. The effective precipitation P_e, includes snowmelt from accumulated snowpack in the sub-catchment, where m_c is the melt coefficient given as,

$$m_c = \begin{cases} 0 & \\ 1 & if \quad T_i < T_s \\ \dfrac{T_i - T_s}{T_l - T_s} & \quad T_i > T_l \\ & \quad T_s \le T_i \le T_l \end{cases}$$

Equation 11.2

where T_i is the observed temperature for month i, and T_l and T_s are the melting and freezing temperature thresholds. Snow accumulation, Ac_i, is a function of m_c and the observed monthly total precipitation, P_i, by the following relation,

$$Ac_i = Ac_{i-1} + (1 - m_c)P_i$$

Equation 11.3

with the melt rate, m_r, defined as,

$$m_r = Ac_i m_c$$

Equation 11.4

The effective precipitation, P_e, is then computed as

$$P_e = P_i m_c + m_r$$

Equation 11.5

If the timestep length is less than one month (General, Years and Time Steps) then the snow accumulation and melt model is modified to restrict the snow melt rate by the total heat available to transform ice to water. The total heat available is calculated as the sum of the net solar radiation and the heat introduced to the snow pack by rainfall. Albedo for the net solar radiation calculation is computed as a function of snow accumulation and ranges from a value of 0.15 to 0.25 with increasing snow pack depth.

In Equation 11.1, the calculation for the potential evapotranspiration, PET, is done using the reference crop calculation described in the Handbook of Hydrology (1993) in section 4.2.5, equation 4.2.31. This is the Penman-Monteith equation modified for a standardized crop of grass, 0.12 m in height and with a surface resistance of 69 s/m. In this implementation two modifications to the equation were made: the albedo varies over a range of 0.15 to 0.25 as a function of snow cover, and the soil heat flux term, G, has been ignored.

Continuing with Equation 11.1, the $k_{c,j}$ is the crop/plant coefficient for each fractional land cover. The third term represents surface runoff, where RRFj is the Runoff Resistance Factor of the land cover. Higher values of RRFj lead to less surface runoff. The fourth and fifth terms are the interflow and deep percolation terms, respectively, where the parameter $k_{s,j}$ is an estimate of the root zone saturated conductivity (mm/time) and f_j is a partitioning coefficient related to soil, land cover type, and topography that fractionally partitions water both horizontally and vertically. Thus total surface and interflow runoff, RT, from each sub-catchment at time t is,

$$RT(t) = \sum_{j=1}^{N} A_j \left(P_e(t) z_{1,j}^{RRF_j} + f_j k_{s,j} z^2{}_{1,j} \right)$$

Equation 11.6

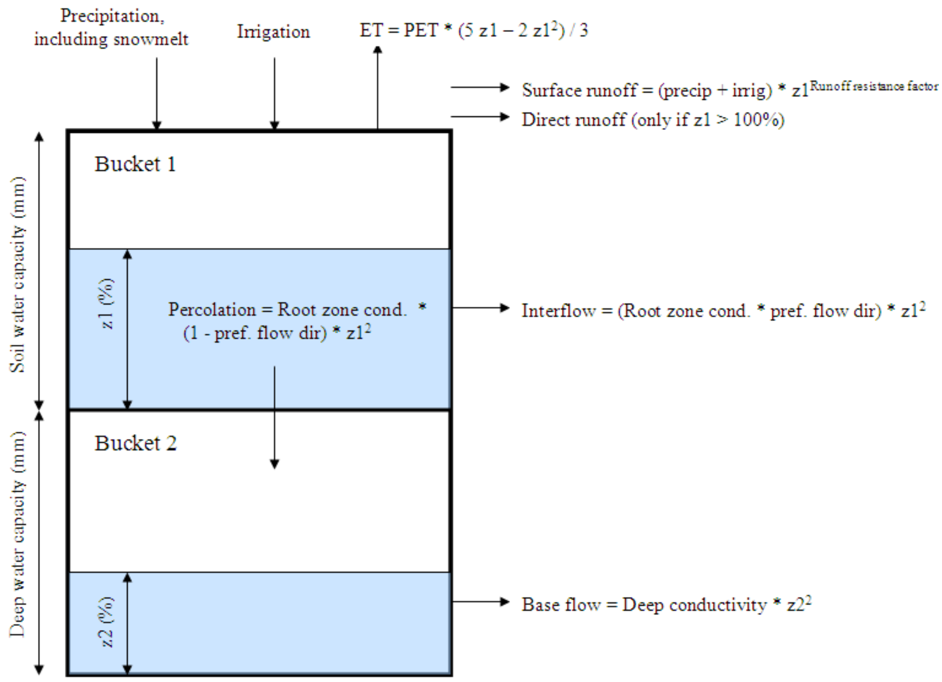
For applications where no return flow link is created from a catchment to a groundwater node, baseflow emanating from the second bucket will be computed as:

$$S_{max}\frac{dz_2}{dt} = \left(\sum_{j=1}^{N}(1-f_j)\,k_{s,j}{z^2}_{1,j}\right) - k_{s2}{z^2}_2$$

Equation 11.7

where the inflow to this storage, S_{max} is the deep percolation from the upper storage given in *Equation 11.1*, and k_{s2} is the saturated conductivity of the lower storage (mm/time), which is given as a single value for the catchment and therefore does not include a subscript, j. *Equation 11.1* and Equation 11.7 are solved using a predictor-corrector algorithm.

Figure 11.1 - Conceptual diagram and equations incorporated in the Soil Moisture model.



D. PMP Input Data Organisation

In order to define the input data for the agricultural model, it was reviewed the more recent update of the water users cadastre in the first irrigation section of the case study (DGA, 2011). Based on this, it was possible to define that all municipalities (*comunas*) in Los Andes province, obtained water from this part of the river. Furthermore, in the San Felipe province, the Santa Maria municipality also obtained all of its water from the case study, and around 52% of the San Felipe municipality used it as well.

These values were used together with the 2007 Agricultural Census[23] in order to define the areas of each crop. For example, in the case of Alfalfa, information was taken from the Forage data in the Microsoft Excel Sheet *"Superficie total sembrada o plantada por grupo de cultivos".*

Table 11.1 – Input data to calculate the area of the alfalfa crops.

Region	Province	Municipality	Forage Surface (ha)
Valparaiso	Los Andes	Los Andes	246.20
Valparaiso	Los Andes	Calle Larga	294.40
Valparaiso	Los Andes	Rinconada	235.10
Valparaiso	Los Andes	San Esteban	470.80
Valparaiso	San Felipe de Aconcagua	San Felipe	615.10
Valparaiso	San Felipe de Aconcagua	Santa María	139.80
Total (ha)			2,001.40
Total including the San Felipe area inside the case study only (ha)			1,705.41

The same procedure was followed for Wheat, Corn and Potato, although this time information was available in the Sheet *"Superficie sembrada, producción y rendimiento de cereales, leguminosas y tubérculos, en riego y secano".* On the other hand, information from all other products was taken from *"Superficie con frutales en plantación compacta o industrial y huertos caseros en formación y producción"*.

In order to calculate the irrigation requirements, it was used the climate data from *La Cruz* station from INIA, together with the crop parameters in Table 11.2. These values were defined following Allen et al. (1998) and SEPOR (2017), while the dates of the different

[23] Available at http://ine.cl/estadisticas/economicas/estad%C3%ADsticas-agropecuarias . Accessed last time on the 19/10/2018. The exact link may be modified, thus, the information can also be accessed by following INE's website www.ine.cl → Estadísticas → Económicas → Estadísticas Agropecuarias → Censos Agropecuarios.

stages of the crops were approximated from Faiguenbaum (2003). It is important to mention that the latter may not necessarily be followed by the farmers in the case study, but they help to estimate the plant behaviour, which in turn allows calculating total irrigation requirements.

Finally, regarding cost, price and yields, most data was taken from the technical sheets of ODEPA, which are defined after surveying farmers in the region and defining average values.

Table 11.2 – Crop characteristics to define irrigation requirements.

Crop	Initial Kc	Mid Kc	Final kc	Initial Date	Mid Date	End Date
Alfalfa 1st Cutting	0.4	0.95	0.9	1-Sep	30-Sep	30-Oct
Alfalfa 2nd Cutting	0.4	0.95	0.9	4-Nov	18-Nov	3-Dec
Alfalfa 3rd Cutting	0.4	0.95	0.9	8-Dec	22-Dec	6-Jan
Alfalfa 4th Cutting	0.4	0.95	0.9	11-Jan	25-Jan	9-Feb
Alfalfa 5th Cutting	0.4	0.95	0.9	14-Feb	28-Feb	15-Mar
Wheat	0.3	1.15	0.3	1-Aug	29-Sep	8-Dec
Corn	0.3	1.2	0.35	16-Oct	9-Dec	17-Feb
Potato	0.5	1.15	0.75	15-Aug	8-Oct	22-Dec
Table grapes	0.45	0.85	0.5	1-Oct	1-Jan	1-May
Avocado	0.6	0.8	0.75	1-Jul	1-Nov	1-Jan
Peach	0.4	0.9	0.65	1-Oct	1-Jan	1-Apr
Olives	0.5	0.65	0.6	1-Jul	1-Sep	1-Apr
Plum	0.4	0.9	0.65	1-Oct	1-Jan	1-Apr
Walnut	0.5	1.1	0.65	1-Aug	30-Aug	6-Feb

Table 11.3 – Technical sheets including the economic information of the crops analysed.

Crop	Year	Region	Link
Wheat	2016	Bio-Bio	Link
Corn	2017	O'higgins	Link
Potato	2014	Metropolitan Region	Link
Table grapes	2014 and 2015	Valparaiso and O'Higgins	Link Valparaiso and Link O'Higgins
Avocado	2014	Valparaiso	Link
Peach	2014	Valparaiso	Link
Olives	2015	Valparaiso	Link
Plum	2012 and 2015	O'higgins	Link 2012 and Link 2015
Walnut	2014	Valparaiso	Link

In the table it can be seen the year and region where the technical sheet was defined, and a link to the information. It is important to clarify that only once (for wheat), data from the Bio-Bio region was used. It is acknowledged that climate conditions in this part of the country are different from Valparaiso (where the Aconcagua River is located), but it was not possible to find alternatives for this crop. It should also be noted that in two cases (Table grapes and plums) two references were analysed in order to reduce uncertainty in some values. Finally, it should be remembered that before including this data in the PMP model, values were transformed to 2007 prices whenever required.