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Water use efficiency: Joint use of life cycle assessment and multiperiod optimisation

Eficiencia en el Uso del Agua: Uso en Conjunto del Análisis de Ciclo de Vida y Optimización Multiperíodo

Tesis para optar al grado de Doctor en Ingeniería Agrícola con mención en Recursos Hídricos en la Agricultura

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Dedication

At the beginning of the program, the definition of what the thesis is about was not easy. Therefore, I thank my advisor Dr. Diego Rivera, who has not only believed in me but also has been a good person when I needed something. I would say, he is not only my professor but also a mate. I also thank Dr. Eduardo Holzapfel who supported me in my professional career, mainly in water concepts, crop yield response to water and optimisation of irrigated crops. Regarding optimisation, I want to thank Dr. Cristian D. Palma who supported me in the development of the code in GAMS (a new programming language for me). The Life Cycle Assessment was also a new concept for me. Therefore, I thank Dr. Alex Godoy-Faúndez. All of them, not only supported me in academic but also in personal issues.

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Part I

Abstract

Water use efficiency: Joint use of life cycle assessment and multiperiod optimisation

With the need to feed an increasing population, the worldwide irrigated area should increase in 30 M ha demanding 40% more water and energy for the next 20 years. Agriculture, however, has contributed to water scarcity. Among different proposed solutions, optimisation has included in this thesis, which aims to assign resources among competitive activities, subject to some restrictions and solved through mathematical algorithms. A key part of the optimisation model is a crop production function, which relates the yield reduction as a result of the relative loss in evapotranspiration. In the literature, most of the researches are based at a seasonal timescale, i.e., they do not account for intraseasonal changes. Therefore, the motivation was to develop in Chapter 1, a monthly crop yield function based on crop features (yield response factor for each growth stage and its duration in days) and sowing dates. This approach presented low values of RMSE and RD (below to 0.03 and 6.75%, respectively) when was compared to the daily approach proposed by Raes et al. (2006).

Once the monthly crop yield function was developed, it was included in a monthly optimisation model to obtain an optimum cropping pattern and monthly water allocation for irrigated agriculture to obtain maximum profits (Chapter 2). The model included improvements in water resource management such as water storage and water transactions, being the latter a monthly decision variable that can increase farmer's profits. Results showed that the model not only attains higher profits but also decreases uncertainty and improves risk management.

With respect to the monthly crop yield function developed in Chapter 1, the yield response factors proposed by Doorenbos and Kassam (1979) and FAO (2017), are not specific for a particular soil type or management. Therefore in Chapter 3 was included AquaCrop-OS (Foster et al., 2017), an open source code version of AquaCrop (Steduto et al., 2009) which was written in MATLAB. AquaCrop simulates attainable yields of crops as a function of water consumption under rainfed, supplemental, deficit and full irrigation conditions and has been used to determine accurately crop yield in some crops. The objective was to estimate the yield response factor (slope of the crop yield function) under local conditions for a given crop, soil, weather, sowing date and management and for each growth stage which depends on the growing degree days (GDD) instead of days. Results showed that there was a good agreement in the proposed methodology (over 85% of the results for each crop presented NRMSE values below to 20%).

Finally Chapter 4 analyses the estimation of crop yield depending on different irrigation management using a Life Cycle Assessment-based methodology, calculating maximum crop yield, water used to get maximum crop yield and water use efficiency considering local conditions of crops, soils, weather, sowing date and management. This Chapter included Crop Water Production Functions (CWPFs) using a problem-specific algorithm for optimal irrigation scheduling with limited water supply (GET-OPTIS). Results showed that there were differences among irrigation management, being GET-OPTIS the strategy with the best performance (highest crop yield, lowest water used and highest WUE), followed by the soil moisture-based management.

In short, in this thesis was developed a monthly crop yield function, a monthly optimisation model, an estimation of the yield response factor under local conditions for each growth stage and an assessment of crop yield depending on different irrigation strategies using an LCA-based methodology.

Eficiencia en el Uso del Agua: Uso en Conjunto del Análisis de Ciclo de Vida y Optimización Multiperíodo

Para alimentar a una población en aumento, el área mundial bajo riego se debe incrementar en 30 M ha, demandando un 40% más de agua y energía para los próximos 20 años. Sin embargo, la agricultura ha contribuido con la escasez de agua. Dentro de las diferentes soluciones propuestas se ha incluido en esta tesis la optimización, cuyo objetivo es asignar recursos entre actividades competitivas sujeta a algunas restricciones y resuelta mediante algoritmos matemáticos. Un componente clave de un modelo de optimización es una función de producción de cultivo, que relaciona la reducción del rendimiento de éste en consecuencia al déficit de evapotranspiración. De acuerdo a la literatura, la mayoría de las investigaciones están basadas en una escala de tiempo estacional, es decir, los cambios intraestacionales no son relevantes. Por lo tanto, el objetivo propuesto en el Capítulo 1 fue desarrollar una función de rendimiento mensual basada en las características del cultivo (factor de respuesta del rendimiento para cada período fenológico y su duración en días) y fecha de siembra. Este enfoque presentó bajos valores de RMSE y RD (por debajo de 0,03 y 6,75%, respectivamente) cuando se comparó con el modelo diario propuesto por Raes et al. (2006).

Una vez que se desarrolló el modelo de rendimiento de cultivo mensual, éste se incorporó en un modelo de optimización mensual para obtener un patrón óptimo de cultivo y una asignación de agua mensual para la agricultura bajo riego, con el fin de obtener los máximos beneficios económicos (Capítulo 2). El modelo incluyó mejoras en la gestión del recurso hídrico como la incorporación de estanques de acumulación y las transacciones de agua, siendo ésta última una variable que permite aumentar los beneficios económicos de los agricultores. Los resultados mostraron que el modelo no solo obtiene los beneficios económicos más altos, sino que también reduce la incertidumbre y mejora la gestión de riesgos.

Con respecto a la función de rendimiento de cultivo mensual desarrollada en el Capítulo 1, los factores de respuesta del rendimiento propuesto por Doorenbos and Kassam (1979) y FAO (2017), no son específicos para un tipo de suelo o manejo. Por esta razón se incluyó en el Capítulo 3 AquaCrop-OS (Foster et al., 2017), una versión de código abierto de AquaCrop (Steduto et al., 2009) que fue desarrollado en MATLAB. AquaCrop simula los potenciales rendimientos de los cultivos en función del agua aplicada bajo condiciones de secano, suplementarias, deficitarias y de riego completo y se ha utilizado para determinar con precisión el rendimiento en algunos cultivos. El objetivo fue determinar el factor de respuesta del rendimiento (pendiente de la función de rendimiento de cultivos) bajo condiciones locales de un cultivo, suelo, clima, fecha de siembra y manejo para cada período fenológico que depende del tiempo termal (en grados-días) en vez de los días de crecimiento. Los resultados mostraron que hubo una buena concordancia en la metodología propuesta (sobre el 85% de los resultados para cada cultivo presentaron valores de NRMSE por debajo del 20%).

Finalmente, el Capítulo 4 analizó la estimación del rendimiento de los cultivos dependiendo de diferentes estrategias de riego utilizando una metodología basada en el Análisis de Ciclo de Vida (ACV), determinando el rendimiento máximo, agua utilizada para obtener rendimiento máximo y la eficiencia en el uso del agua (EUA) considerando condiciones locales de un cultivo, suelo, clima, fecha de siembra y manejo. Este Capítulo incluyó las funciones de producción de cultivos utilizando un algoritmo problema-específico para determinar la óptima programación de riego bajo suministro limitado de agua (GET-OPTIS). Los resultados indicaron que hubo diferencias entre las distintas opciones de manejo del riego, siendo GET-OPTIS la estrategia con los mejores resultados (máximo rendimiento de cultivos, mínima agua utilizada y máxima EUA, seguida del manejo basado en la humedad del suelo.

En resumen, en esta tesis se desarrolló una función de rendimiento de cultivos mensual, un modelo de optimización mensual, una estimación del factor de respuesta del rendimiento bajo condiciones locales para cada período fenológico y una evaluación del rendimiento de los cultivos en función de diferentes estrategias de riego utilizando una metodología basada en el ACV.

Part II

Introduction

Current world population is around 7.5 billion, but by 2025 there will be an expected nine billion people (Al-Ansari et al., 2014). To feed this population, the worldwide irrigated area should increase in 30 M ha, with 40% higher water and energy demand for the next 20 years (FAO et al., 2015). According to McMichael et al. (2007), agriculture has depleted natural resources, contributing to water scarcity. Also, planetary boundaries will be surpassed if nothing changes in the way we produce and consume foods (Notarnicola et al., 2016). This inextricable interaction is known as the water, energy and food (WEF) nexus. Within this framework, it is not possible to address water, energy or food security in isolation in an effective way without considering the implications on the other two (De Laurentiis et al., 2016). Therefore, sustainable agriculture for food is necessary to integrate three main goals: economic profitability, environmental health and social and economic equity (Horrigan et al., 2002).

To face this problem, strategies have been proposed such as increasing water use efficiency (Gohari et al., 2017), desalination (Assouline et al., 2015; Harmancioglu, 2017), water transactions (Erfani et al., 2014; Garrick et al., 2009), use of infrastructure for water storage (Cosgrove and Loucks, 2015; Iglesias et al., 2017), and optimisation of resources (Homayounfar et al., 2014; Liu et al., 2010; Maneta et al., 2009; Zhu et al., 2015). Optimisation assigns resources among competitive activities, subject to some restrictions and solved through mathematical algorithms (Hillier and Lieberman, 2001).

A key part of the optimisation model is a crop production function, which relates the yield reduction as a result of the relative loss in evapotranspiration (Steduto et al., 2012).

Regarding seasonal timescale, literature shows the use of polynomial regressions (Carvallo et al., 1998; Maneta et al., 2009; Singh, 2012) and the equation proposed by the Food and Agriculture Organization of the United Nations (FAO) Irrigation and Drainage Paper 33 (Doorenbos and Kassam, 1979):

$$1 - \frac{Y}{Ym} = Ky\left(1 - \frac{ETa}{ETc}\right) \tag{1}$$

where Y and Ym are actual and maximum crop yield, respectively. On the other hand, ETa and ETc corresponds to actual and maximum evapotranspiration, respectively. The coefficient Ky denotes the yield response factor, which relates the yield reduction $(1 - Y/Y_m)$ to water stress $(1 - ET_a/ET_c)$ for a given environment (Raes et al., 2006).

On the other hand, investigations have included multiperiod crop yield functions (mostly at time scales for each growth stage), i.e., crop yield reduction as a result of the water stress at intraseasonal timescale, using the multiplicative approach of Doorenbos and Kassam (1979) (Garg and Dadhich, 2014; Karamouz et al., 2010; Moghaddasi et al., 2010; Raes et al., 2006), where n is the index representing each growth stage and N corresponds to the number of functions:

$$\frac{Y}{Ym} = \prod_{n=1}^{N} \left[1 - Ky_n \left(1 - \frac{ETa_n}{ETc_n} \right) \right] \tag{2}$$

and on the other hand, the model proposed by Jensen (1968) (Homayounfar et al., 2014; Kipkorir et al., 2002; Zhang and Guo, 2016), where λ_n represents the relative sensitivity of the crop to water stress during the growth stage:

$$\frac{Y}{Ym} = \prod_{n=1}^{N} \left(\frac{ETa_n}{ETc_n} \right)^{\lambda_n} \tag{3}$$

Regarding the multiplicative approach of the equation proposed by Doorenbos and Kassam (1979) (Equation 2), Ky values reported by Doorenbos and Kassam (1979) and FAO (2017) are not specific for a particular soil type or management practices. In this way, the Food and Agricultural Organization of the United Nations (FAO) developed the AquaCrop model (Steduto et al., 2009). This model simulates attainable yields of crops as a function of water consumption under rainfed, supplemental, deficit, and full irrigation conditions and has been used to determine accurately crop yield in maize (Heng et al., 2009; Nyakudya and Stroosnijder, 2014; Paredes et al., 2014), wheat (Andarzian et al., 2011; Mkhabela and Paul, 2012; Toumi et al., 2016), sugar beet (Alishiri et al., 2014; Malik et al., 2017; Stricevic et al., 2011), potatoes (Garcia-Vila and Fereres, 2012; Montoya et al., 2016), barley (Araya et al., 2010), quinoa (Geerts et al., 2009), rice (Maniruzzaman et al., 2015), and others. Later, Foster et al. (2017) developed the AquaCrop-OS model, an open source code written in MATLAB, giving the opportunity to assess some farming scenarios.

Although optimisation is a good tool to maximise profits or minimise environmental impacts, it does not allow assessing how agriculture is performed. Life Cycle Assessment (LCA) analyses the whole life of a product, from raw material extraction to its end-of-life disposal (cradle to grave approach) and has already been used to address water depletion uses related to irrigated crops (Milà i Canals et al., 2010). According to ISO 14040 (2006), an LCA comprises four main stages: goal and scope definition, related to the definition of the functional unit; Life Cycle Inventory

(LCI), related to the listed flows which have an influence on the whole process (input and output); Life Cycle Impact Assessment (LCIA) which analyses the impact overall process and finally the interpretation of the results. There are LCA reports on maize (Boone et al., 2016; Wang et al., 2015; Xue et al., 2014), sugar beet (Brentrup et al., 2001; Chauhan et al., 2011; Tzilivakis et al., 2005; Vaccari et al., 2005), wheat (Achten and Van Acker, 2016; Brock et al., 2012; Masuda, 2016), soybean (Mohammadi et al., 2013; Raucci et al., 2015), rice (Blengini and Busto, 2009; Hayashi et al., 2016) and tomatoes (He et al., 2016; Houshyar et al., 2015). Thus, LCA allows comparing among options, given a fixed allocation of resources.

None of the above-mentioned studies includes an optimisation method that allocates water and cropping area on a monthly basis, using multiperiod production function, as well as an assessment of the water use using an LCA-based methodology. Literature shows the potential of the joint use of optimisation and LCA to obtain higher economic profits as well to reduce the water use.

Part III

Hypothesis and Objectives

0.1 Hypothesis

I propose the following hypotheses:

a) Water storage and water transactions increase profits and the capacity of adaptation and mitigation of climate change effects.

b) An LCA-based methodology allows to compare water use among different irrigation management scenarios.

0.2 Main Objective

To assess the environmental impact of water use scenarios for main irrigated crops in Chile using an LCA-based methodology and multiperiod optimisation.

0.2.1 Specific Objectives

a) To develop a monthly crop yield model which relates yield reduction as a consequence of water scarcity at a monthly time scale.

b) To develop and test optimisation models at seasonal and monthly time scale.

c) To propose a methodology to estimate the yield response factor (slope of the crop yield function which relates yield reduction as a result of the relative loss in evapotranspiration) under local conditions for each growth stage.

d) To evaluate the potential environmental effects of irrigated agricultural systems under different management scenarios.

0.3 Expected contributions

Both optimisation and LCA techniques allow making better decisions, obtaining higher economic profits as well to reduce the water use and environmental impacts.

Part IV

Global Methodology

This thesis consists of four Chapters:

Chapter 1 describes the development of a monthly crop yield function, based on crop features (yield response factor for each growth stage and its duration in days) and sowing date. Crop yield parameters were extracted from CROPWAT 8.0 database (Allen et al., 1998; FAO, 2017) and the monthly crop yield function was based on the crop yield model proposed by Raes et al. (2006).

Chapter 2 presents the multiperiod optimisation model carried out at a monthly time scale, considering monthly crop yield functions developed in Chapter 1. The model included improvements in water resource management such as water storage and water transactions, being the latter a monthly decision variable that can increase farmer's profits.

Chapter 3 develops a methodology to estimate the yield response factor under local conditions for a given crop, soil, weather, sowing date and management, and for each growth stage using AquaCrop-OS. Results show differences for coefficients for local conditions (estimated by AquaCrop-OS) and those proposed by CROPWAT 8.0 (FAO, 2017).

Chapter 4 analyses the estimation of crop yield depending on different irrigation management using an LCA-based methodology, calculating maximum crop yield, water used to get maximum crop yield and water use efficiency considering local conditions of crops, soils, weather, sowing date and management. Results show differences for crop yield and water use among irrigation management, being an interesting concept to produce "more crop per drop" and improving in this way the water use efficiency.

Chapter 1 supports Chapter 2, which has been published, Chapter 3 is already submitted and Chapter 4 is nearly to be submitted for publication.

Part V

Summary of results

Chapter 1

Development of a monthly crop yield function

Abstract

A methodology was proposed to estimate a monthly crop yield model which depends mainly on crop features (yield response factor for each growth stage and its duration in days) and sowing date. The results show that the methodology is reliable to determine monthly crop yield values, presenting RMSE and RD values below to 0.03 and 6.75%, respectively. Including this proposed methodology into a multiperiod optimisation model, is a good chance for coping with seasonal changes, unlike seasonal approaches.

1.1 Introduction

A crop production function relates yield reduction with the relative loss in evapotranspiration (Steduto et al., 2012). Researchers considered crop yield reduction as a consequence of a deficit in evapotranspiration at seasonal and at lower timescales (multiperiod). Regarding the seasonal time scale, literature shows the use of polynomial regressions (Carvallo et al., 1998; Maneta et al., 2009; Singh, 2012) and the equation proposed by the Food and Agriculture Organization of the United Nations (FAO) Irrigation and Drainage Paper 33 (Doorenbos and Kassam, 1979). On the other hand, investigations have included multiperiod crop yield functions, i.e., crop yield reduction as a result of the water stress at intraseasonal timescale, using the multiplicative approach of Doorenbos and Kassam (1979) (Garg and Dadhich, 2014; Karamouz et al., 2010; Moghaddasi et al., 2010;

Raes et al., 2006) and Jensen (1968) (Homayounfar et al., 2014; Kipkorir et al., 2002; Zhang and Guo, 2016). None of the mentioned studies included a monthly crop yield model. Therefore, the main objective of this Chapter is to develop and test a monthly crop yield equation based on the multiperiod model proposed by Raes et al. (2006) which depends mainly on crop features and sowing date.

1.2 Methodology

1.2.1 Seasonal and multiperiod crop yield function

Doorenbos and Kassam (1979) proposed the following equation to estimate crop yield:

$$1 - \frac{Y}{Ym} = Ky\left(1 - \frac{ETa}{ETc}\right) \tag{1.1}$$

where Y and Ym are respectively actual and maximum yield for the crop, Ky is the yield response factor (slope of the equation regarding Figure 1.1) and ETa and ETc are respectively actual and maximum evapotranspiration.

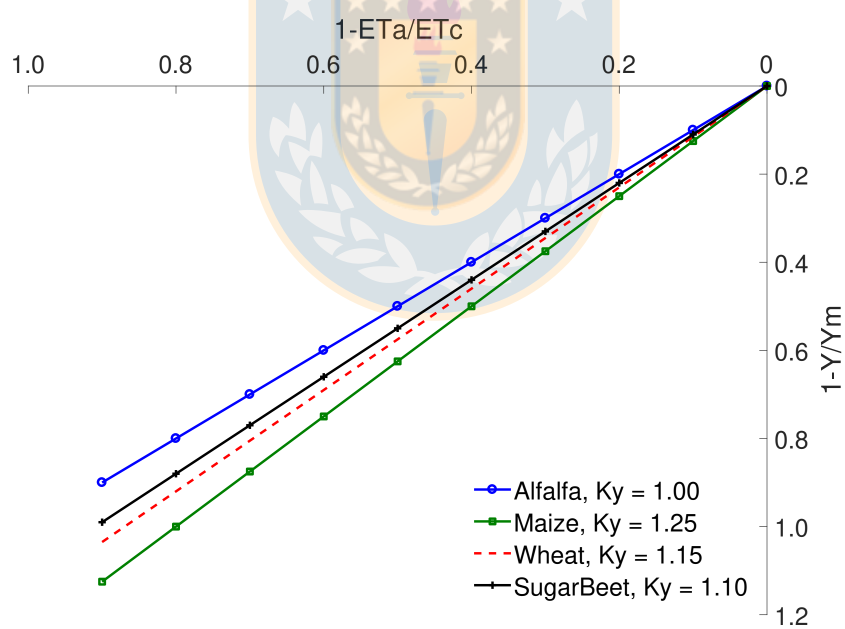

Figure 1.1: Seasonal crop yield reduction proposed by Doorenbos and Kassam (1979). *Ky* is the yield response factor and corresponds to the slope of the yield reduction due to a decrease of applied water

On the other hand, has the multiplicative approach of this equation been proposed to estimate crop yield as a consequence of water stress for specific growth stages:

$$\frac{Y}{Ym} = \prod_{i=1}^{N} \left[1 - Ky_i \left(1 - \frac{ETa_i}{ETc_i} \right) \right] \tag{1.2}$$

where i is the index representing each growth stage and N corresponds to the number of functions. To express crop yield reduction as a result of water deficiency at time steps smaller than the growth stages length, Raes et al. (2006) proposed the following approach:

$$\frac{Y}{Ym} = \prod_{j=1}^{M} \left[1 - Ky_i \left(1 - \frac{ETa_j}{ETc_j} \right) \right]^{\Delta t_j / L_i} \tag{1.3}$$

where M is the number of time steps with length Δt_j during the growth stage i and L_i for the total length (days) of the stage. Figure 1.2 shows maize's response to water at daily time steps, considering the equation proposed by Raes et al. (2006). Relative yield keeps constant when water demand is satisfied and decreases when not. Thus, in a growing season, the slope (Ky) changes for each growth stage.

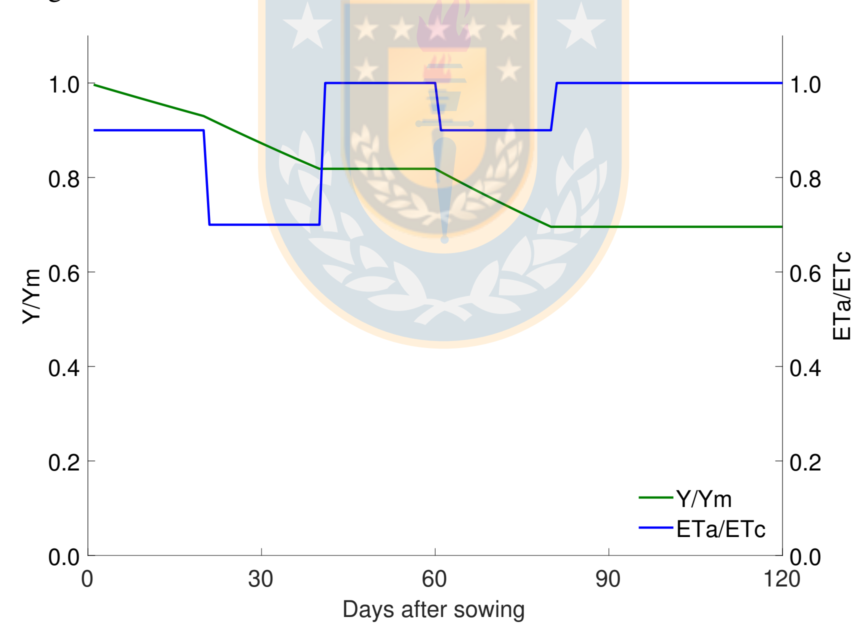

Figure 1.2: Daily crop yield reduction for maize, where Y/Ym and ETa/ETc are relative crop yield (Yr) and evapotranspiration, respectively (Source: Own elaboration)

1.2.2 Monthly crop yield function

The model proposed by Raes et al. (2006) was used to develop a monthly crop yield function, where yield response factors (Ky) are not depending on each growth stage (i) but a month (k). Therefore, the proposed monthly approach is:

$$\frac{Y_i}{Ym_i} = \prod_{k=1}^{N}\left[1 - Ky_k\left(1 - \frac{ETa_k}{ETc_k}\right)\right]^{\Delta t_k^*/L_k^*} \tag{1.4}$$

The yield response factor corresponds to the slope between the loss of evapotranspiration (independent variable, x) and the crop yield reduction (dependent variable, y). The equation for the slope (b) of a regression line is defined by:

$$b = \frac{\sum(x-\overline{x})(y-\overline{y})}{\sum(x-\overline{x})^2} \tag{1.5}$$

Replacing both respective terms, the equation to estimate yield response factor at a monthly time scale is:

$$Ky_k = \frac{\sum_{j=1}^{M}\left[\left(1-\frac{ETa}{ETc}\right)_j - \overline{\left(1-\frac{ETa}{ETc}\right)}\right]\left[\left(1-\frac{Y}{Ym}\right)_j - \overline{\left(1-\frac{Y}{Ym}\right)}\right]}{\sum_{j=1}^{M}\left[\left(1-\frac{ETa}{ETc}\right)_j - \overline{\left(1-\frac{ETa}{ETc}\right)}\right]^2} \tag{1.6}$$

Figure 1.3 presents the flowchart to estimate the yield response factor for each month (k). This flowchart starts with indices which represent the amount of ETa (z, an array which goes from 0 to 1 with a step of 0.1) and the day after sowing (j). If j belongs to the desired month (k), ETa includes values from 0 to 1. On the contrary, ETa does not consider water stress ($ETa = 1$). Once ETa is calculated, crop yield Yr_z for the day (j) is estimated using the daily model (Equation 1.3) proposed by Raes et al. (2006). When crop yield for the whole growing season is calculated (for M days), crop yield is determined considering the last value of the array. Once all (eleven) combinations of ETa are completed, Ky_k is estimated using the Equation 1.6.

The parameter Δt, defined by Raes et al. (2006), corresponds to a scalar which represents the time step. This is considered as an array that contains the number of the days for each month while the crop is growing. On the other hand, L, which defined by Raes et al. (2006) represents the total length (days) of every growth stage (i), is considered in this research as a fit parameter when is it

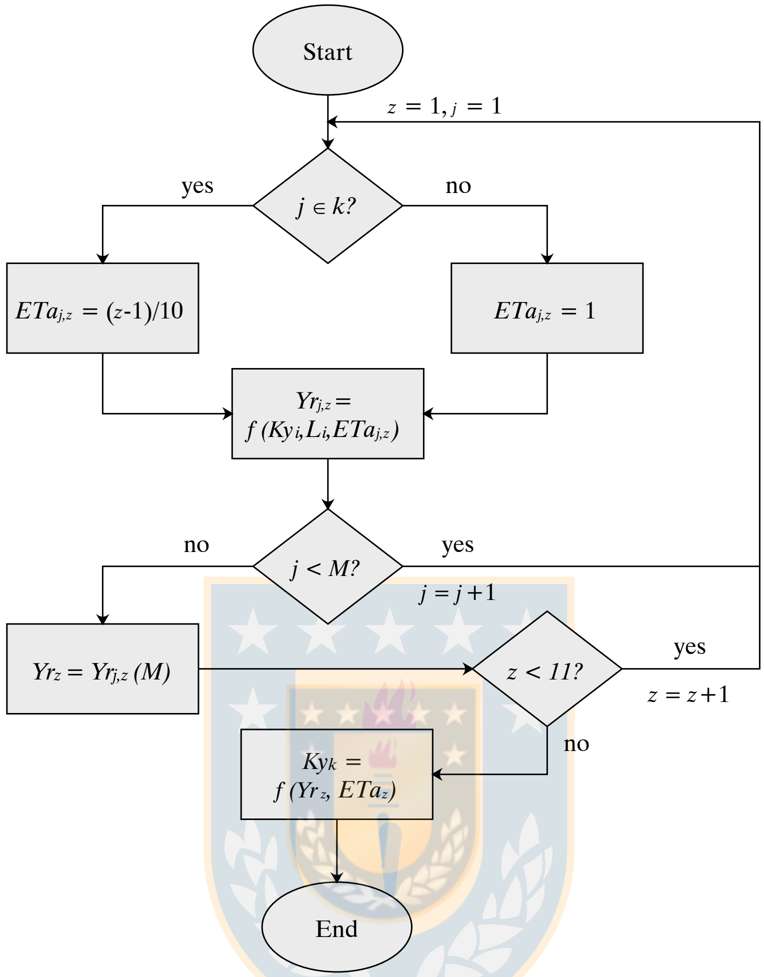

Figure 1.3: Flowchart considered to estimate Ky values at a monthly timescale. Indices j and k represent day after sowing and month, respectively (Source: Own elaboration)

compared to the relative yield at daily timestep (Yd):

$$L_k^* = \frac{\Delta t_k^*}{ln\left(\frac{Yd}{Y_{k-1}}\right)} ln\left[1 - Ky_k\left(1 - \frac{ETa_k}{ETc_k}\right)\right] \tag{1.7}$$

where Yd is the crop yield at a day d which is equivalent to the difference of the last day of the month (k) and the sowing day for the first month and the last day of each month for the following months while the crop is growing. For example, if the sowing and harvest day are November 15th

Table 1.1: Days after sowing (d) for each month for maize. Sowing and harvest days correspond to November 15th and March 3rd, respectively (Source: Own elaboration)

Month	Number of days for month	d
November	30	15
December	31	46
January	31	77
February	28	105
March	31	108

and March 3rd, respectively, d corresponds to 15 for November, 46 for December (15+31), 77 for January, 105 for February and 108 for March (105+3) (Table 1.1).

1.3 Case study

The proposed model was applied to conditions prevailing in the central valley of Chile (Figure 1.4). The annual mean precipitation is approximately 1,025 mm and the average high and low temperatures are 20.6 and 7.6°C, respectively. Crop yield parameters (Ky and L) were extracted from CROPWAT 8.0 database (Allen et al., 1998; FAO, 2017) for alfalfa, maize, wheat and sugar beet. Then, values were fitted according to the sowing date of crops to the study area (Faiguenbaum, 2003). Monthly parameters of crop yield equations are presented in Table 1.2.

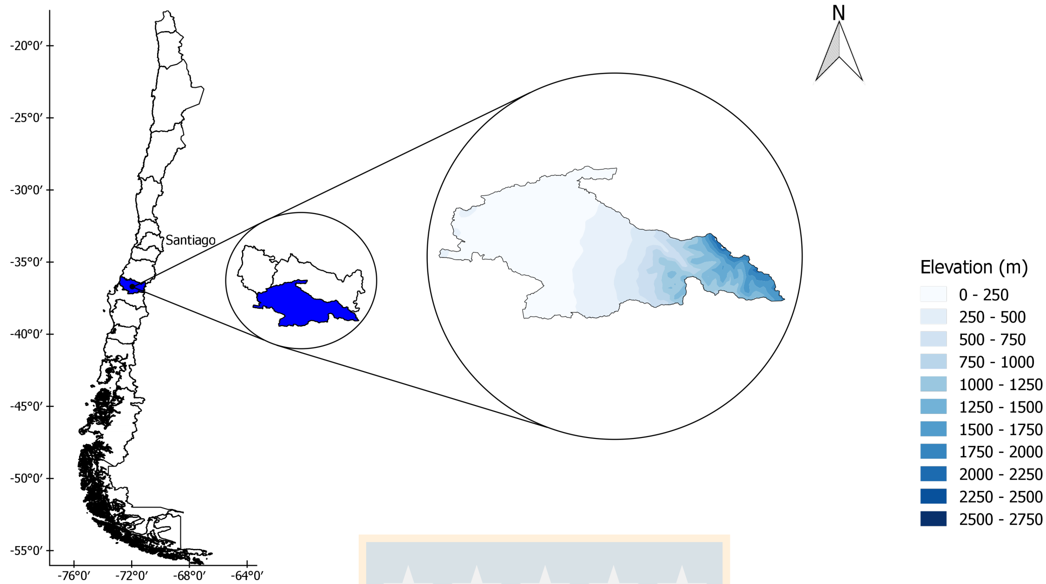

Figure 1.4: Study area location (Source: Own elaboration)

Table 1.2: Parameters used for monthly crop yield functions (Source: Own elaboration)

Crop	Parameter	Month Sep	Oct	Nov	Dec	Jan	Feb	Mar	Apr	Sowing
Alfalfa	Ky	1.0	0.9	0.7	0.7	0.7	0.7	0.9	0.8	01-Sep
	Δt	30	31	30	31	31	28	31	13	
	L^*	18.6	50.1	80.0	81.0	81.0	78.1	40.2	24.1	
Maize	Ky	-	-	0.5	0.7	1.2	0.5	0.1	-	01-Nov
	Δt	-	-	30	31	31	28	5	-	
	L^*	-	-	29.2	32.0	29.3	24.4	5.5	-	
Wheat	Ky	0.4	0.6	0.7	0.5	0.1	-	-	-	01-Sep
	Δt	30	31	30	31	8	-	-	-	
	L^*	30.0	30.9	32.5	32.6	8.5	-	-	-	
Sugar beet	Ky	0.6	0.8	1.0	1.0	0.9	0.6	-	-	01-Sep
	Δt	30	31	30	31	31	7	-	-	
	L^*	29.9	31.9	34.5	36.5	42.8	23.6	-	-	

1.4 Results and Discussion

To evaluate the proposed methodology, statistical indicators such as Root Mean Square Error (RMSE), Relative Differences (RD) and Scatter Plots 1:1 were used. The methodology was compared to the daily approach (i.e., $\Delta t = 1$) proposed by Raes et al. (2006), through 200 random values of ETa to generate 200 values of relative crop yield (Yr). Figure 1.5 shows the scatter plot 1:1 which relates daily and monthly relative crop yield. Each dot corresponds to the relative yield estimated by the monthly model, while the red line is that proposed by the daily approach. The largest differences appeared in maize which mainly sub-estimates the results with an RD value of around 7% (Table 1.3). According to the Table 1.3, RMSE and RD present low values (0.03 and 6.75%, respectively), being a reliable methodology to determine crop yield at a monthly timescale.

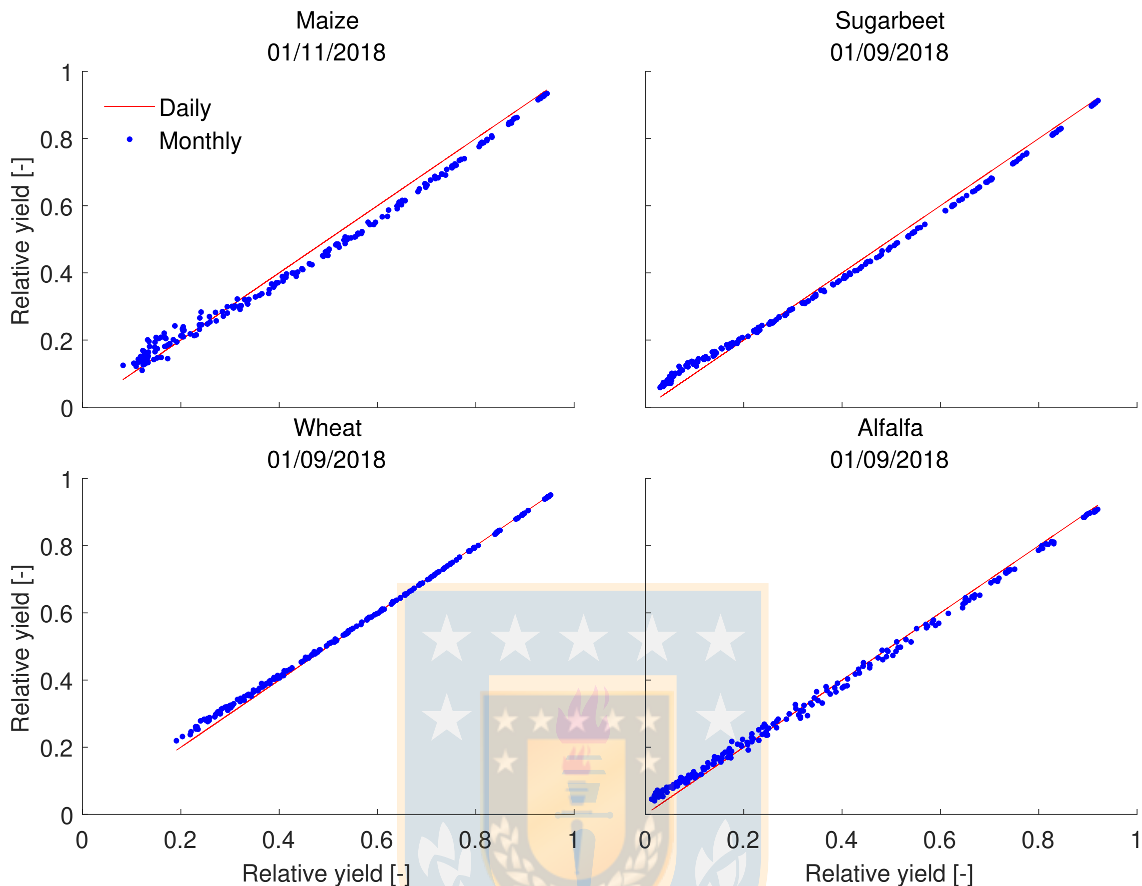

Figure 1.5: Comparison between relative crop yield at daily (red line) and monthly (blue dots) timescale for maize, sugar beet, wheat and alfalfa established in Chillán, Chile (Source: Own elaboration)

1.5 Conclusions

A monthly model was developed to estimate crop yield and considered the recommended sowing dates for Chillán, Chile. This chapter proposed new values for the multiperiod model based on Raes et al. (2006) analysis. The monthly approach was assessed by 200 randomly arrays of ETa for determining 200 values for crop yield and compared to daily values considering the equation proposed by Raes et al. (2006) considering maize, sugar beet, wheat and alfalfa. Results present low values of RMSE and RD being a reliable methodology to estimate crop yield at a monthly timescale. Including this proposed model into an optimisation model is a good chance for coping

Table 1.3: RMSE and RD for the monthly crop yield model (Source: Own elaboration)

Crop	Sowing date	RMSE	RD (%)
Maize	01-Nov	0.03	6.75
Sugar beet	01-Sep	0.02	6.16
Wheat	01-Sep	0.01	2.44
Alfalfa	01-Sep	0.02	5.97

with seasonal changes, unlike seasonal optimisation models.

Chapter 2

Development of a multiperiod optimisation model

Kuschel-Otárola, M., Rivera, D., Holzapfel, E., Palma, C.D., and Godoy-Faúndez, A. (2018). Multiperiod optimisation of irrigated crops under different conditions of water availability. *Water, 10, 1434*.

Abstract

We propose a nonlinear optimisation model which maximises profits by resource allocation on a monthly time scale, considering a monthly crop yield model. The proposed model was applied to six management scenarios (two seasonal and four monthly), nine conditions of water availability, and two situations of resource availability under Chilean conditions. These situations provided the same seasonal amount of resources, but different distributions over time. The model included improvements in water resource management such as water storage and water transactions, being the latter a monthly decision variable that can increase farmers' profits. According to our results, monthly scenarios gave high profits, even better with appropriate resource distribution. When water costs are high, water transactions allow loss reduction of up to 50%. Regarding labour, the lack of availability is more critical than the wages.

2.1 Introduction

Current world population is around 7.5 billion, but by 2025 there will be an expected nine billion people (Al-Ansari et al., 2014). To feed this population, the worldwide irrigated area should increase in 30 M ha, with 40% higher water and energy demand for the next 20 years (FAO et al., 2015). According to (McMichael et al., 2007), agriculture has depleted natural resources, contributing to water scarcity. To face this problem, strategies have been proposed such as increasing water use efficiency (Gohari et al., 2017), desalination (Assouline et al., 2015; Harmancioglu, 2017), water transactions (Erfani et al., 2014; Garrick et al., 2009), use of infrastructure for water storage (Cosgrove and Loucks, 2015; Iglesias et al., 2017), and optimisation of resources (Homayounfar et al., 2014; Liu et al., 2010; Maneta et al., 2009; Zhu et al., 2015).

Optimisation assigns resources among competitive activities, subject to some restrictions and solved through mathematical algorithms (Hillier and Lieberman, 2001). In agriculture, optimisation has been employed for resource management, especially regarding water allocation and cropping patterns. Models have been developed in the literature to maximise profits by optimal cropping patterns. For example, Sethi et al. (2002) considered groundwater management through linear programming to maximise profits. Mishra et al. (2009) developed a multiobjective optimisation model to determine optimal cropping pattern and optimal size of an auxiliary storage reservoir. Fasakhodi et al. (2010) used a multiobjective fractional goal programming method to find the optimal cropping pattern and sustain water availability. Ponce et al. (2014) developed a nonlinear water supply model for analysing the economic impacts of changes in crop yields due to climate change. Su et al. (2014) improved agricultural water use efficiency and the proportion of green water utilization by multiobjective optimisation. Das et al. (2015) developed a menu-driven user friendly software based on a linear programming model for optimal land and water allocation. Tan et al. (2017) developed a multiobjective fuzzy robust programming model for allocation of water and land resources and Varade and Patel (2018) determined an optimal cropping pattern to maximise the net annual returns in order to conserve natural resources. On the other hand, there are researches that have included crop production functions that relate yield reduction as a result of the relative loss in evapotranspiration (Steduto et al., 2012). In these studies, the equation proposed by Doorenbos and Kassam (1979) (Banihabib et al., 2016; Mainuddin et al., 1997; Prasad et al., 2006) and polynomial regressions were considered (Carvallo et al., 1998; Maneta et al., 2009; Singh, 2012). Moreover, there are investigations which include multiperiod crop yield functions related to crop yield reduction as a result of the water stress at an intraseasonal timescale (Raes et al., 2006). These studies considered the multiplicative approach of the equation proposed by Doorenbos and Kassam (1979) (Garg and Dadhich, 2014; Karamouz et al., 2010; Moghaddasi et al., 2010) and Jensen (1968) (Homayounfar et al., 2014; Kipkorir et al., 2002; Sadati et al., 2014; Zhang and Guo, 2016).

Considering the importance of sub-seasonal management in food production, we formed the following research question: What is the method to cope with seasonal changes, and how does variability affect profits for a given number of resources? None of the mentioned studies included a monthly optimisation model subject to monthly constraints, such as labour and capital (separately) and the possibility of including improvements in water resource management such as water transactions and water storage. Therefore, the principal objective was to develop and test nonlinear optimisation models at seasonal and monthly time scales and then compare them under Chilean conditions. This started with developing a monthly crop yield equation based on the multiperiod model proposed by Raes et al. (2006) which depends mainly on crop features and sowing date. A monthly optimisation model allows adequate resource allocation due to monthly demand for labour and capital, often reported by technical-economic reports. Improvements in water resource management such as water storage and water transactions, are also monthly decision variables that can increase profits.

2.2 Methodology

Our proposed nonlinear optimisation model consists of an objective function which includes a monthly crop yield function and constraints on a monthly basis for resources. The objective is to maximise profits by the allocation of water and land to be cultivated on a monthly time scale.

2.2.1 Multiperiod Crop Yield Function

For planning with limited data availability, a simple equation was proposed by Doorenbos and Kassam (1979), which describes crop yield reduction due to water scarcity:

$$\left(1 - \frac{Y_i}{Ym_i}\right) = Ky_i \left(1 - \frac{ETa_i}{ETc_i}\right) \tag{2.1}$$

where i represents crop type. Y_i and Ym_i (in yield unit ha^{-1}) are the actual and maximum crop yields, respectively. Ky_i is the yield response factor, which has been documented by Doorenbos and Kassam (1979) for many crops at different stages and corresponds to the slope of the yield reduction due to a decrease of applied water (Figure 2.1a). ETa_i and ETc_i (both in mm) are the actual and crop evapotranspiration for the whole growing period, respectively. Later, Raes et al. (2006) proposed a multiperiod crop yield equation at constant time scales smaller than growth periods.

$$\frac{Y_i}{Ym_i} = \prod_{k=1}^{t}\left[1 - Ky_{i,s}\left(1 - \frac{ETa_{i,k}}{ETc_{i,k}}\right)\right]^{\Delta t_{i,k}/L_{i,s}} \tag{2.2}$$

where t is the number of periods, $Ky_{i,s}$ is the yield response factor at growth stage s, $ETa_{i,k}$ and $ETc_{i,k}$ are the actual and crop evapotranspiration at time k; $\Delta t_{i,k}$ is the length of time (in days) of each step during the growth stage s (1 if daily) and $L_{i,s}$ is the growth stage length (in days). Figure 2.1b represents the daily yield response to water (Raes et al., 2006) for maize, where relative yield stays constant when water demand is satisfied, and decreases when it is not. We propose modification to this equation for this research for monthly time steps, considering a parameter $\Delta t^*_{i,k}$ as an array which maintains the number of the days in each month while the crop is growing (instead of considering it as scalar); and $L^*_{i,k}$ as a fit parameter when it compared to the relative yield at daily time step:

$$L^*_{i,k} = \frac{\Delta t^*_{i,k}}{ln\left(\frac{Y_{i,d}}{Y_{i,k-1}}\right)} ln\left[1 - Ky_{i,k}\left(1 - \frac{ETa_{i,k}}{ETc_{i,k}}\right)\right] \tag{2.3}$$

where $Y_{i,d}$ is the actual crop yield at day d which is equivalent to the difference of the last day of the month k, and the sowing day for the first month and the last day of each month for the following months while the crop is growing. For example, if the sowing and harvest day of crop i are 15 November and 3 March, respectively, d corresponds to 15 for November, 46 for December (15 + 31), 77 for January, 105 for February, and 108 for March (105 + 3). Finally, the monthly crop yield equation has the following form:

$$\frac{Y_i}{Ym_i} = \prod_{k=1}^{t}\left[1 - Ky_{i,k}\left(1 - \frac{ETa_{i,k}}{ETc_{i,k}}\right)\right]^{\Delta t^*_{i,k}/L^*_{i,k}} \tag{2.4}$$

A comparison between the daily and monthly approach for maize is illustrated in Figure 2.1c. Here, yield reduction is due to seasonal water shortage as a function of time, showing that there are not significant differences between the approaches.

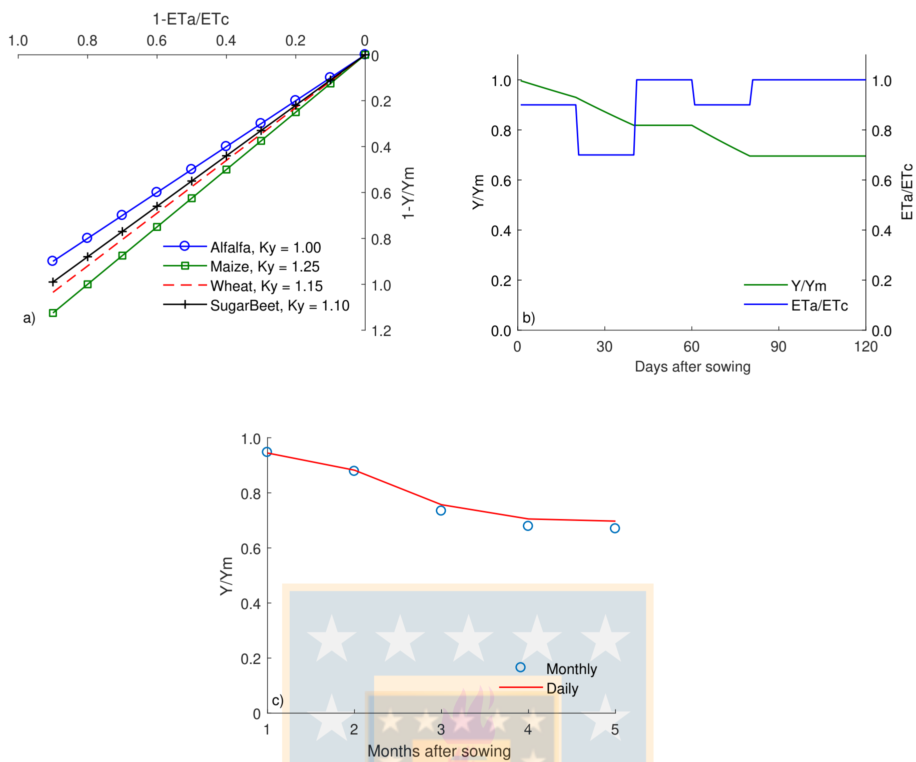

Figure 2.1: Representation of crop yield reduction, where (**a**) is the seasonal crop yield reduction function proposed by Doorenbos and Kassam (1979) where *Ky* is the slope; (**b**) is the daily crop yield reduction for maize proposed by Raes et al. (2006) where relative yield stays constant when the water demand is satisfied and decreases when it is not; and (**c**) represents daily and monthly approaches for maize (Source: Own elaboration)

2.2.2 Optimisation of Irrigated Crops

The objective function to maximise has the following form:

$$Max\ U = \sum_{i=1}^{n} P_i A_i Y_i - \sum_{i=1}^{n}\sum_{k=1}^{t} A_i C_{i,k} \tag{2.5}$$

where P_i is the price per crop i (in US\$ yield unit^{-1}), A_i is the area to be cultivated with crop i (in ha), and $C_{i,k}$ represents the production costs per unit area (in US\$ ha^{-1}). Some components of $C_{i,k}$ are (Carvallo et al., 1998): labour and other costs such as seed, fertiliser and pesticides.

Thus, the complete form of the objective function is:

$$Max\ U = \sum_{i=1}^{n} P_i A_i Ym_i \prod_{k=1}^{t} \left[1 - Ky_{i,k}\left(1 - \frac{ETa_{i,k}}{ETc_{i,k}}\right)\right]^{\Delta t^*_{i,k}/L^*_{i,k}} - LC \sum_{i=1}^{n}\sum_{k=1}^{t} A_i NL_{i,k} - \sum_{i=1}^{n}\sum_{k=1}^{t} A_i OC_{i,k} - Wcr \sum_{k=1}^{t} Wr_k - Wcb \sum_{k=1}^{t} Vwb_k + Wcs \sum_{k=1}^{t} Vws_k \tag{2.6}$$

where LC is the labour cost (in US\$ person-day^{-1}), $NL_{i,k}$ is the labour needed per unit area (in person- day ha^{-1} month^{-1}), $OC_{i,k}$ corresponds to other costs, and Wr_k is the amount of water rights in month k (in m^3 month^{-1}) with its respective cost (Wcr) (in US\$ m^{-3}). If farmers have the possibility to buy water (to increase the area to be irrigated) and to sell water (when not using it), they can obtain higher profits. Therefore, the monthly amounts of water to buy (Vwb_k) and to sell (Vws_k) are also included, with the corresponding costs to buy (Wcb) and to sell (Wcs) water (in US\$ m^{-3}).

Constraints of resources on a monthly basis are as follows:

1. Water availability: Assuming that the farmer has the infrastructure to store water at monthly scale (Rc m^3 of capacity), available water is defined as:

$$0 \leq \sum_{k'=1}^{k}\left[(Wr_{k'} + Vwb_{k'}) - \left(10\sum_{i=1}^{n} A_i \frac{ETa_{i,k'}}{AE_i} + Vws_{k'}\right)\right] \leq Rc, \quad \forall k \tag{2.7}$$

   where AE_i is the application efficiency of the irrigation system for crop i. It is important to mention that $ETa_{i,k}$ refers to the water contained in the soil after applied an initial volume of water $ETa_{i,k}/AE_i$, where there are losses due to irrigation system efficiency. This variable is multiplied by 10 for conversion to m^3 per hectare.

2. Land availability: This constraint defines the area to be cultivated.

$$\sum_{i=1}^{n} A_i \leq At \tag{2.8}$$

   where At is the land availability (in ha).

3. Labour availability: Assuming that the labour availability can change for each month, this constraint is defined as:

$$\sum_{i=1}^{n} A_i NL_{i,k} \leq La_k, \quad \forall k \tag{2.9}$$

where La_k is the labour availability at month k (in person-d month^{-1}).

4. Capital availability: Assuming that farmers can save money if it is not spent, the monthly capital availability is considered as:

$$\sum_{k'=1}^{k} \left[(Wcr \cdot Wr_{k'} + Wcb \cdot Vwb_{k'}) + LC \sum_{i=1}^{n} A_i NL_{i,k'} + \sum_{i=1}^{n} A_i OC_{i,k'} \right] \leq \sum_{k'=1}^{k} Ca_{k'}, \quad \forall k \tag{2.10}$$

where $Ca_{k'}$ is the economic capital availability at month k' (in US\$ month^{-1}).

5. Crop area considerations: It is necessary to consider agricultural, market and productive diversity management criteria to restrict the maximum or minimum crop areas. This is due to marketing situations, rotations, or other agricultural limitations. These constraints are expressed as:

$$min\ S_i \leq A_i \leq max\ S_i, \quad \forall i \tag{2.11}$$

where $min\ S_i$ and $max\ S_i$ are the minimum and maximum areas assigned to farm with crop i, respectively.

6. Complementary considerations: To force the crop water requirement to be zero when the cultivated area is also zero, the constraint is expressed as:

$$Kz \cdot A_i - \sum_{k=1}^{t} ETa_{i,k} \geq 0, \quad \forall i \tag{2.12}$$

where Kz is a positive constant (Kz = 10,000 mm ha^{-1}). In order to not apply more water than required by the crop, the following constraint is also considered:

$$ETa_{i,k} \leq ETc_{i,k}, \quad \forall i,k \tag{2.13}$$

Finally, there are non-negativity constraints expressed as:

$$A_i, ETa_{i,k}, Vwb_k, Vws_k \geq 0 \tag{2.14}$$

2.2.3 Case Study

Our proposed model was applied to conditions characteristic of the Central Valley of Chile (Figure 2.2). Annual mean precipitation for this area is about 1025 mm, and the average high and low temperatures are 20.6 and 7.6 °C, respectively (DGA, 2004). This sector contains about 28% of the national crop production surface. Some of the most produced crops are wheat (34.3%), maize (11.6%), and sugar beets (6%), which contribute to the national planted surface with 27.9, 22.5, and 60%, respectively. On the other hand, fodder crops represent 6.1% of the regional cultivated area (11% national) (ODEPA, 2018), alfalfa being the most common, mainly destined to intensive dairy farming.

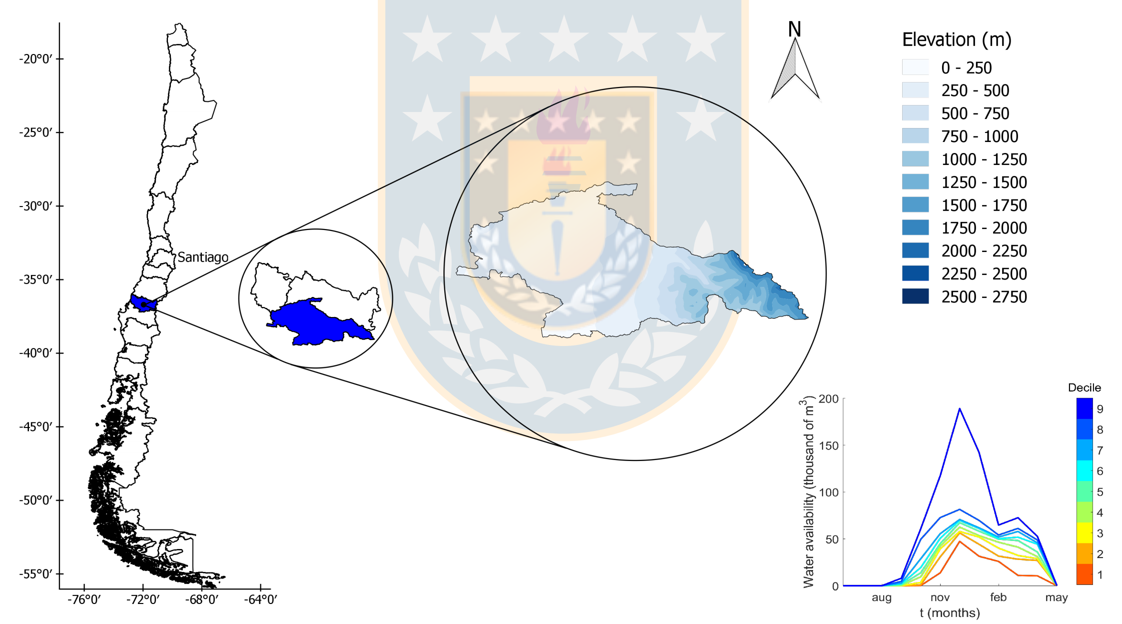

Figure 2.2: Study area location. The right-bottom panel shows available water based on streamflow records of a distribution channel (Source: Own elaboration)

2.2.3.1 Model Inputs

In this research, alfalfa, maize, wheat, and sugar beets were the crops considered for the case study. Crop yield parameters (Ky and L) were extracted from the database of CROPWAT 8.0 (Allen et al., 1998; FAO, 2017). Then, values were fitted to the study area according to crop sowing date, as recommended by Faiguenbaum (2003). This gave the monthly parameters of crop yield equations presented in Table 2.1. Price, costs, and maximum yield for each crop considered in Equation (2.6) (Table 2.2) were extracted from technical-economic reports from the Office of Agricultural Studies and Policies (ODEPA) and the National Institute of Agricultural Research (INIA). Prices were adjusted to May 2017 using the Consumer Price Index (CPI) calculator which is available on the National Statistics Institute (INE) website. A value of 575 Chilean Pesos (CLP) per US dollar $ was considered for this study as the long-term mean. Monthly water demand for each crop was determined using the ASCE Standardised Reference Evapotranspiration Equation (Allen et al., 2005). Monthly water availability was estimated using streamflow data from distribution channels. Then, a decile analysis was carried out to assess different conditions of water availability. Deciles 1 and 9 represented the driest and wettest conditions, respectively.

Table 2.1: Parameters used for monthly crop yield functions based on the CROPWAT 8.0 database and the sowing date recommended by Faiguenbaum (2003) (Source: Own elaboration)

Crop	**Parameter**	**Month**							**Sowing**
		Sep	**Oct**	**Nov**	**Dec**	**Jan**	**Feb**	**Mar**	
Alfalfa	Ky	1.0	1.0	1.0	1.0	1.0	1.0	1.0	01-Sep
	Δt^*	30.0	31.0	30.0	31.0	31.0	28.0	15.0	
	L^*	49.0	49.0	49.0	49.0	49.0	49.0	49.0	
Maize	Ky	-	-	0.5	0.7	1.2	0.5	0.1	01-Nov
	Δt^*	-	-	30.0	31.0	31.0	28.0	5.0	
	L^*	-	-	28.4	35.1	35.6	34.3	33.4	
Wheat	Ky	0.4	0.6	0.7	0.5	0.1	-	-	01-Sep
	Δt^*	30.0	31.0	30.0	31.0	8.0	-	-	
	L^*	30.0	30.9	32.5	32.6	8.5	-	-	
Sugar beet	Ky	0.6	0.8	1.0	1.0	0.9	0.6	-	01-Sep
	Δt^*	30.0	31.0	30.0	31.0	31.0	7.0	-	
	L^*	29.5	31.5	35.2	37.3	38.8	38.4	-	

Table 2.2: Price and maximum yield for each crop (Source: Own elaboration)

Crop	Price		Maximum Yield		Source
	Value	Units	Value	Units	
Alfalfa	5.1	US$ bale^{-1}	400	bales ha^{-1}	INIA (2005)
Maize	22.3	US$ qqm^{-1}	150	qqm ha^{-1}	ODEPA (2017)
Wheat	22.5	US$ qqm^{-1}	70	qqm ha^{-1}	ODEPA (2017)
Sugar beet	62.7	US$ ton^{-1}	100	ton ha^{-1}	ODEPA (2011)

2.2.3.2 Model Application

The model was applied to two situations that provided the same seasonal amount of resources (for labour and capital) but different distributions in time (Figure 2.3). The seasonal availability of resources (labour and capital) was the same for both situations, but its distribution differed. Moreover, the model was applied to six scenarios, and their features can be summarised as follows:

- Scenario 1: Optimisation subject to seasonal constraints. This scenario assumes that resources are available for the season, but does not consider intraseasonal variability. In this scenario, for the whole growing period, only one value of Ky and ETa for each crop i was considered. Water storage and water transactions were not considered.

- Scenario 2: Optimisation subject to seasonal constraints. For the whole growing period, monthly values of Ky and ETa for each crop i were considered. In this scenario, water storage and water transactions were not considered.

- Scenario 3: Optimisation subject to monthly constraints, i.e., water and other resources availability at a monthly scale are considered. In this scenario, water storage and water transactions were not considered.

- Scenario 4: Optimisation subject to monthly constraints with water transactions.

- Scenario 5: Optimisation subject to monthly constraints with water storage.

- Scenario 6: Optimisation subject to monthly constraints with water storage and transactions. This scenario is the most complete, considering all possible factors involved in the process.

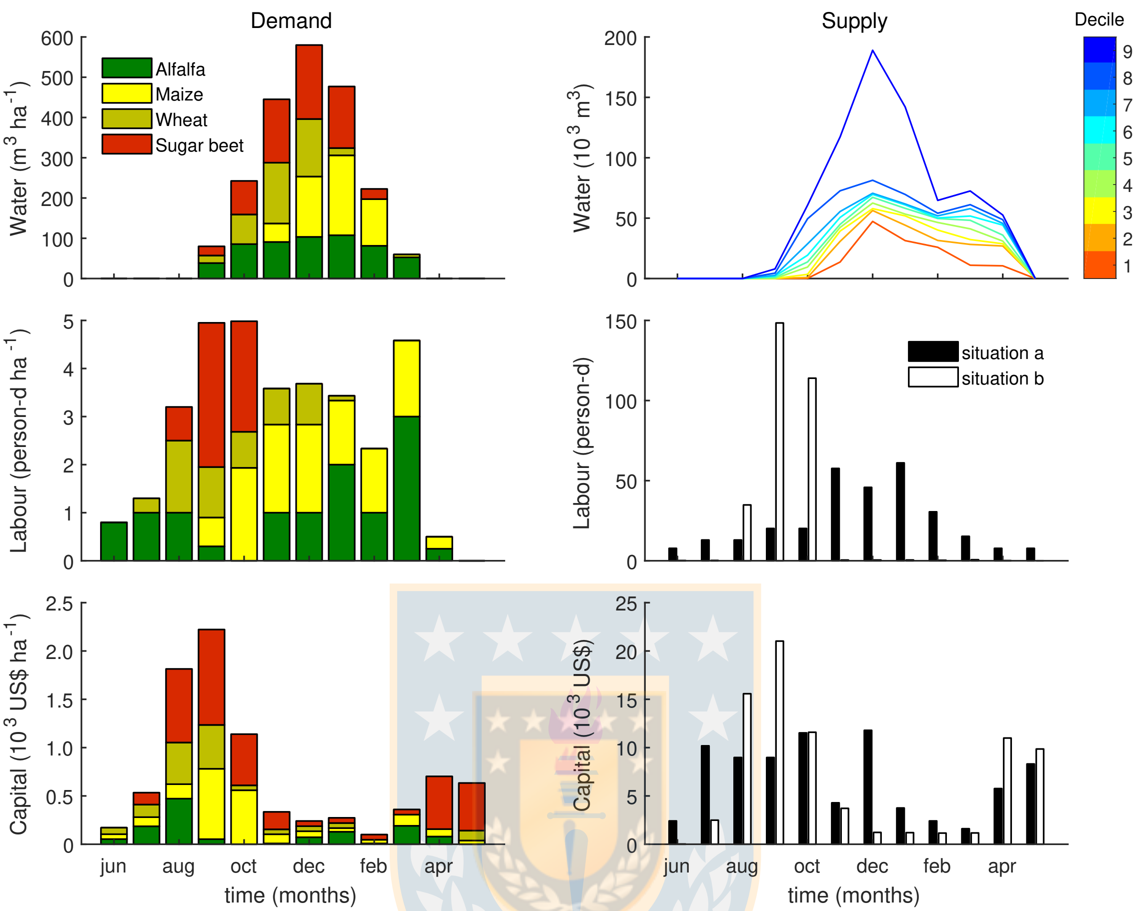

Figure 2.3: Monthly demand and supply of resources using collated data. Deciles 1 and 9 are the driest and the wettest conditions, respectively. Distribution of labour and capital are provided by the situation a (black bar) and b (white bar). Seasonal amount of labour and capital availability is 300 person-day and 80,000 US$, respectively. See ODEPA (2017), ODEPA (2011), and INIA (2005) for more detailed sources of information (Source: Own elaboration)

A summary of the equations considered in the optimisation algorithm is presented in Table 2.3 for each scenario. Figure 2.4 summarises the aforementioned methodology, where parameters such as price received for crop and its maximum yield, monthly demand and supply of water, labour, and economic capital are available in the database. The six scenarios described above were assessed by the model proposed by Doorenbos and Kassam (1979) for scenario 1, and by the monthly proposed crop yield equation (scenarios 2 through 6), subject to seasonal constraints (scenarios 1 and 2), and monthly constraints (scenarios 3 through 6).

Table 2.3: Objective functions and constraints used in each scenario (Source: Own elaboration)

Function or Constraint	Equation	Scenarios
Objective	$Max\ U = \sum_{i=1}^{n} P_i A_i Ym_i \left[1 - Ky_i \left(1 - \frac{ETa_i}{ETc_i}\right)\right] - LC \sum_{i=1}^{n} \sum_{k=1}^{t} A_i NL_{i,k} - \sum_{i=1}^{n} \sum_{k=1}^{t} A_i OC_{i,k} - Wcr \sum_{k=1}^{t} Wr_k$	1
	$Max\ U = \sum_{i=1}^{n} P_i A_i Ym_i \prod_{k=1}^{t} \left[1 - Ky_{i,k} \left(1 - \frac{ETa_{i,k}}{ETc_{i,k}}\right)\right]^{\Delta t^*_{i,k}/L^*_{i,k}} - LC \sum_{i=1}^{n} \sum_{k=1}^{t} A_i NL_{i,k} - \sum_{i=1}^{n} \sum_{k=1}^{t} A_i OC_{i,k} - Wcr \sum_{k=1}^{t} Wr_k$	2, 3, 5
	$Max\ U = \sum_{i=1}^{n} P_i A_i Ym_i \prod_{k=1}^{t} \left[1 - Ky_{i,k} \left(1 - \frac{ETa_{i,k}}{ETc_{i,k}}\right)\right]^{\Delta t^*_{i,k}/L^*_{i,k}} - LC \sum_{i=1}^{n} \sum_{k=1}^{t} A_i NL_{i,k} - \sum_{i=1}^{n} \sum_{k=1}^{t} A_i OC_{i,k} - Wcr \sum_{k=1}^{t} Wr_k - Wcb \sum_{k=1}^{t} Vwb_k + Wcs \sum_{k=1}^{t} Vws_k$	4, 6
Capital	$Wcr \sum_{k=1}^{t} Wr_k + LC \sum_{i=1}^{n} \sum_{k=1}^{t} A_i NL_{i,k} + \sum_{i=1}^{n} \sum_{k=1}^{t} A_i OC_{i,k} \leq \sum_{k=1}^{t} Ca_k$	1, 2
	$\sum_{k'=1}^{k} \left[(Wcr \cdot Wr_{k'} + Wcb \cdot Vwb_{k'}) + LC \sum_{i=1}^{n} A_i NL_{i,k'} + \sum_{i=1}^{n} A_i OC_{i,k'}\right] \leq \sum_{k'=1}^{k} Ca_{k'}, \quad \forall k$	3–6
Water	$10 \sum_{i=1}^{n} A_i \frac{ETa_i}{AE_i} \leq \sum_{k=1}^{t} Wr_k$	1
	$10 \sum_{i=1}^{n} \sum_{k=1}^{t} A_i \frac{ETa_{i,k}}{AE_i} \leq \sum_{k=1}^{t} Wr_k$	2
	$10 \sum_{i=1}^{n} A_i \frac{ETa_{i,k}}{AE_i} \leq Wr_k, \quad \forall k$	3
	$10 \sum_{i=1}^{n} A_i \frac{ETa_{i,k}}{AE_i} + Vws_k \leq Wr_k + Vwb_k, \quad \forall k$	4
	$0 \leq \sum_{k'=1}^{k} \left[Wr_{k'} - 10 \sum_{i=1}^{n} A_i \frac{ETa_{i,k'}}{AE_i}\right] \leq Rc, \quad \forall k$	5
	$0 \leq \sum_{k'=1}^{k} \left[(Wr_{k'} + Vwb_{k'}) - \left(10 \sum_{i=1}^{n} A_i \frac{ETa_{i,k'}}{AE_i} + Vws_{k'}\right)\right] \leq Rc, \quad \forall k$	6

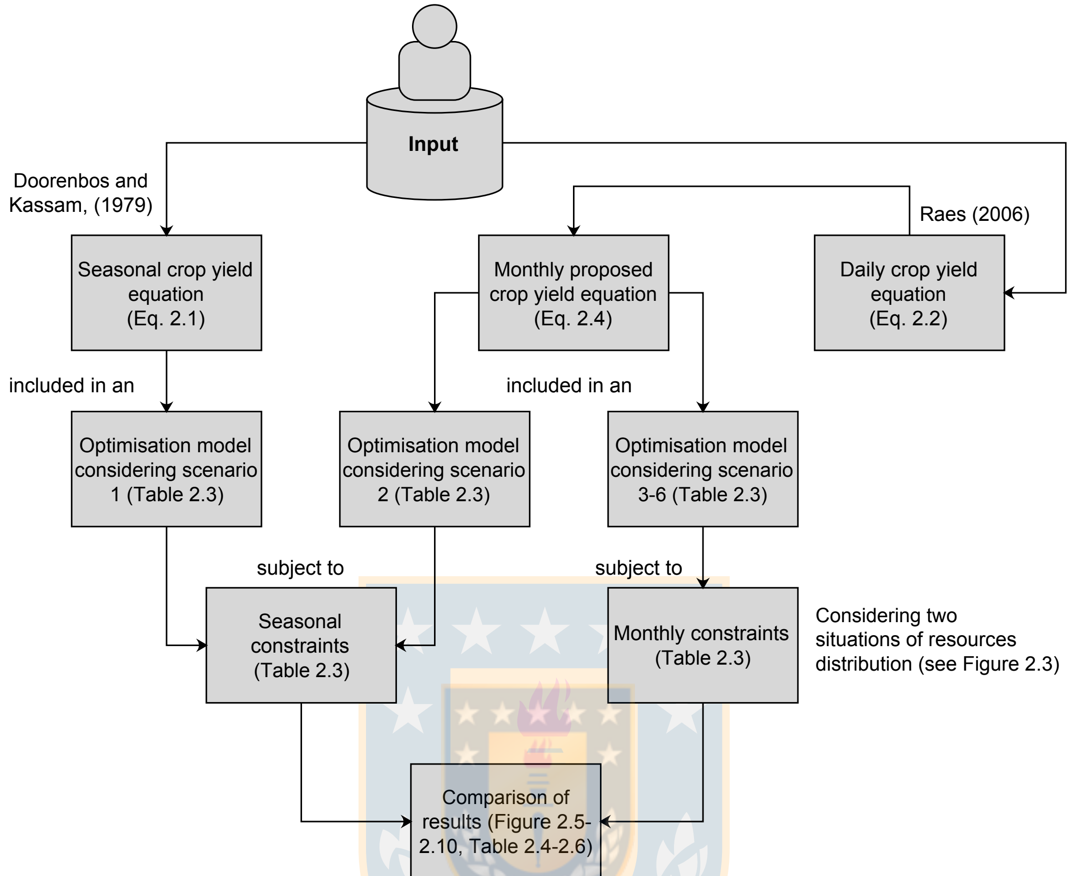

Figure 2.4: Methodology used for this research. The six scenarios were assessed by two situations of time and resource distribution (Source: Own elaboration)

The model was run using the General Algebraic Modelling System (GAMS) (Brooke et al., 2014) software, Version 24.7, and solved with the CONOPT 3 solver.

For implementation of the six scenarios, the following values were considered:

For the whole scenarios, At was 25 ha, Wcr was 0.0016 US\$ m^{-3}, and LC was 20 US\$ person-day^{-1} (ODEPA, 2011). In this study, it was considered that alfalfa, maize, and sugar beet were watered by sprinklers ($AE_i = 0.75$) and wheat by furrow ($AE_i = 0.60$). For scenario 1, Ky_i values of 1.00, 1.25, 1.15, and 1.10 were considered for alfalfa, maize, wheat, and sugar beet, respectively, according to the recommended values by Doorenbos and Kassam (1979) (Figure 2.1a). For scenarios 2 through 6, the values considered are shown in Table 2.1. For scenarios where water transactions were considered (4 and 6), Wcb and Wcs corresponded to 0.0018 and 0.0014 US$ m^{-3}, respectively. On the other hand, for scenarios where water storage was considered (5 and 6), *Rc* assumed a value of 30,000 m^3.

On the other hand, the same amount of resource availability (labour and capital) was considered for both situations, but at different distributions in time, where labour and capital availability was 300 person-days and 80,000 US$, respectively.

To test the effectiveness of the optimisation model once it reached an optimum irrigated cropping pattern and water allocation, a sensitivity analysis was conducted. This analysis included scenario 1 and 6. Both situations of resources distribution (a and b) as water, capital and labour were considered in the sixth scenario (Figure 2.3). The analysis was conducted considering land, labour, capital, and mean water availability (25 ha, 300 person-d, 80,000 US$, and 357,334 m^3 for the whole season, respectively). The analysis tested the variation in profits by changing export prices, crop area, irrigation systems, water and labour costs, labour availability and other costs, as well as capital availability.

2.3 Results and Discussion

2.3.1 Seasonal Use of Resources and Profits

Seasonal use of resources and profits are presented in the form of radar charts (Figures 2.6 and 2.7) in which each axis corresponds to a decile of a probability (DI) of water availability for each scenario. Each ring represents a resource index, organised as follows (from inside to outside): Land, water, labour, capital used, and profit (Figure 2.5). These resources were relativized to consider an index number from 0 to 1, and this was carried out in the following manner: (1) For land used, an index of 1 was considered to represent 25 ha of land, which is the available resource for this case study. (2) For water used, an index of 1 depended on the seasonal amount of water of every decile. (3) For labour used, an index of 1 was considered to represent the whole labour availability (300 person-day) distributed at monthly time scales. (4) For capital used, an index of 1 was considered to represent the whole capital availability (80,000 US$) also distributed at monthly time scales. (5) For profit, an index of 1 was considered to represent the maximum profit obtained from the runs (46,269 US$).

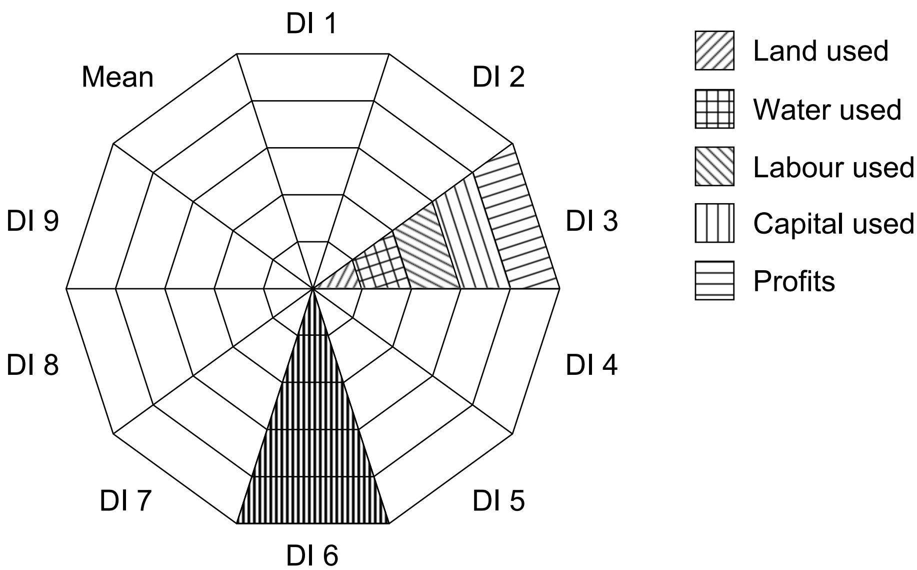

Figure 2.5: Interpretation of radar plots (Figures 2.6 and 2.7) showing profits and seasonal use of resources for each scenario at a situation of resource distribution. Each ring represents a resource index organised as follows (from inside to outside): Land, water, labour and capital used, and profit; each slice corresponds to a decile of water availability (DI) (Source: Own elaboration)

2.3.1.1 Situation a

Figure 2.6 shows profits and seasonal use of resources at situation a. Scenarios 1 and 2 present the highest profits because these scenarios are subject to seasonal constraints, i.e., it is not relevant how resources are divided up in time. In these scenarios, restrictions are scalars instead of arrays, in contrast to monthly scenarios (3, 4, 5, and 6). Water is the limiting resource for these scenarios in decile 1, while capital from decile 2. The third scenario is subject to monthly constraints, and the higher the water supply, the higher the profits. In the fourth scenario, which considers water transactions, the area to be sowed does not increase as water supply increase, because of being limited mainly the labour availability in September, October, and March (Figure 2.11). Under the fifth scenario, which considers water storage, a similar behaviour is presented as in scenario 3, showing slightly greater profits, but lower than the fourth scenario, which includes water transactions. According to Arnell (2004); De Vries and Weatherhead (2005); Luo et al. (2010); Xu et al. (2016), water markets are regarded as an effective way for improving water-use benefits. The sixth scenario, which factors in both improvements in water resources management (water transactions and water storage) shows greater profits than the fifth scenario because it includes water markets.

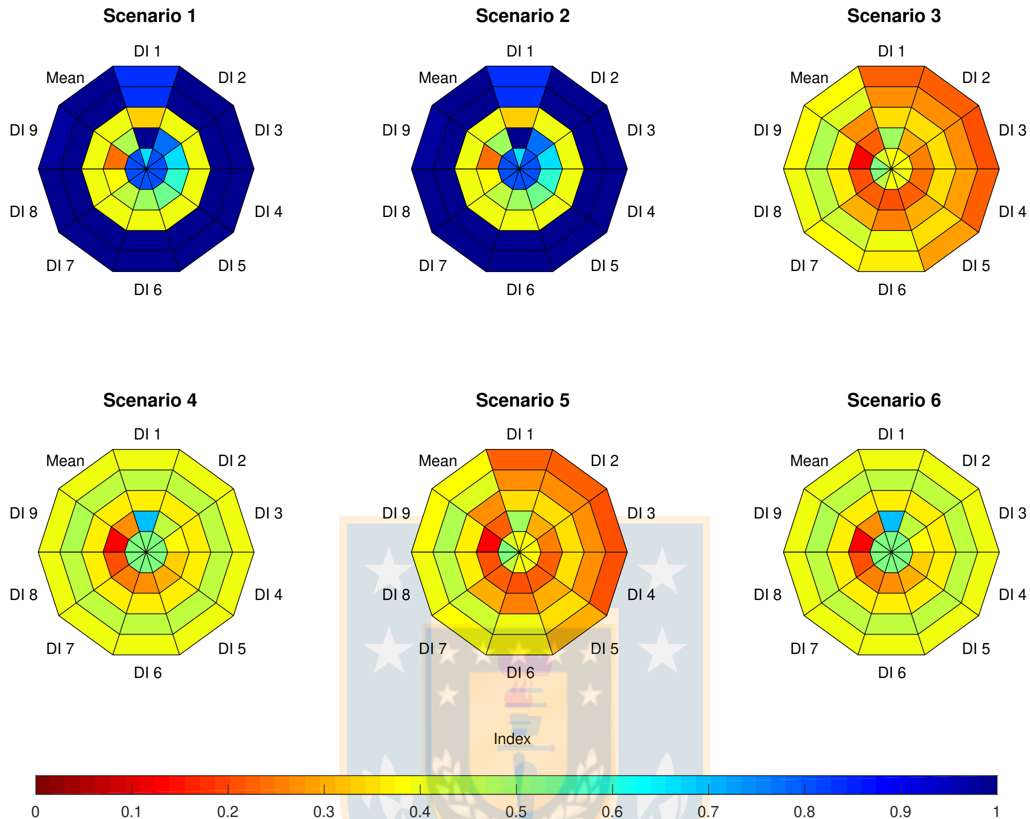

Figure 2.6: Profits and seasonal use of resources obtained from the optimisation process for each scenario at situation a. Each ring represents a resource index organised as follows (from inside to outside): Land, water, labour and capital used, and profit; each slice corresponds to a decile of water availability (DI) (Source: Own elaboration)

2.3.1.2 Situation b

Figure 2.7 shows profits and seasonal use of resources under situation b. Scenarios 1 and 2 present the same values as situation a. As mentioned before, because these scenarios are subject to seasonal constraints, it is not relevant how resources are divided over time. Regarding the third and fifth scenarios, more water availability means the higher the area to sow, water, labour, and capital used, as well as profits. As far as the fourth and sixth scenarios, profits are as high as seasonal scenarios (1 and 2) and in some cases, even better (in decile 1). Due to capital limitations, profits do not increase, in spite of having the chance to buy, sell, and store water. Carvallo et al. (1998) found that by reducing labour availability, profits were affected by almost 5%, compared to their optimum cropping pattern.

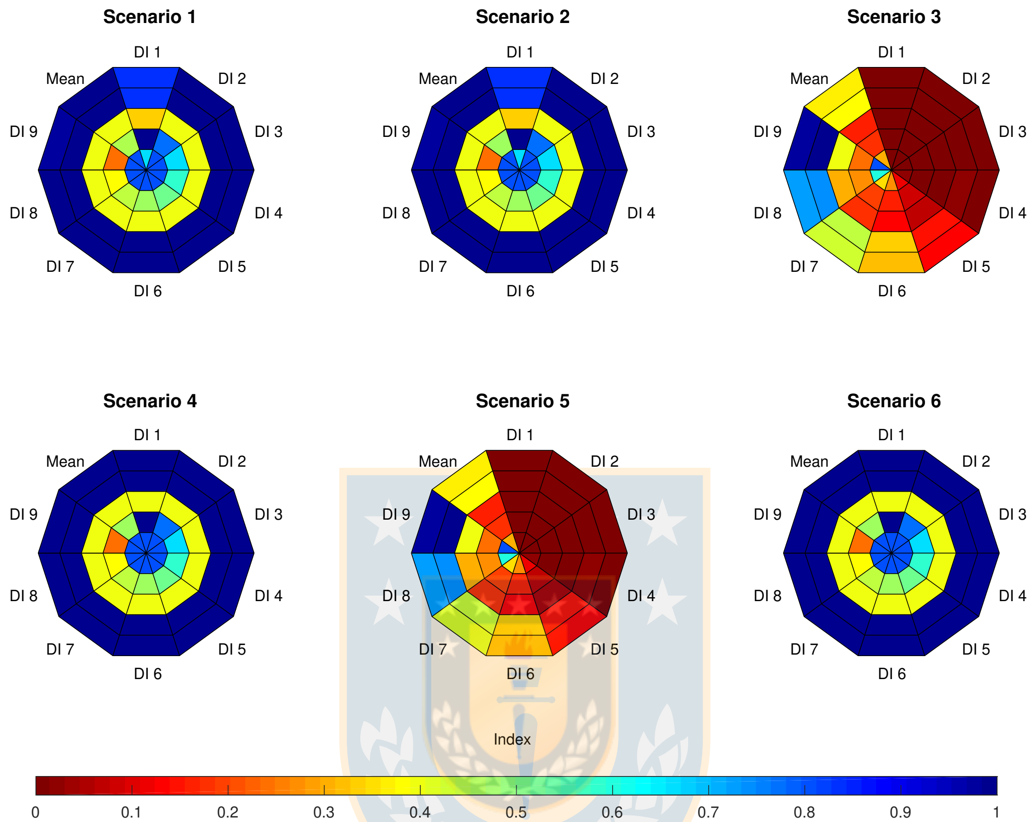

Figure 2.7: Profits and seasonal use of resources obtained from the optimisation process for each scenario at situation b. Each ring represents a resource index organised as follows (from inside to outside): Land, water, labour and capital used, and profit; each slice corresponds to a decile of water availability (DI) (Source: Own elaboration)

2.3.2 Crop Allocation

Figures 2.8 and 2.9 show the crop allocation suggested by the runs to obtain the highest profit.

2.3.2.1 Situation a

Figure 2.8 shows crop allocation for situation a. Scenarios 1 and 2 present the same results, sowing only sugar beet is the best choice, which requires low labour but high capital (Figure 2.3). Regarding the third and fifth scenario, sowing maize is the best choice for the first four deciles due to the low water availability and the sowing date of this crop (1 November). From decile 5, there is enough water in September, the month when sugar beet starts to grow. From the sixth decile, the area to plant with sugar beet continues to increase and the area to sow with alfalfa appears as an option, being a better choice than maize because this crop demands less capital (Figure 2.3). On the other hand, in the fourth and sixth scenarios, sugar beet is the main crop suggested because there is enough water for irrigation.

2.3.2.2 Situation b

Figure 2.9 shows crop allocation for situation b. Scenarios 1 and 2 present the same results as situation a. In the third and fifth scenarios, there is not enough water before decile 5. Compared to the situation a, there is lower labour availability in November, the month when maize could be sowed (Figure 2.3). However, after decile 5, there is enough water to irrigate sugar beet. As far as the fourth and sixth scenarios, sugar beet is the only suggested crop because of the possibility of having more water (water transactions and water storage).

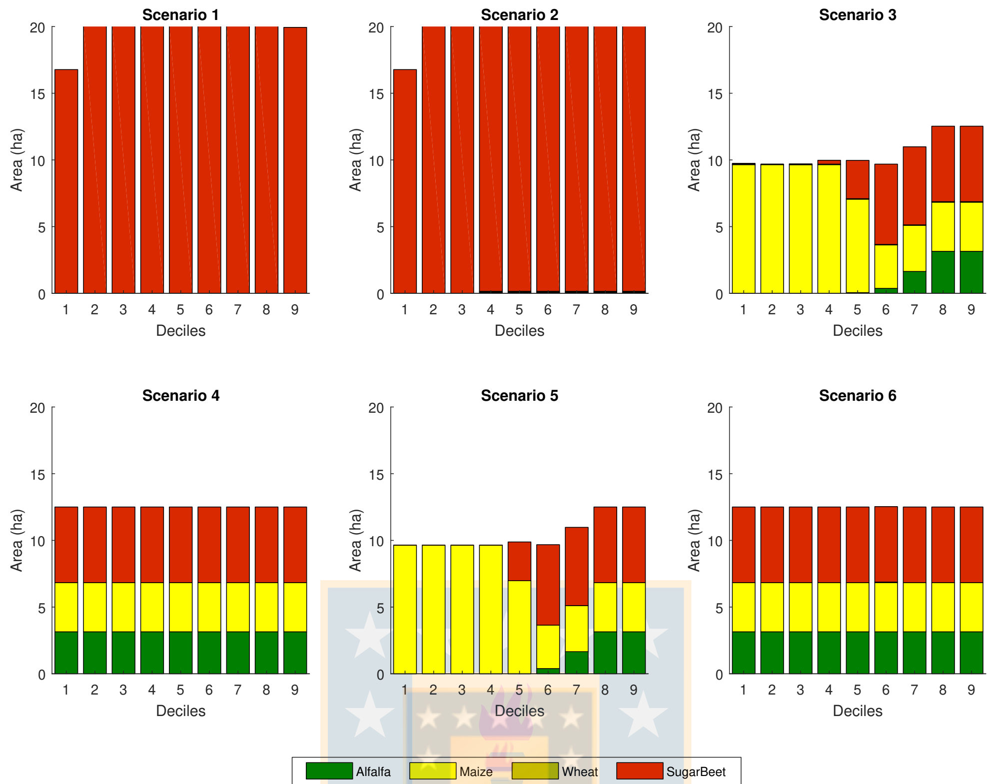

Figure 2.8: Crop allocation as a result of the optimisation processes for each decile of water supply and for each scenario at the situation a (Source: Own elaboration)

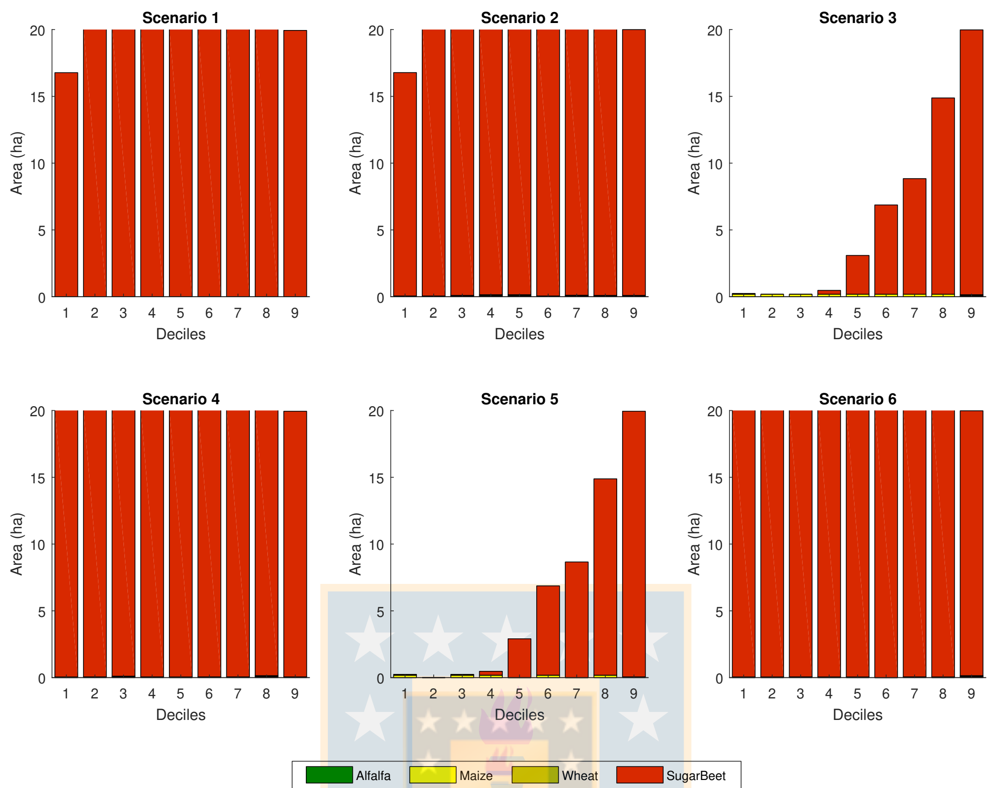

Figure 2.9: Crop allocation as a result of the optimisation processes for each decile of water supply and for each scenario at the situation b (Source: Own elaboration)

2.3.3 Monthly Limiting Resource

Figures 2.10 and 2.11 present resource availability for each month in order to find the monthly limiting resource. Labour and capital are relativized to consider an index number from 0 to 1. An index of 1 is used to represent the labour (300 person-day) and capital availability (80,000 US$). However, water availability indices depend on different scenarios. Regarding the third scenario which does not consider improvements in water resource management, an index of 1 represents the seasonal amount of water for every decile. For the fourth scenario, an index of 1 is considered to represent the maximum difference between income (water rights and water to buy) and outcome fluxes (water applied and water to sell). Regarding the last two scenarios, an index of 1 is considered to represent the maximum capacity of the reservoir (30,000 m^3).

2.3.3.1 Situation a

Figure 2.10 shows the monthly limiting resource presented as water, labour, and capital availability for situation a. Regarding the third scenario, which does not consider improvements in water resource management, water is the limiting resource in September for the first four deciles of water supply. For this reason, the model does not recommend establishing sugar beet. Also, during September, October, and March labour is the limiting resource for the most deciles of water supply.

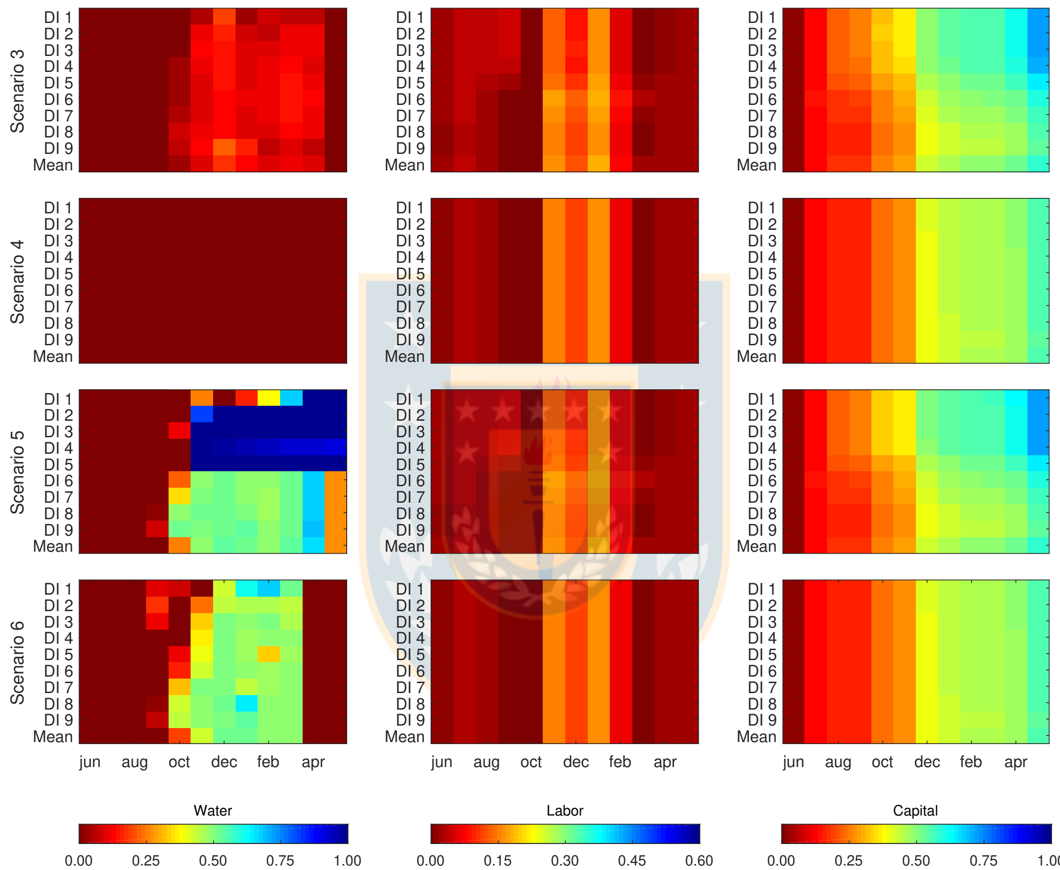

Figure 2.10: Monthly limiting resources presented as water, labour, and capital availability for each decile of water supply (DI) and for each monthly scenario (from 3 to 6) for situation a (see Section 2.3.3) (Source: Own elaboration)

2.3.3.2 Situation b

Figure 2.11 shows the monthly limiting resources presented as water, labour, and capital availability under situation b. In the third scenario, water is a limiting resource for the first four deciles of water supply. On the other hand, labour is also a limiting resource after October (as well as in scenarios 4, 5, and 6), which is a reason not to sow maize in this scenario (Figure 2.3). Analysing the capital, this resource is limiting for decile 9. For the fourth scenario, which considers water transactions, water and capital are limiting resources. The water constraint equation (Table 2.3), does not consider storage. Regarding the fifth scenario, which factors in water storage, water is the limiting resource in September. Moreover, starting from decile 4, water availability increases due to the capacity to store water; but because of the labour constraints, it is not feasible to increase profits. Regarding the sixth scenario, capital is the limiting resource. Therefore, under this scenario, profits do not increment in spite of higher water availability.

2.3.4 Sensitivity Analysis

Sensitivity analysis was carried out to test the proposed optimisation model. This analysis included the first (seasonal) and the sixth scenario (the monthly scenario which considers water transactions and storage). This latter was assessed by both situations of resource distribution (a and b).

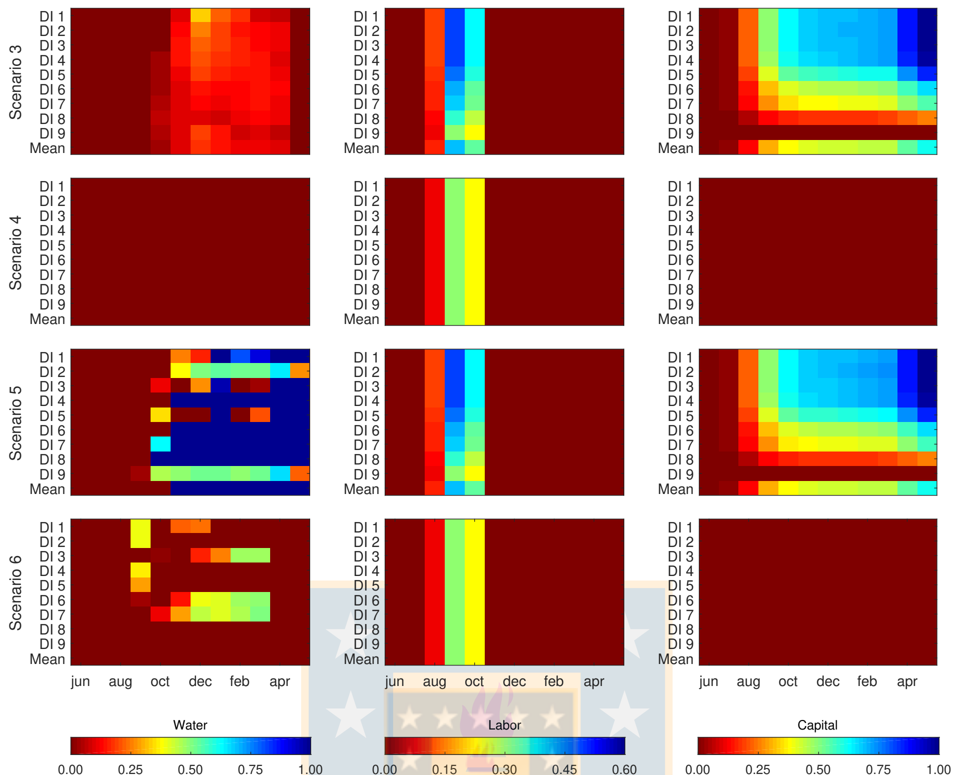

Figure 2.11: Monthly limiting resources presented as water, labour, and capital availability for each decile of water supply (DI) and for each monthly scenario (from 3 to 6) for situation b (see Section 2.3.3) (Source: Own elaboration)

2.3.4.1 Scenario 1

Table 2.4 shows the sensitivity analysis for the scenario 1. The best profit, according to the local conditions, corresponds to 45,917 US$, allocating only sugar beet. Under this regime, capital is the limiting resource. Changes in export prices do not affect profits when maize and wheat decrease and increase their values, respectively. A reduction of 50% in the export price of sugar beet means that the farmer must only establish maize. Consequently, profits reduce by about 42%. An increase of 50% in the export price of alfalfa means that this crop and sugar beet share the available land, raising profits by 13%. When the crop area consideration is taken into account, all crops share the available area. Although profits are reduced by 9%, it is recommended to sow more than one crop due to marketing, rotations, or other agricultural limitations (Carvallo et al., 1998; Das et al., 2015; Kipkorir et al., 2002; Mainuddin et al., 1997; Prasad et al., 2006; Singh, 2012, 2015; Varade and

Patel, 2018). By changing the irrigation system, i.e., sugar beet irrigated by furrow (AE = 0.60) instead of sprinkler (AE = 0.75), and wheat by sprinkler instead of furrow, profits are not affected due to that the model still suggests establish only sugar beet. Moreover, water is not the limiting resource, but capital. Consequently, water use increases by 25%. An increase in water costs means that profits are reduced by almost 60%. Here, the model recommends sowing only sugar beet. In this case, improvements in water resource management such as water transactions (Erfani et al., 2014; Garrick et al., 2009) and water storage (Cosgrove and Loucks, 2015; Iglesias et al., 2017) can be useful to mitigate this problem. An increase in labour costs does not considerably affect profits (4%) in comparison to the lack of labour availability. The latter reduces profits by 17%. Therefore, according to Carvallo et al. (1998), it is recommended to increase wages to avoid the lack of labour availability. Changes in other costs do not considerably affect profits when maize and wheat increase and decrease their values, respectively. An increment of 50% in the values for sugar beet means that the farmer sows only maize. Consequently, profits are reduced by about 43%. The same response happens when export prices for this crop decrease in 50%. A reduction of 50% in the export price for alfalfa means that this crop and sugar beet share the available land, raising profits by 10%. A decrease in capital availability reduces profits by more than 50%. For this reason, the model suggests sowing only sugar beet when capital is the limiting resource.

2.3.4.2 Scenario 6, Situation a

Sensitivity analysis for scenario 6, considering the distribution of resources for situation a is presented in Table 2.5. According to local conditions, the best choice is to allocate 3, 4, and 6 ha of alfalfa, maize, and sugar beet, respectively, resulting in profits of 18,754 US$. Changes in export prices considerably affect profits; sugar beet decreases its value by 50%, and consequently, profits are reduced by 85%. A decrease of 50% in the export price for maize means that alfalfa and sugar beet should be sowed, decreasing profits by almost 9%. When alfalfa price increases by 50%, this situation involves planting the same cropping pattern as the previous situation (reduction of 50% in the export price for maize) but profits increase by almost 20%. The reason is that the price of one of the recommended crops (alfalfa) increases, despite having the same resources consumption. When crop area is taken into account, all crops share the available area, but as a result, profits are reduced by 12%. By changing the irrigation system, profits are not considerably affected. Water use, however, increases by 12%. When water costs are high, profits are reduced by 33%. As mentioned before, an increase in labour costs does not considerably affect profits (6%) in comparison to the lack of labour availability (67%). Changes in other costs do not considerably affect profits when maize and wheat increase and decrease their values, respectively. A 50% increment of this value for sugar beet suggests that the farmer only sows 10 ha of maize, reducing profits by 44%. A 50% reduction in the export price of alfalfa leads to a rise in profits of 10%. When capital availability decreases by 50%, profits are reduced by nearly 12%. In this case, the model suggests sowing 3 and 6 ha of alfalfa and sugar beets, respectively.

2.3.4.3 Scenario 6, Situation b

Table 2.6 shows the sensitivity analysis for scenario 6, considering the resources distribution for situation b. The best profits, according to the local conditions are 46,177 US$, 0.57% higher than the seasonal scenario and 146% higher than the situation a. The latter is due to the monthly distribution of resources. According to the resource distribution of labour and capital, sugar beet is the only feasible crop to be sowed. Therefore, a reduction of 50% in the export price of this crop results in no positive returns due to costs of water rights, which farmers must pay if they use them or not. When crop area is taken into account, the model suggests establishing a minimum of 3 ha of each crop, reducing profits by 84%. However, this is an infeasible solution; sugar beet is the only feasible crop to be established for this situation of resource distribution. When water costs are high, profits decrease by 30%. That is only 50% compared to scenario 1, which does not consider water transactions. An increment of labour costs does not considerably affect profits (5%) in comparison to the lack of labour availability (18%). On the other hand, if other costs of sugar beet increase by 50%, profits decrease by almost 90%. As in the first scenario, a decrease in capital availability reduces profits by more than 50%.

Table 2.4: Sensitivity analysis for scenario 1 (Source: Own elaboration)

	Crop Allocation				Use of Resources				
	Alfalfa	Maize	Wheat (ha)	Sugar Beet	Land (ha)	Water (m^3)	Labor (Person-d)	Capital (US$)	Profits (US$)
1. Optimum cropping pattern	0	0	0	20	20	167,477	120	80,000	45,917
2. Export prices									
2.1 Decrease in 50% for sugar beet	0	25	0	0	25	172,417	267	57,114	26,671
2.2 Decrease in 50% for maize	0	0	0	20	20	167,477	120	80,000	45,917
2.3 Increase in 50% for alfalfa	8	0	0	17	25	201,623	192	80,000	51,708
2.4 Increase in 50% for wheat	0	0	0	20	20	167,477	120	80,000	45,917
3. Agronomic management									
3.1 Minimum area to be sowed corresponds to 3 ha	3	3	3	16	25	196,754	178	79,578	41,695
4. Application efficiency of the irrigation system									
4.1 Sugar beet is irrigated by furrow ($AE = 0.60$) and wheat by sprinkler ($AE = 0.75$)	0	0	0	20	20	209,346	120	80,000	45,917
5. Water costs									
5.1 Costs of water rights increase to 0.05 US$/$m^3$	0	0	0	16	16	131,010	94	80,000	18,500
6. Labour									
6.1 Costs increase to 30 US$/person-d	0	0	0	20	20	164,974	119	80,000	44,036
6.2 Availability decreases to 100 person-d	0	0	0	17	17	139,015	100	66,502	38,017
7. Other costs									
7.1 Increase in 50% for sugar beet	0	25	0	0	25	172,417	267	57,114	26,671
7.2 Increase in 50% for maize	0	0	0	20	20	167,477	120	80,000	45,917
7.3 Decrease in 50% for alfalfa	6	0	0	19	25	203,014	184	80,000	50,321
7.4 Decrease in 50% for wheat	0	0	6	19	25	198,643	146	80,000	47,781
8. Capital									
8.1 Availability decreases to 50%	0	0	0	10	10	83,136	60	40,000	22,506

Table 2.5: Sensitivity analysis for scenario 6, situation a (Source: Own elaboration)

	Crop Allocation				Use of Resources				
	Alfalfa	**Maize**	**Wheat (ha)**	**Sugar Beet**	**Land (ha)**	**Water (m^3)**	**Labor (Person-d)**	**Capital (US$)**	**Profits (US$)**
1. Optimum cropping pattern	3	4	0	6	13	96,212	109	36,000	18,754
2. Export prices									
2.1 Decrease in 50% for sugar beet	5	0	0	0	5	37,995	58	8098	2805
2.2 Decrease in 50% for maize	5	0	0	6	11	89,835	95	32,687	17,122
2.3 Increase in 50% for alfalfa	5	0	0	6	11	89,835	95	32,687	22,349
2.4 Increase in 50% for wheat	3	4	5	4	16	114,625	125	36,687	19,046
3. Agronomic management									
3.1 Minimum area to be sowed corresponds to 3 ha	3	4	3	5	14	107,854	119	36,434	16,578
4. Application efficiency of the irrigation system									
4.1 Sugar beet is irrigated by furrow ($AE = 0.60$) and wheat by sprinkler ($AE = 0.75$)	3	4	0	6	13	108,040	109	36,000	18,737
5. Water costs									
5.1 Costs of water rights increase to 0.05 US$/$m^3$	3	4	0	6	13	96,212	109	53,350	12,505
6. Labour									
6.1 Costs increase to 30 US$/person-d	3	4	0	6	13	96,212	109	37,091	17,662
6.2 Availability decreases to 100 person-d	1	1	0	2	4	32,071	36	12,380	6204
7. Other costs									
7.1 Increase in 50% for sugar beet	0	10	2	0	12	81,744	115	25,683	10,416
7.2 Increase in 50% for maize	5	0	0	6	11	89,835	95	32,687	17,122
7.3 Decrease in 50% for alfalfa	3	4	0	6	13	96,212	109	34,032	20,722
7.4 Decrease in 50% for wheat	3	4	0	6	13	96,212	109	36,000	18,754
8. Capital									
8.1 Availability decreases to 50%	3	0	0	6	10	79,035	78	30,922	16,577

Table 2.6: Sensitivity analysis for scenario 6, situation b (Source: Own elaboration)

	Crop Allocation				Use of Resources				
	Alfalfa	Maize	Wheat (ha)	Sugar Beet	Land (ha)	Water (m^3)	Labor (Person-d)	Capital (US$)	Profits (US$)
1. Optimum cropping pattern	0	0	0	20	20	167,460	120	80,000	46,177
2. Export prices									
2.1 Decrease in 50% for sugar beet	0	0	0	0	0	0	0	572	−71
2.2 Decrease in 50% for maize	0	0	0	20	20	167,460	120	80,000	46,177
2.3 Increase in 50% for alfalfa	0	0	0	20	20	167,739	121	80,000	46,224
2.4 Increase in 50% for wheat	0	0	0	20	20	167,760	121	79,958	46,135
3. Agronomic management									
3.1 Minimum area to be sowed corresponds to 3 ha	3	3	3	5	14	101,803	113	36,395	7464
4. Application efficiency of the irrigation system									
4.1 Sugar beet is irrigated by furrow ($AE = 0.60$) and wheat by sprinkler ($AE = 0.75$)	0	0	0	20	20	209,292	120	80,000	46,108
5. Water costs									
5.1 Costs of water rights increase to 0.05 US$/$m^3$	0	0	0	17	17	143,133	103	77,493	32,014
6. Labour									
6.1 Costs increase to 30 US$/person-d	0	0	0	20	20	163,870	118	79,363	43,920
6.2 Availability decreases to 100 person-d	0	0	0	16	16	137,558	99	65,815	37,919
7. Other costs									
7.1 Increase in 50% for sugar beet	0	0	0	13	14	112,451	82	79,277	5221
7.2 Increase in 50% for maize	0	0	0	20	20	167,433	121	79,988	46,074
7.3 Decrease in 50% for alfalfa	0	0	0	20	20	168,256	122	79,980	46,268
7.4 Decrease in 50% for wheat	0	0	0	20	20	168,256	122	79,980	46,268
8. Capital									
8.1 Availability decreases to 50%	0	0	0	10	10	83,074	60	39,972	22,872

2.4 Conclusions

We developed a monthly optimisation model to obtain an optimum cropping pattern and monthly water allocation for irrigated agriculture under Chilean conditions. The objective function included a monthly crop yield model, which was developed from the Raes et al. (2006) equation, being a valid alternative for handling resources on a monthly timescale. This model also included monthly water transactions as a decision variable (besides cropping pattern and monthly water allocation for crops), giving the possibility to farmers to buy water (to increase the irrigated area) and to sell water (when not using it) to improve their profits. Regarding our results, optimizing resources on a monthly basis attained higher profits as it allowed farmers to tailor their management practices and manage costs to cope with less available resources.

Scenarios based on single run optimisation at the beginning of the season assume that how resources are distributed in time is not significant, or that resources will be available. However, this approach does not account for intraseasonal changes. Thus, in seasonal-based scenarios, water is the limiting resource when available water is less than the requirements for the whole season. In the studied monthly scenarios, which include improvements in water resource management (such as water transactions and water storage), the model not only attains higher profits (even better than the seasonal approaches), but also decreases uncertainty and improves risk management. The main advantage of considering a multiperiod model is that is the best option for coping with seasonal changes because income is received from crop production and water transactions. When water transactions are taken into account, labour is the main limiting resource. According to sensitivity analysis, it is not always feasible to consider crop area criteria due to resource distribution (Table 2.6). On the other hand, when water costs are high, water transactions could reduce losses by up to 50%. As far as labour, the lack of availability is more critical than wages. Future studies should focus on the estimation of the yield response factor (*Ky*) under local conditions in order to include them in the proposed monthly optimisation model.

Seasonal scenarios for crop management are highly beneficial because they consider that certain resources are only available at the start of the season (the timescale "growing season" is longer than monthly). On the other hand, monthly scenarios increase profits when they consider improvements in water resource management, such as water transactions and water storage.

Chapter 3

Estimation of yield response factor under local conditions using AquaCrop

Kuschel-Otárola, M., Schütze, N., Holzapfel, E., Godoy-Faúndez, A., Mialyk, O., Rivera, D. (2019). Estimation of yield response factor for each growth stage under local conditions using AquaCrop-OS. *Submitted to Agricultural Water Management*.

Abstract

We propose a methodology to estimate the yield response factor (slope of the water-yield function) under local conditions for a given crop, weather, sowing date and management for each growth stage using AquaCrop-OS. The methodology was applied to three crops (maize, sugar beet and wheat) and four soil types (clay loam, loam, silty clay loam and silty loam) considering three levels of bulk density: low, medium and high. Yields were estimated for different weather and management scenarios using a problem-specific algorithm for optimal irrigation scheduling with limited water supply (GET-OPTIS). Results show a good agreement between benchmarking (mathematical approach) and benchmark (estimated by AquaCrop-OS) using the Normalised Root Mean Square Error (NRMSE), allowing to estimate reliable yield response factors (Ky) under local conditions and to dispose of a simple mathematical approach which estimates the yield reduction as a result of water scarcity for each growth stage.

3.1 Introduction

Water is the main factor for crop development. In the world, irrigated agriculture uses about 70% of the available fresh water resources (FAO, 2016), so improving its management will increase water use efficiency (WUE), defined as the amount of water necessary to achieve a given yield (Hubick et al., 1986). According to Saccon (2017), effective planning and management of water for crop production requires a deep knowledge of the system, as experimental results are generally site specific and are not applicable to different conditions of weather, soil, crops and management. Carrying out field experiments are expensive, laborious (Malik et al., 2017) and time-consuming.

To address the above concerns, the Food and Agriculture Organization of the United Nations (FAO) developed the AquaCrop model (Steduto et al., 2009). This model simulates attainable yields of crops as a function of water consumption under rainfed, supplemental, deficit, and full irrigation conditions and has been used to determine accurately crop yield in maize (Heng et al., 2009; Nyakudya and Stroosnijder, 2014; Paredes et al., 2014), wheat (Andarzian et al., 2011; Mkhabela and Paul, 2012; Toumi et al., 2016), sugar beet (Alishiri et al., 2014; Malik et al., 2017; Stricevic et al., 2011), potatoes (Garcia-Vila and Fereres, 2012; Montoya et al., 2016), barley (Araya et al., 2010), quinoa (Geerts et al., 2009) and rice (Maniruzzaman et al., 2015). AquaCrop has also been linked to crop production functions (Banihabib et al., 2016; Carvallo et al., 1998; Doorenbos and Kassam, 1979; Jensen, 1968; Kipkorir et al., 2002; Kuschel-Otárola et al., 2018; Raes et al., 2006; Schütze et al., 2012; Singh, 2012) that relate yield reduction as a result of the relative loss in evapotranspiration (Steduto et al., 2012).

For yield reduction due to water stress, Doorenbos and Kassam (1979) proposed:

$$1-\frac{Y}{Ym}=Ky\left(1-\frac{ETa}{ETc}\right) \tag{3.1}$$

where Y and Ym are actual and maximum crop yield, respectively. ETa and ETc corresponds to actual and maximum evapotranspiration, respectively. The coefficient Ky denotes the yield response factor, which relates the yield reduction $(1-Y/Y_m)$ to water stress $(1-ET_a/ET_c)$ for a given environment (Raes et al., 2006).

In the literature, researchers have included the multiplicative approach of the equation proposed by Doorenbos and Kassam (1979) (Karamouz et al., 2010; Kuschel-Otárola et al., 2018; Raes et al., 2006). This approach relates the crop yield reduction as a function of the water stress for specific growth stages. According to Shrestha et al. (2010), with the rise in average yields and the increase in sensitivity to water stress of crops, the coefficients *Ky* need to be updated. In the literature, *Ky* values have been estimated for maize, wheat and sugar beet. For maize, Kresović et al. (2016) assessed the effects of different irrigation amounts, estimating grain yield functions depending on seasonal irrigation and water consumption. The latter depends on seasonal *Ky*. Djaman et al. (2013) measured and evaluated crop response to several variables under different levels of irrigation, quantifying seasonal values of *Ky*. With respect to sugar beet, Kiymaz and Ertek (2015) determined the effect of different irrigation and nitrogen levels on yield and other components, obtaining *Ky* for 2 growing seasons. Tarkalson et al. (2018) quantified the yield response to water input and actual evapotranspiration. They also obtained *Ky* for 2 growing seasons. Regarding wheat, Bandyopadhyay et al. (2010) analysed the effect of different combinations of sprinkler and surface flooding on crop production functions, obtaining *Ky* for each irrigation treatment and Liu et al. (2013) evaluated the winter wheat performance under different irrigation amounts, estimating *Ky* for four growing seasons.

Foster et al. (2017) developed the AquaCrop-OS model, an open source code which was written in MATLAB, giving the opportunity to link this with other concepts to assess farming scenarios. Considering the importance of the sub-seasonal application of water in food production, we defined the following research question: Is it possible to incorporate the multiplicative approach of Doorenbos and Kassam (1979) into AquaCrop-OS, in order to estimate *Ky* at each growth stage? Therefore, the main objective was to develop and test a methodology to estimate *Ky* under local conditions for a given crop, soil, weather, sowing date and management for each growth stage using AquaCrop-OS. Reliable *Ky* values under local conditions for each growth stage allows farmers to decrease uncertainty and improve risk management due to intraseasonal changes.

3.2 Methodology

Our proposed methodology aims to include the AquaCrop-OS model into the multiplicative approach of Doorenbos and Kassam (1979). The objective is to determine *Ky* under local conditions (for a given crop, soil, weather, sowing date and management) for each growth stage.

3.2.1 Crop yield equation

The multiplicative approach of the equation proposed by Doorenbos and Kassam (1979) (Equation (3.1)) is:

$$\frac{Y}{Ym} = \prod_{n=1}^{N} \left[1 - Ky_n \left(1 - \frac{ETa_n}{ETc_n} \right) \right] \tag{3.2}$$

where n is the index representing each growth stage and N corresponds to the number of functions between square brackets (Raes et al., 2006).

3.2.2 Estimation of Ky using AquaCrop-OS

This section was developed in MATLAB and splits into two parts: A benchmark definition and a benchmarking (Figure 3.1).

As a benchmark definition, we started with a database of historical weather scenarios for a given area, where for each year, the water-yield functions (WYF) were determined using AquaCrop-OS (Foster et al., 2017) and a problem-specific algorithm for optimal irrigation scheduling with limited water supply. This is named Global Evolutionary Technique for OPTimal Irrigation Scheduling (GET-OPTIS) (Schütze et al., 2012). The main objective of GET-OPTIS is to maximise the crop yield (Y) by finding an optimal irrigation schedule (S) composed by the date (d_i) and the irrigation depth (v_i).

$$\begin{aligned} Y^* &= max\, Y\left(S\right) : S = \left\{s_i\right\}_{i=1\ldots n} \\ &= \left\{\left(d_1, v_1\right), \ldots, \left(d_i, v_i\right), \ldots, \left(d_n, v_n\right)\right\} n, d_i \in \mathbb{N}; v_i \in \mathbb{R} \end{aligned} \tag{3.3}$$

This process required high computational efforts due to building 34,020 scenarios (21 points for 45 years, 3 crops and 12 soil types). So, we used parallel run mode in MATLAB R2017a (MathWorks, 2017). Parallel computing allows to carry out many calculations simultaneously, accelerating the code runs. Once the WYFs were built, Ky values (slope of WYF) were estimated considering the Equation (3.2) through the least square method for each growth stage; (1) emergency or transplant recovery, (2) vegetative stage, (3) flowering stage, and (4) yield formation and ripening (Raes et al., 2012). Finally, we considered discrete mean values of Ky every 5 years. It should be noted that there is no measured data used in this case, and the simulation results from AquaCrop-OS is used as comparison benchmark for evaluation.

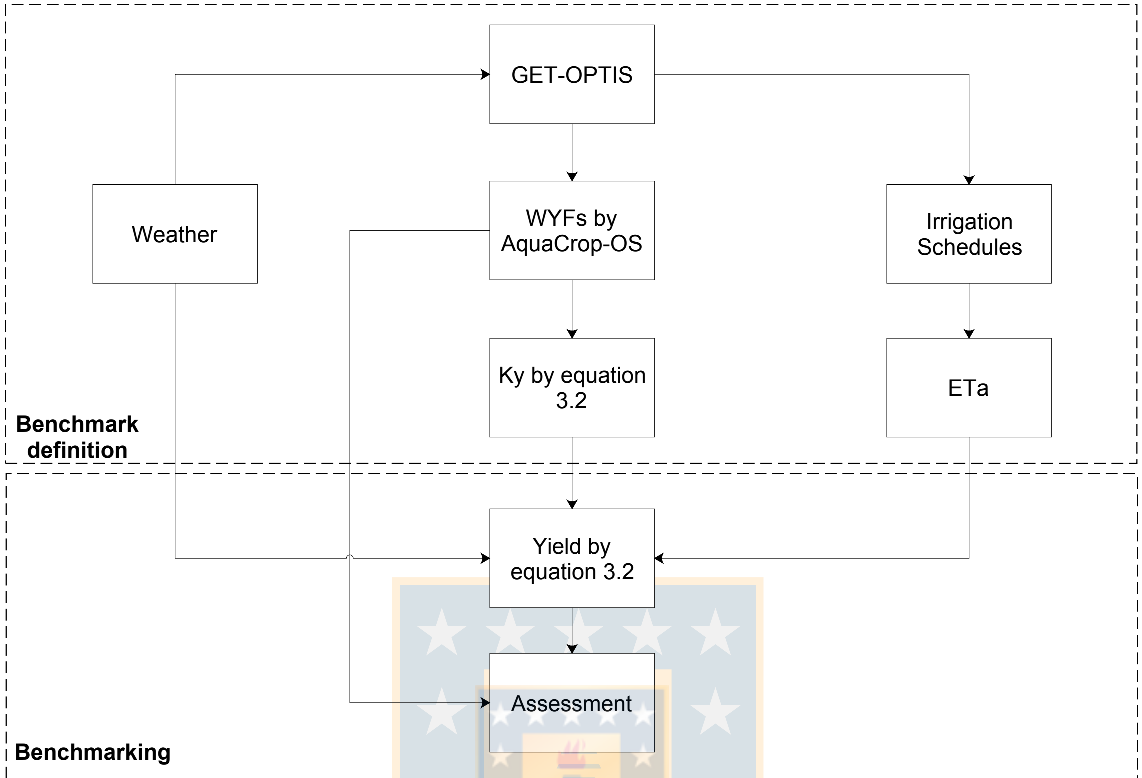

Figure 3.1: The methodology used for this research to estimate *Ky* values for each growth stage under local conditions (for a given crop, soil, weather, sowing date and management) using AquaCrop-OS (Source: Own elaboration)

The benchmarking was carried out by determining crop yield using the Equation (3.2) considering *Ky* values for each combination of crop, soil type and weather scenario for each year. Different statistic indices were used, such as Normalized Root Mean Square Error (NRMSE) and linear regression for comparison of the results obtained from AquaCrop-OS and estimated using the proposed methodology. The NRMSE (in %) was calculated according to Loague and Green (1991):

$$NRMSE = \left[\sqrt{\frac{\sum_{s=1}^{S} \left(Y_{AOS,k} - Y_{Prop,k}\right)^2}{S}} \right] \times \frac{100}{\overline{Y_{AOS,k}}} \tag{3.4}$$

where $Y_{AOS,k}$ and $Y_{Prop,k}$ correspond respectively to the crop yield estimated by AquaCrop-OS and the proposed methodology for the year k and $\overline{Y_{AOS,k}}$ represents the mean value of the crop yields estimated by AquaCrop-OS for the year *k*. The simulation is considered excellent if the NRMSE is less than 10%, good if the NRMSE is greater than 10% and less than 20%, fair if NRMSE is greater than 20% and less than 30%, and poor if the NRMSE is greater than 30% (Jamieson et al., 1991).

3.2.3 Case study

Our proposed model was applied to conditions characteristic of the Central Valley of Chile (Figure 3.2). Annual mean precipitation for this area is about 1,025 mm, and the average maximum and minimum temperatures are 20.6 and 7.6°C, respectively (DGA, 2004). This region contains about 28% of the national cropping area. Some of the most produced crops are wheat (34.3%), maize (11.6%) and sugar beet (6%), which contribute to the national planted surface with 27.9, 22.5 and 60%, respectively (ODEPA, 2018). The soils are formed from volcanic ashes (Andisols) deposited over a nonrelated substrate of andesitic tuff and fluvioglacial materials. The texture is predominately silty clay loam, silty loam, and loam and the bulk density ranges from 0.71 to 1.35 Mg m^{-3} (Granda et al., 2013; Rivera et al., 2011, 2015).

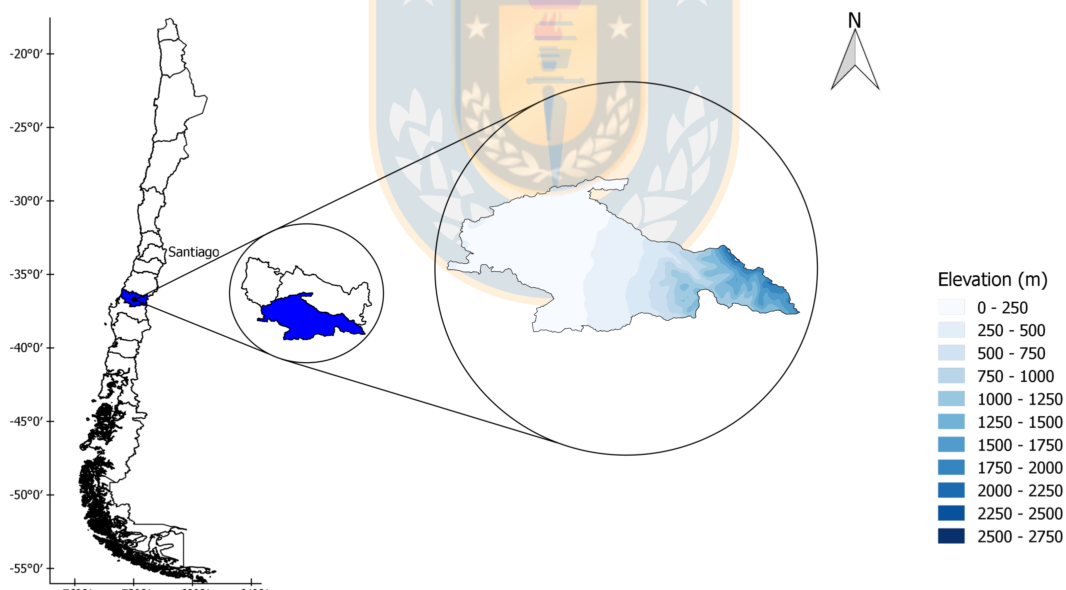

Figure 3.2: Study area location (Source: Own elaboration)

3.2.4 Model inputs

Sowing dates for maize, wheat and sugar beet for each year correspond to the first day of November, September and August, respectively (Faiguenbaum, 2003). A weather database from 1970 to 2014 (Figure 3.3) was extracted from the Explorador Climático website (http://explorador.cr2.cl/). Reference evapotranspiration was estimated according to Allen et al. (2005). Crops parameters were considered from the AquaCrop-OS (Foster et al., 2017) database (Table 3.1). On the other hand, soil hydraulic parameters (Table 3.2) were extracted from Granda et al. (2013) and saturated hydraulic conductivity was estimated using the RETC model (van Genuchten et al., 1991). For soils, numbers 1, 2 and 3 correspond to low, medium and high bulk density, respectively. Each growing season started with a 50% of the total available water.

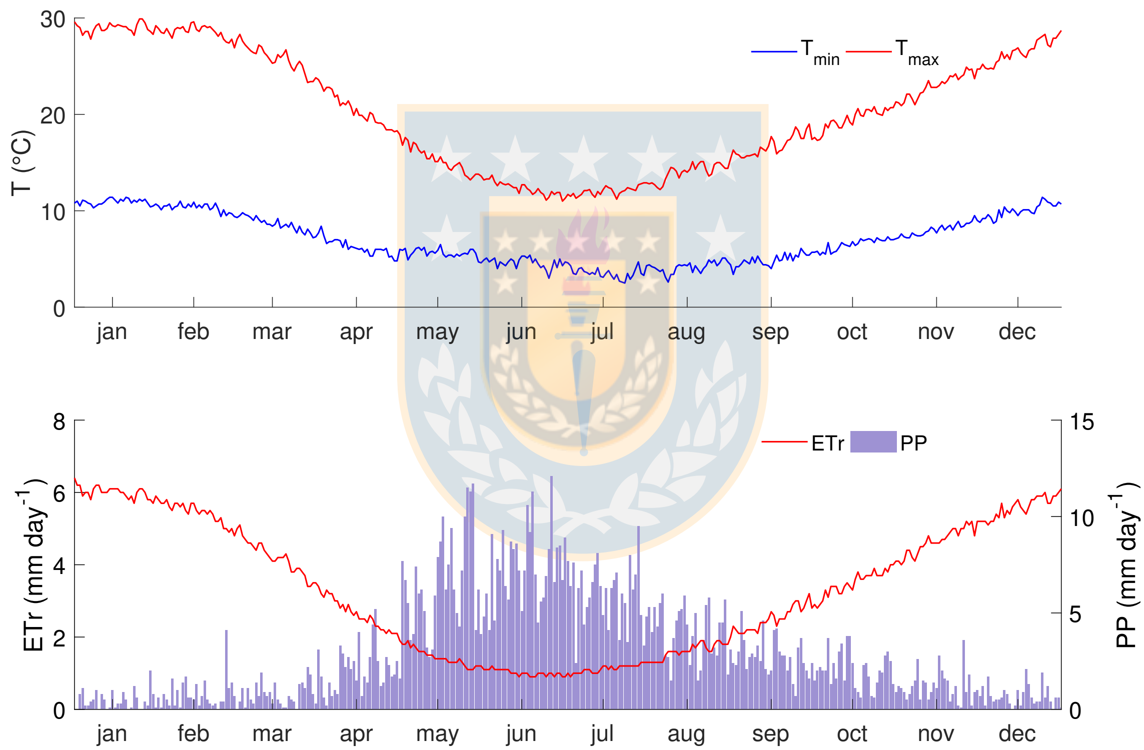

Figure 3.3: Minimum and maximum temperature (T_{min} and T_{max}), reference evapotranspiration (ETr) and precipitation (PP) for the study area, presented as mean values from 1970 to 2014 (Source: Own elaboration)

Table 3.1: Conservative (constant) and generally applicable parameters for maize, sugar beet and wheat in the Central Valley of Chile (Source: Own elaboration)

Parameter	Crop		
	Maize	Sugar beet	Wheat
Conservative (generally applicable)			
Base temperature (°C)	8.00	5.00	0.00
Cut-off temperature (°C)	30.00	30.00	26.00
Canopy cover per seedling at 90% emergence (CC_o)	6.50	1.00	1.50
Canopy growth coefficient (CGC)	1.25	1.05	0.50
Maximum canopy cover (CCx)	96.00	98.00	96.00
Crop coefficient for transpiration at CC = 100%	1.05	1.10	1.10
Decline in crop coef. after reaching CCx	0.30	0.15	0.15
Canopy decline coefficient (CDC) at senescence	1.00	0.39	0.40
Water productivity, normalized to year 2000 (WP*)	33.70	17.00	15.00
Leaf growth threshold (P_{upper})	0.14	0.20	0.20
Leaf growth threshold (P_{lower})	0.72	0.60	0.65
Leaf growth stress coefficient curve shape	2.90	3.00	5.00
Stomatal conductance threshold (P_{upper})	0.69	0.65	0.65
Stomata stress coefficient curve shape	6.00	3.00	2.50
Senescence stress coefficient (P_{upper})	0.69	0.75	0.70
Senescence stress coefficient curve shape	2.70	3.00	2.50
Considered to be conservative but can or may be cultivar-specific			
Reference harvest index (HI_o)	48	70	48
GDD from 90% emergence to start of anthesis	800	842	1100
Duration of anthesis, in GDD	180	0	200
Coefficient, inhibition of leaf growth on HI	7	4	10
Coefficient, inhibition of stomata on HI	3	-	7

Table 3.2: Bulk density (ρ_a), saturation (θ_s), field capacity (θ_{fc}), and permanent wilt water content (θ_{pwp}) and saturated hydraulic conductivity (K_s) representative of Central Valley of Chile (Source: Own elaboration)

Soil	Sand	Silt (%)	Clay	ρ_a (g cm^{-3})	θ_s	θ_{fc} (m^3 m^{-3})	θ_{pwp}	K_s (mm day^{-1})
ClayLoam 1	22	48	30	0.72	0.73	0.45	0.30	3415.9
ClayLoam 2	35	38	27	0.97	0.64	0.57	0.33	269.1
ClayLoam 3	39	28	33	1.39	0.47	0.34	0.26	132.4
Loam 1	34	42	24	0.71	0.73	0.44	0.28	3517.8
Loam 2	31	46	23	1.07	0.60	0.59	0.40	69.5
Loam 3	41	37	22	1.13	0.57	0.55	0.34	110.3
SiltyClayLoam 1	10	52	38	0.78	0.70	0.46	0.32	2382.0
SiltyClayLoam 2	11	52	37	0.81	0.69	0.50	0.32	1903.3
SiltyClayLoam 3	15	49	36	0.86	0.68	0.50	0.36	1534.2
SiltyLoam 1	27	50	23	0.71	0.73	0.44	0.28	3571.7
SiltyLoam 2	22	51	27	0.98	0.63	0.59	0.38	183.9
SiltyLoam 3	24	51	25	1.03	0.61	0.59	0.44	76.3

3.3 Results and discussions

3.3.1 Yield response factor for each growth stage

Ky for each growth stage (emergency or transplant recovery, vegetative stage, flowering stage, and yield formation and ripening) are presented in form of box plots for maize, sugar beet and wheat (Figure 3.4, 3.5 and 3.6, respectively). These figures represent *Ky* as discrete mean value every 5 years for benchmarking, i.e., 1970-1974, 1975-1979, 1980-1984, 1985-1989, 1990-1994, 1995-1999, 2000-2004, 2005-2009 and 2010-2014 for different soil types of the study area with low (1), medium (2) and high (3) bulk density (Table 3.2) considering optimal irrigation scheduling (GET-OPTIS). On each box, the central mark indicates the median, and the bottom and top edges of the box indicate the 25th and 75th percentiles, respectively. The whiskers extend to the most extreme data points not considered outliers, and the outliers are plotted individually using the "+" symbol.

3.3.1.1 Yield response factor for maize

Figure 3.4 shows Ky values for maize for each growth stage and for each soil with low (1), medium (2) and high (3) bulk density. According to Steduto et al. (2012), $Ky > 1$ implies that crop response is very sensitive to water deficit, $Ky < 1$ means that crop is more tolerant to water deficit and $Ky = 1$ corresponds to a direct proportion of yield reduction to reduced water use. Ky for the first growth stage is close to zero for all soil types. On the other hand, this value always reaches its maximum in the third growth stage (flowering). These values range from 0.9 to 1.4, indicating that maize in this stage is very sensitive to water deficit. Thus, water stress during this stage allows larger reductions than other stages (Doorenbos and Kassam, 1979; Steduto et al., 2012). For clay loam soil, the higher the bulk density, the lower Ky for the third growth stage is. With the exception of the fourth growth stage, the obtained values are lower than those proposed by FAO (2017).

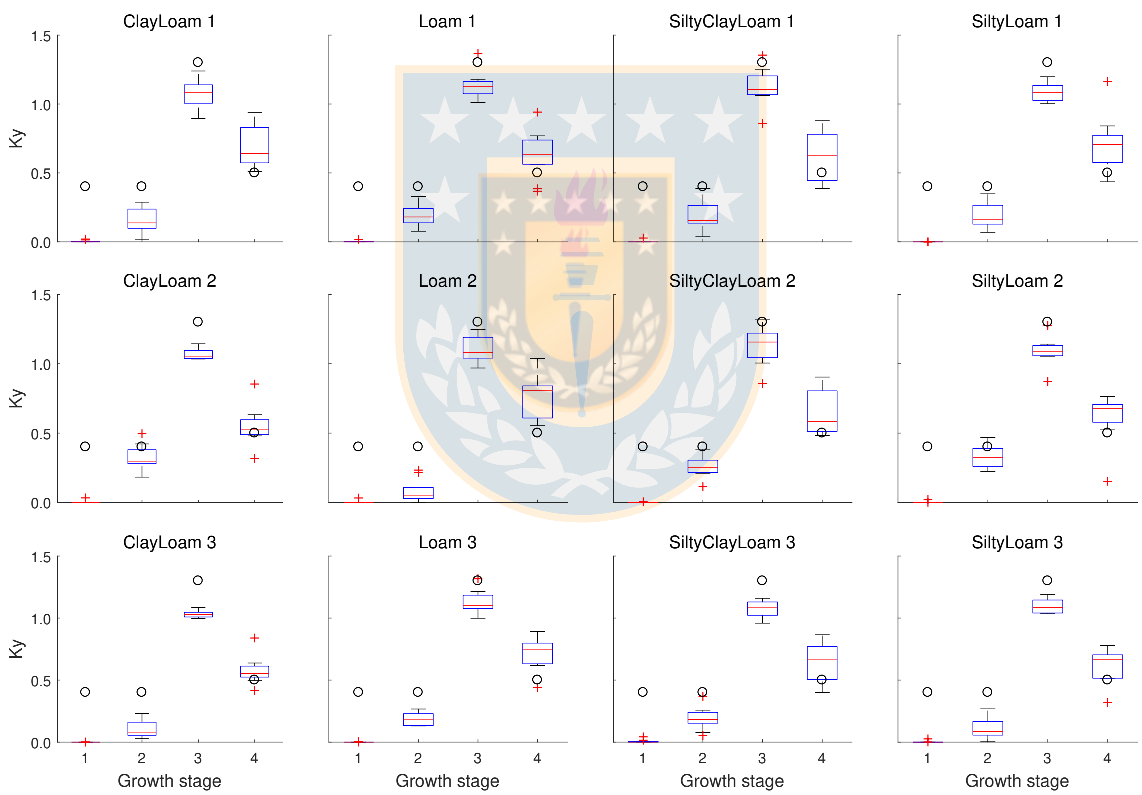

Figure 3.4: Yield response factor (Ky) obtained for maize for every soil type considering the benchmark process. Circles represent Ky values proposed by FAO (2017) (Source: Own elaboration)

3.3.1.2 Yield response factor for sugar beet

Figure 3.5 shows *Ky* values for sugar beet for each growth stage and for each soil type. Similarly to the results obtained for maize (Figure 3.4), *Ky* for the first growth stage is close to zero for all soil types, indicating that yield is not affected when there is enough water in the soil profile. *Ky* reaches the maximum value in the third growth stage for the most soil types, except for clay loam soil with high bulk density, where this value is the lowest compared to other soils types. Besides, this soil type presents the highest value for the second and fourth growth stage. The obtained values are lower compared to those proposed by FAO (2017) for each growth stage.

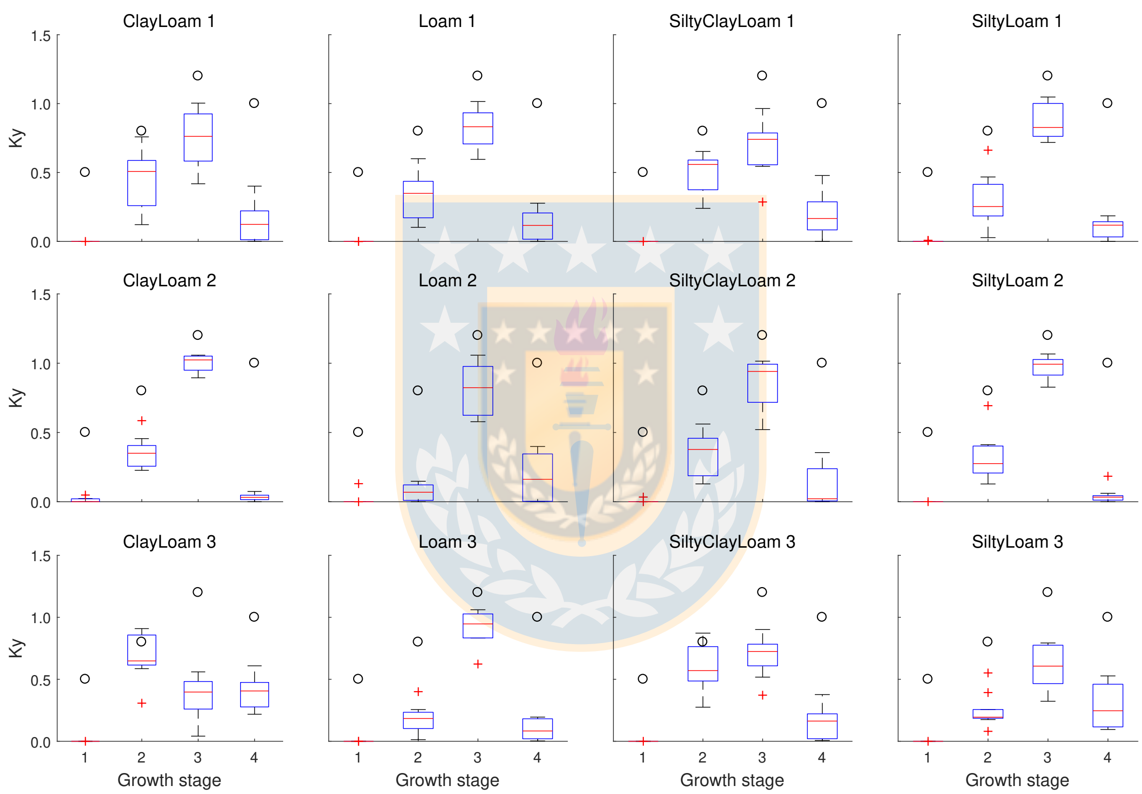

Figure 3.5: Yield response factor (*Ky*) obtained for sugar beet for every soil type considering the benchmark process. Circles represent *Ky* values proposed by FAO (2017) (Source: Own elaboration)

3.3.1.3 Yield response factor for wheat

Figure 3.6 shows *Ky* values for sugar beet for each growth stage and for each soil type. Similarly to the results obtained for maize (Figure 3.4) and sugar beet (Figure 3.5), *Ky* for the first growth stage is close to zero, except for the loam soil with medium bulk density (*Ky* = 0.15). Regarding the value for the third growth stage, this value is relatively low when compared to maize and sugar beet. The lowest value for the third growth stage is presented in the loam soil with medium bulk density (*Ky* = 0.73), where this soil type presents also a value over the 70th percentiles for the second growth stage (*Ky* = 0.30). With the exception of the third growth stage, the obtained values are lower than those proposed by FAO (2017). Soils with high bulk density (index number 3) show lower differences with respect to the values proposed by the literature.

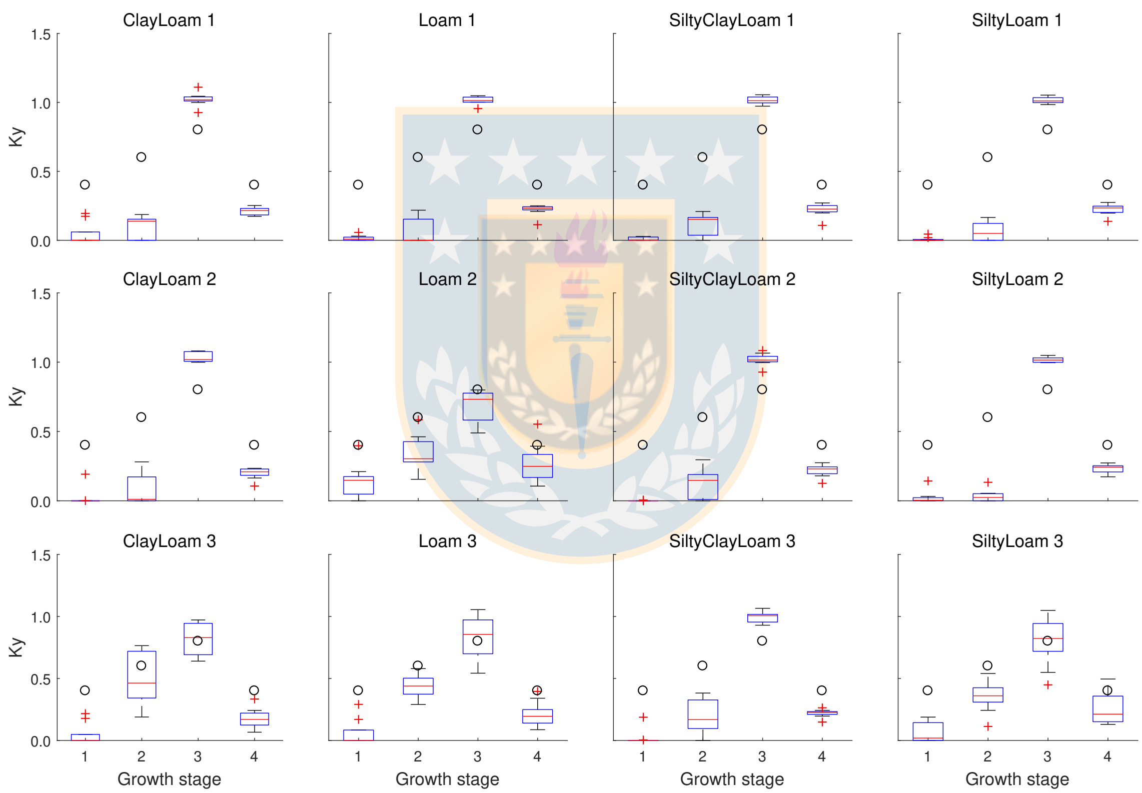

Figure 3.6: Yield response factor (*Ky*) obtained for wheat for every soil type considering the benchmark process. Circles represent *Ky* values proposed by FAO (2017) (Source: Own elaboration)

3.3.2 Benchmarking of the proposed methodology

3.3.2.1 Benchmarking for a specific year

Figure 3.7 shows the comparison between dry yield obtained from AquaCrop-OS (red line 1:1) and the estimations using the proposed methodology (blue dots). There was generally a good agreement between the results obtained from AquaCrop-OS and the proposed methodology, with NRMSE values which range from 1.62% (wheat in a silty loam soil) to 15.80% (sugar beet in a loam soil). *Ky* values used in this case were extracted from the benchmark between 2010-2014 (see Table 3.3). According to Steduto et al. (2012), sugar beet (*Beta vulgaris*) is a biennial plant that produces a large storage root as a part of tap root containing 14 to 20 percent sucrose on a fresh mass basis, thus, sugar beet can reach values of crop yield from 80 to 120 ton ha^{-1}.

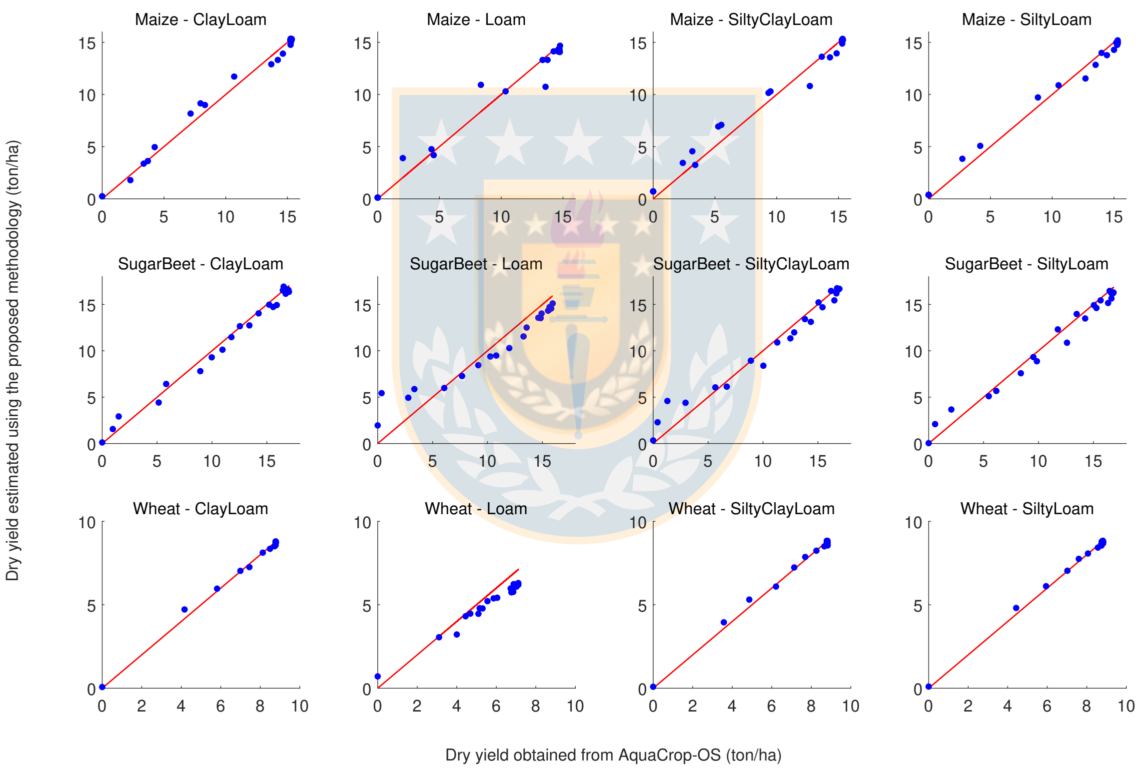

Figure 3.7: Crop yield (Y) obtained from the benchmarking for maize, sugar beet and wheat in the soils considering a mean value of bulk density in the year 2014. Red lines present the benchmark estimated by AquaCrop-OS, while each blue dot corresponds to the crop yield estimated by the proposed methodology (Source: Own elaboration)

Table 3.3: Yield response factor (Ky) obtained for maize, sugar beet and wheat in the soils considering a mean value of bulk density, valid for the years 2010-2014 (Source: Own elaboration)

Crop	Soil	1st	2nd	3rd	4th	Total
Maize	ClayLoam	0.00	0.29	1.04	0.48	1.07
	Loam	0.00	0.05	0.97	0.73	1.01
	SiltyClayLoam	0.00	0.22	0.86	0.58	1.10
	SiltyLoam	0.00	0.47	1.05	0.15	1.10
Sugar beet	ClayLoam	0.00	0.59	1.02	0.00	1.16
	Loam	0.00	0.12	0.82	0.21	1.13
	SiltyClayLoam	0.00	0.51	0.96	0.00	1.15
	SiltyLoam	0.00	0.41	1.00	0.00	1.16
Wheat	ClayLoam	0.00	0.00	1.01	0.23	1.05
	Loam	0.16	0.40	0.73	0.26	1.09
	SiltyClayLoam	0.00	0.00	1.01	0.25	1.09
	SiltyLoam	0.00	0.00	1.02	0.25	1.04

3.3.2.2 Benchmarking for all years

The benchmarking for all years was carried out determining the Normalized Root Mean Square Error (NRMSE) for every year. Figure 3.8 shows the NRMSE values for each year for maize (a), sugar beet (b) and wheat (c) for all soil types, where the lowest and highest values are presented with blue and red colours, respectively. According to the classification suggested by Jamieson et al. (1991), values are ranged from 0% to $\geq$ 30%, where wheat presented the best performance.

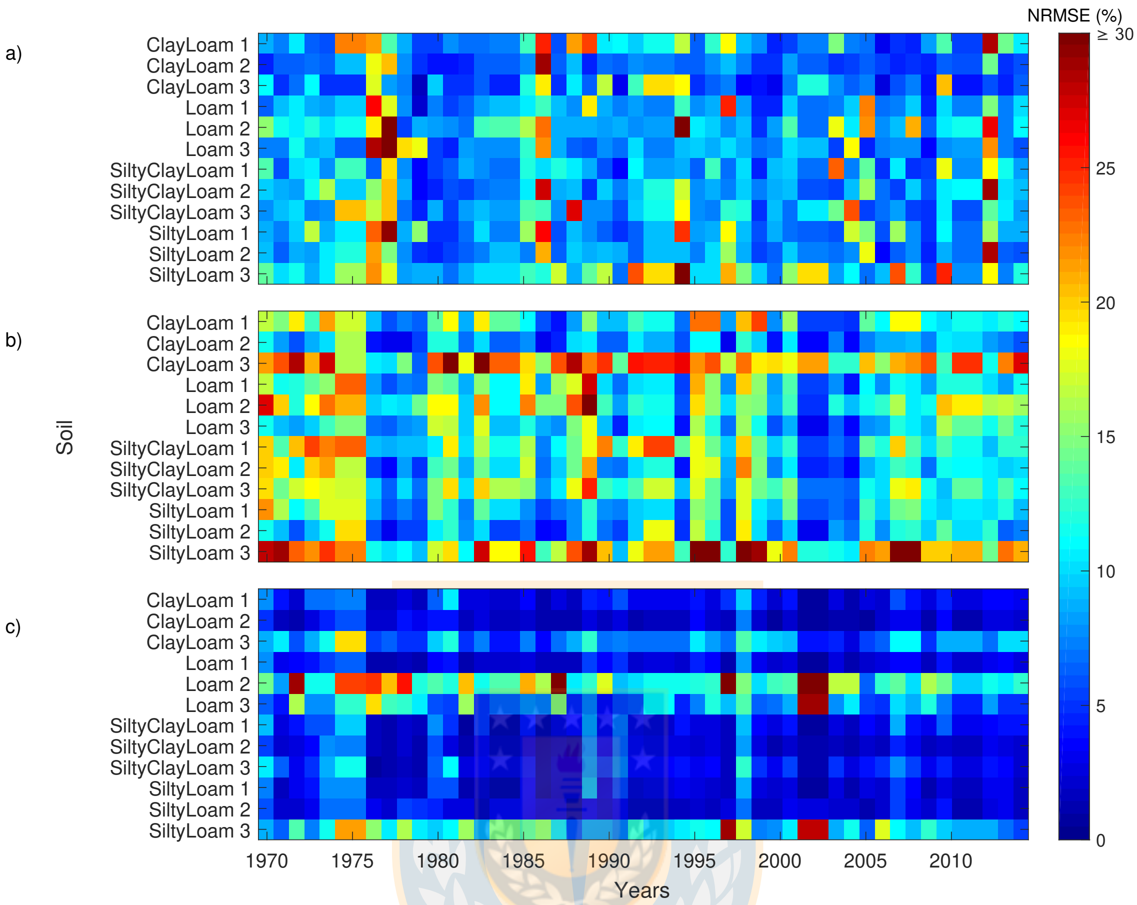

Figure 3.8: Normalized Root Mean Square Error (NRMSE) for maize (a), sugar beet (b) and wheat (c) for every soil type from 1970 to 2014 (Source: Own elaboration)

On the other hand, Figure 3.9 shows a comparison of the frequency of NRMSE values suggested by Jamieson et al. (1991). Local estimation of *Ky* values presented better performance compared to those values reported by the literature (Doorenbos and Kassam, 1979; FAO, 2017), because those are not specific for a particular soil type or management. The local estimation increased the frequency of the best performance (excellent) in maize (from 0 to 67%), sugar beet (from 0 to 35%) and wheat (from 46 to 82%). Wheat, however, presents the best performance considering *Ky* values suggested by FAO (2017).

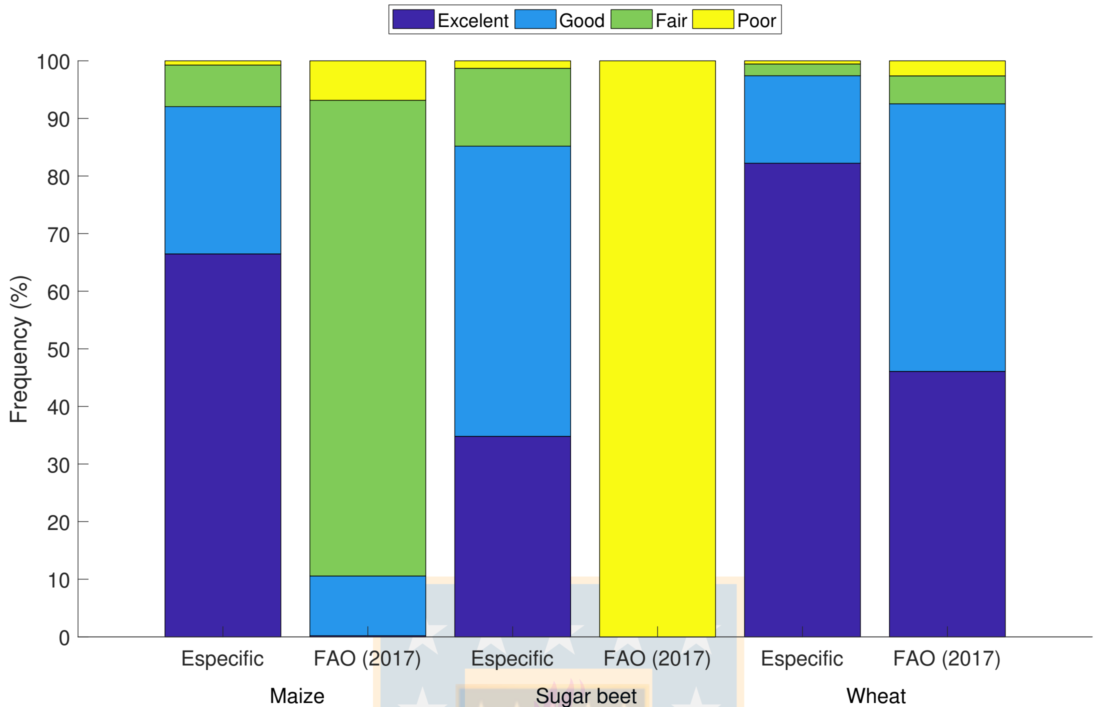

Figure 3.9: Comparison of the frequency of NRMSE values obtained by the proposed methodology and recommended by CROPWAT database (FAO, 2017) (Source: Own elaboration)

3.4 Conclusions

We developed and assessed a methodology to estimate *Ky* under local conditions for a given crop, soil, weather, sowing date and management and for each growth stage using AquaCrop-OS under Chilean conditions. The proposed methodology presented a good agreement; excellent simulation of 67%, 35% and 82% for maize, sugar beet and wheat, respectively (Figure 3.9), allowing to estimate *Ky* values under local conditions and to dispose of a simple mathematical approach to estimate yield reduction as a result of water scarcity for each growth stage.

The main advantage of considering local-estimated values of *Ky* is the best option to include into optimisation models which consider crop yield reduction as a function of water scarcity at timescales lower than seasonal (Kuschel-Otárola et al., 2018), allowing farmers to make decisions at a real-time when water is limited. Future studies should focus on the estimation of Ky under more management scenarios.

Chapter 4

Life Cycle Assessment of irrigated crops

Abstract

We propose a methodology to estimate crop yield depending on different irrigation management, using a Life Cycle Assessment (LCA)-based methodology, calculating maximum crop yield, water used to get maximum crop yield and water use efficiency. The proposed methodology was applied to three crops (maize, sugar beet and wheat) and four soil types (clay loam, loam, silty clay loam and silty loam) considering three levels of bulk density: low, medium and high. The strategies were: rainfed (no irrigation), soil moisture-based, a fixed interval every 1, 3, 5 and 7 days and a problem-specific algorithm for optimal irrigation scheduling with limited water supply (GET-OPTIS). According to our results, differences among irrigation management were found, where GET-OPTIS presented the best performance (highest crop yield values, lowest water used and highest water use efficiency), followed by the soil moisture-based strategy.

4.1 Introduction

Water is the main factor for crop development. In the world, irrigated agriculture uses about 70% of the available fresh water resources (FAO, 2016), so improving its management will increase water use efficiency (WUE), defined as the amount of water necessary to achieve a given yield (Hubick et al., 1986). According to Saccon (2017), effective planning and management of water for crop production require deep knowledge of the system, due to experimental results are generally site specific and are not applicable to different conditions for weather, soil, crops and management. Carrying out field experiments are expensive, laborious (Malik et al., 2017) and time-consuming.

Therefore, to address the above concerns, the Food and Agriculture Organization of the United Nations (FAO) developed the AquaCrop model (Steduto et al., 2009). This model simulates attainable yields of crops as a function of water consumption under rainfed, supplemental, deficit, and full irrigation conditions and has been used to determine accurately crop yield in maize (Heng et al., 2009; Nyakudya and Stroosnijder, 2014; Paredes et al., 2014), wheat (Andarzian et al., 2011; Mkhabela and Paul, 2012; Toumi et al., 2016), sugar beet (Alishiri et al., 2014; Malik et al., 2017; Stricevic et al., 2011), potatoes (Garcia-Vila and Fereres, 2012; Montoya et al., 2016), barley (Araya et al., 2010), quinoa (Geerts et al., 2009) and rice (Maniruzzaman et al., 2015). Later, Foster et al. (2017) developed the AquaCrop-OS model, an open source code which was written in MATLAB, giving the opportunity to link this with other concepts to assess some farming scenarios. On the other hand, there is a standardised method, named Life Cycle Assessment (LCA) (ISO 14040, 2006), which allows calculating the environmental impacts caused by a product during its life cycle. This methodology has already been used to address water depletion uses related to irrigated crops (Milà i Canals et al., 2010). Considering the importance of the sub-seasonal application of water in food production, we formed the following research question: How can be included AquaCrop-OS and an LCA-based methodology into a single framework? Therefore, the main objective was to develop and test a methodology to estimate crop yield depending on different irrigation strategies, calculating maximum crop yield, water used to get maximum crop yield and water use efficiency considering local conditions of crops, soils, weather, sowing date and management.

4.2 Methodology

The proposed methodology aims to compare different irrigation management using AquaCrop-OS. The objective is to determine dry yield, water used and water use efficiency considering local conditions of crops, soils, weather, sowing date and management.

4.2.1 Life Cycle Assessment

The Life Cycle Assessment (LCA) is a standardised method (ISO 14040, 2006) whose first applications date back to the early 1990s. It calculates the potential impacts on the environment of the production of a given product or service (called functional unit). This is a four-step method, starting with the definition of goal and scope, following with the Life Cycle Inventory (LCI), related to the listed flows which have an influence on the whole process (input and output). The third step, the Life Cycle Impact Assessment (LCIA) means to analyse the impact overall process, finishing with the last phase, the interpretation. In this research, the functional unit was defined as the dry yield produced in one hectare of soil. Regarding the LCI, were considered water applied for irrigation. As far as the LCIA, was considered AquaCrop-OS to estimate the water use to get the corresponding crop yield values depending on the irrigation management.

4.2.2 Irrigation management

In this research, seven irrigation strategies were compared; rainfed (no irrigation), soil moisture based, a fixed interval every 1, 3, 5 and 7 days, and a problem-specific algorithm for optimal irrigation scheduling with limited water supply. The latter is named Global Evolutionary Technique for OPTimal Irrigation Scheduling (GET-OPTIS) (Schütze et al., 2012). The main objective of GET-OPTIS is to maximise the crop yield (Y) by finding an optimal irrigation schedule (S) composed by the date (d_i) and the irrigation depth (v_i).

$$\begin{aligned} Y^* &= max\, Y(S) : S = \{s_i\}_{i=1\ldots n} \\ &= \{(d_1, v_1), \ldots, (d_i, v_i), \ldots, (d_n, v_n)\}\, n, d_i \in \mathbb{N}; v_i \in \mathbb{R} \end{aligned} \tag{4.1}$$

This process required high computational efforts due to building 39,312 scenarios (21 points for 52 years, 3 crops and 12 soil types). So, we used parallel run mode in MATLAB R2017a (MathWorks, 2017). Parallel computing allows to carry out many calculations simultaneously, accelerating the code runs.

4.2.3 Water Use Efficiency

WUE (in kg m^{-3}) is defined as the water required by the crop to produce crop yield (Du et al., 2017):

$$WUE = \left(\frac{Y}{ETa}\right) \times 100 \tag{4.2}$$

where Y and ETa correspond to crop yield (in ton ha^{-1}) and actual crop evapotranspiration (in mm), respectively.

4.2.4 Case study

Our proposed model was applied to conditions characteristic of the Central Valley of Chile (Figure 4.1). Annual mean precipitation for this area is about 1,025 mm, and the average maximum and minimum temperatures are 20.6 and 7.6°C, respectively (DGA, 2004). This region contains about 28% of the national cropping area. Some of the most produced crops are wheat (34.3%), maize (11.6%) and sugar beet (6%), which contribute to the national planted surface with 27.9, 22.5 and 60%, respectively (ODEPA, 2018). The soils are formed from volcanic ashes (Andisols) deposited over a nonrelated substrate of andesitic tuff and fluvioglacial materials. The texture is predominately silty clay loam, silty loam, and loam and the bulk density ranges from 0.71 to 1.35 Mg m^{-3} (Granda et al., 2013; Rivera et al., 2011, 2015).

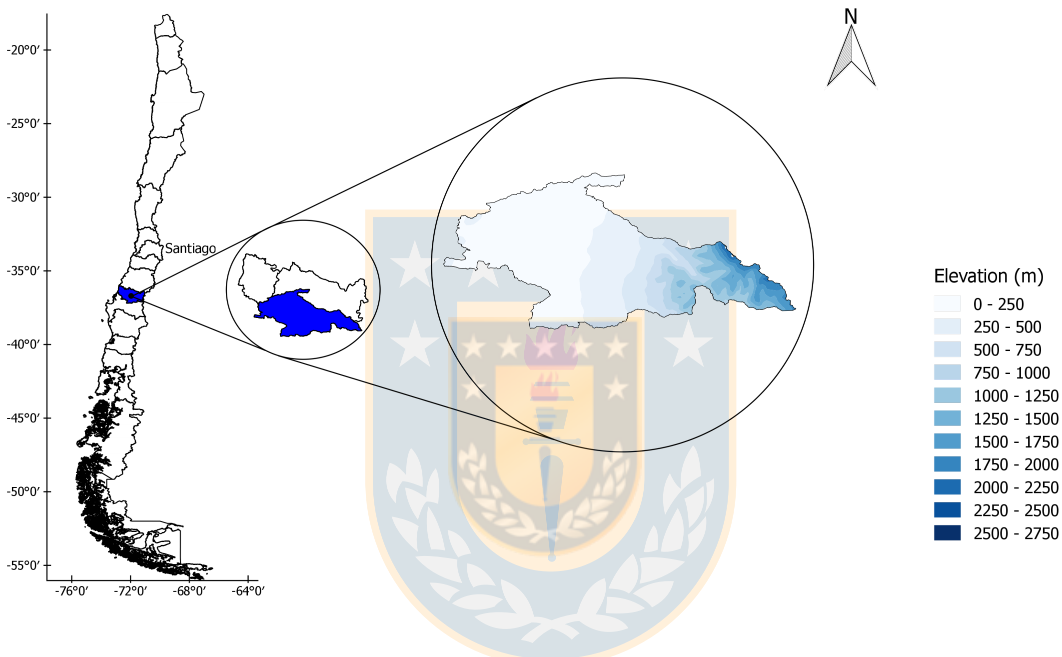

Figure 4.1: Study area location (Source: Own elaboration)

4.2.5 Model inputs

Sowing dates for maize, wheat and sugar beet for each year correspond to the first day of November, September and August, respectively (Faiguenbaum, 2003). A weather database from 1965 to 2016 (Figure 4.2) was extracted from the Explorador Climático website (http://explorador.cr2.cl/).

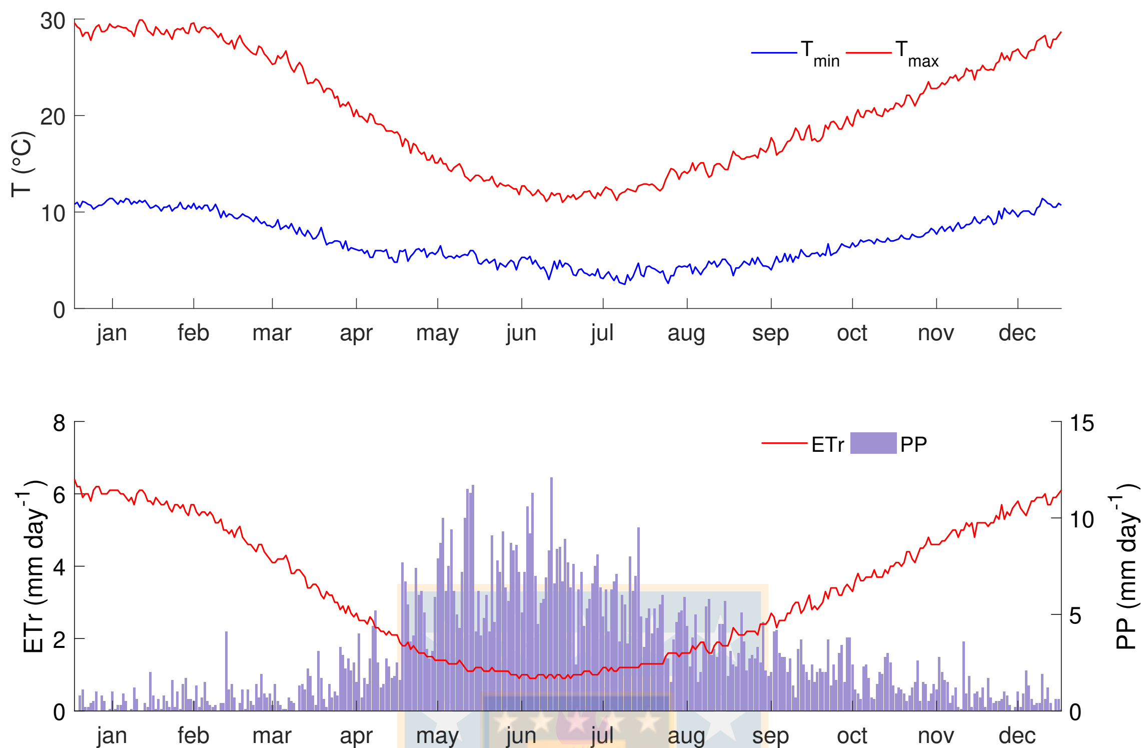

Figure 4.2: Minimum and maximum temperature (T_{min} and T_{max}), reference evapotranspiration (ETr) and precipitation (PP) for the study area, presented as mean values from 1965 to 2016 (Source: Own elaboration)

Reference evapotranspiration was estimated according to Allen et al. (2005). Crops parameters were considered from the AquaCrop-OS (Foster et al., 2017) database (Table 4.1). On the other hand, soil hydraulic parameters (Table 4.2) were extracted from Granda et al. (2013) and saturated hydraulic conductivity was estimated using the RETC model (van Genuchten et al., 1991). For soils, numbers 1, 2 and 3 correspond to low, medium and high bulk density, respectively. Each growing season started with a 50% of the total available water.

Table 4.1: Conservative (constant) and generally applicable parameters for maize, sugar beet and wheat in the Central Valley of Chile (Source: Own elaboration)

Parameter	Crop		
	Maize	Sugar beet	Wheat
Conservative (generally applicable)			
Base temperature (°C)	8.00	5.00	0.00
Cut-off temperature (°C)	30.00	30.00	26.00
Canopy cover per seedling at 90% emergence (CC_o)	6.50	1.00	1.50
Canopy growth coefficient (CGC)	1.25	1.05	0.50
Maximum canopy cover (CCx)	96.00	98.00	96.00
Crop coefficient for transpiration at CC = 100%	1.05	1.10	1.10
Decline in crop coef. after reaching CCx	0.30	0.15	0.15
Canopy decline coefficient (CDC) at senescence	1.00	0.39	0.40
Water productivity, normalized to year 2000 (WP*)	33.70	17.00	15.00
Leaf growth threshold (P_{upper})	0.14	0.20	0.20
Leaf growth threshold (P_{lower})	0.72	0.60	0.65
Leaf growth stress coefficient curve shape	2.90	3.00	5.00
Stomatal conductance threshold (P_{upper})	0.69	0.65	0.65
Stomata stress coefficient curve shape	6.00	3.00	2.50
Senescence stress coefficient (P_{upper})	0.69	0.75	0.70
Senescence stress coefficient curve shape	2.70	3.00	2.50
Considered to be conservative but can or may be cultivar-specific			
Reference harvest index (HI_o)	48	70	48
GDD from 90% emergence to start of anthesis	800	842	1100
Duration of anthesis, in GDD	180	0	200
Coefficient, inhibition of leaf growth on HI	7	4	10
Coefficient, inhibition of stomata on HI	3	-	7

Table 4.2: Bulk density (ρ_a), saturation (θ_s), field capacity (θ_{fc}), and permanent wilt water content (θ_{pwp}) and saturated hydraulic conductivity (K_s) representative of Central Valley of Chile (Source: Own elaboration)

Soil	Sand	Silt (%)	Clay	ρ_a (g cm^{-3})	θ_s	θ_{fc} (m^3 m^{-3})	θ_{pwp}	K_s (mm day^{-1})
ClayLoam 1	22	48	30	0.72	0.73	0.45	0.30	3415.9
ClayLoam 2	35	38	27	0.97	0.64	0.57	0.33	269.1
ClayLoam 3	39	28	33	1.39	0.47	0.34	0.26	132.4
Loam 1	34	42	24	0.71	0.73	0.44	0.28	3517.8
Loam 2	31	46	23	1.07	0.60	0.59	0.40	69.5
Loam 3	41	37	22	1.13	0.57	0.55	0.34	110.3
SiltyClayLoam 1	10	52	38	0.78	0.70	0.46	0.32	2382.0
SiltyClayLoam 2	11	52	37	0.81	0.69	0.50	0.32	1903.3
SiltyClayLoam 3	15	49	36	0.86	0.68	0.50	0.36	1534.2
SiltyLoam 1	27	50	23	0.71	0.73	0.44	0.28	3571.7
SiltyLoam 2	22	51	27	0.98	0.63	0.59	0.38	183.9
SiltyLoam 3	24	51	25	1.03	0.61	0.59	0.44	76.3

4.3 Results and discussions

4.3.1 Results for a specific soil type

Dry yield and water used obtained from 1965 to 2016 are presented in the form of scatter plots (Figure 4.3), in which x-axis represents the water used and the y-axis represents the dry yield using different irrigation management for maize (a), sugar beet (b) and wheat (c) in a clay loam soil considering a medium level of bulk density (clay loam 2). Results show that for maize, there are no significant differences in dry yield among irrigation management compared to the water used. Soil moisture-based irrigation shows good behaviour reaching high yields values using less water (over 15 ton ha^{-1} applying less than 800 mm) than the other strategies. However, GET-OPTIS can reach good yield values with even less water (350 mm), saving over a 50% water with respect to the soil moisture-based strategy and over a 70% with respect to the other ways of management. Regarding sugar beet, there are larger differences in dry yield than the analysed scenario for maize. Sugar beet reached dry yield values over 18 ton ha^{-1}, but according to Steduto et al. (2012), this crop produces from 14 to 20 percent sucrose on a fresh mass basis. Thus, sugar beet can achieve values of crop yield from 80 to even greater than 130 ton ha^{-1}.

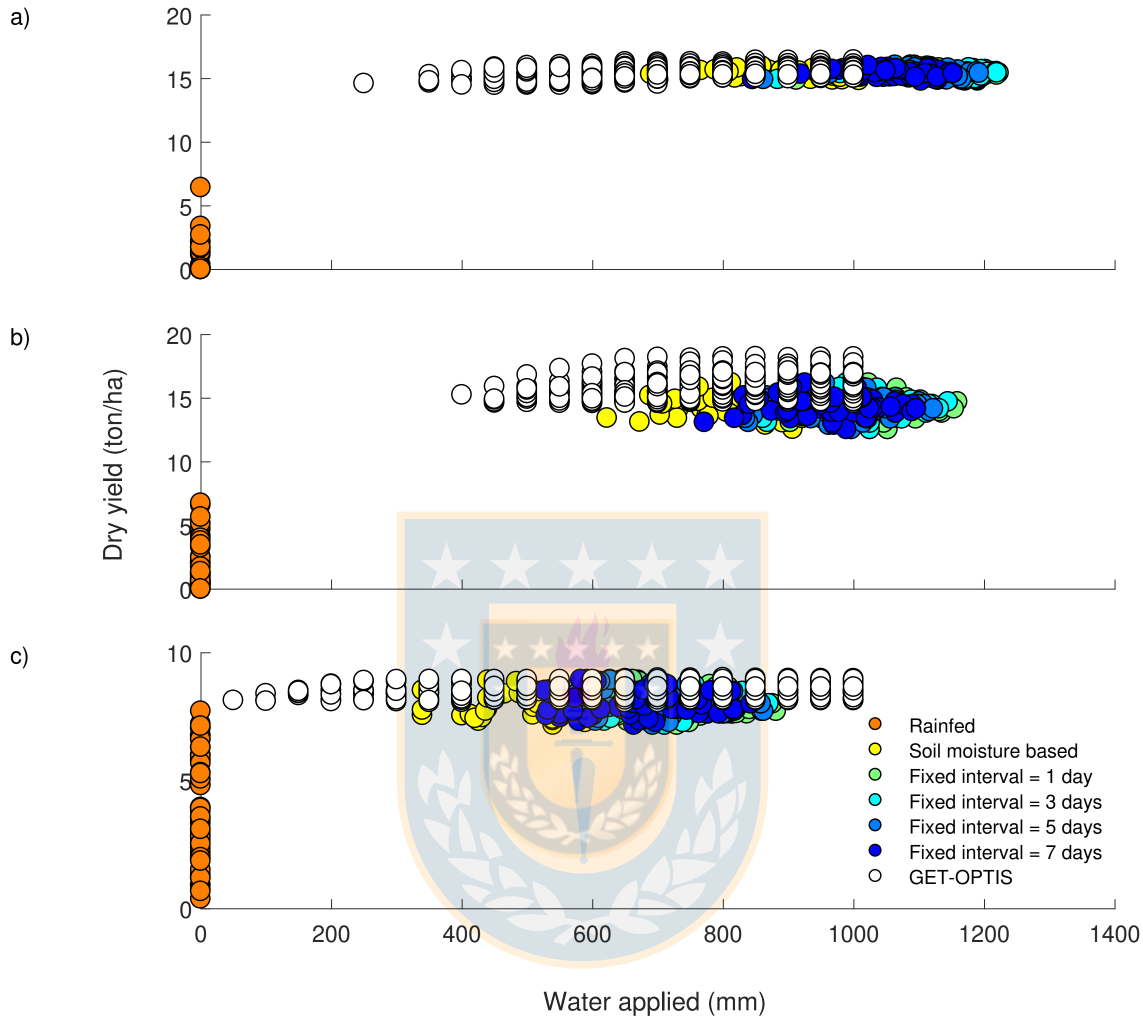

Figure 4.3: Dry yield and water used obtained from 1965 to 2016 using different irrigation strategies for maize (a), sugar beet (b) and wheat (c) in a clay loam soil considering a medium level of bulk density (clay loam 2) (Source: Own elaboration)

Similarly to the results obtained for maize, soil moisture-based irrigation presents good behaviour reaching high values using a low amount of water, but, GET-OPTIS shows better performance, saving over a 41% water with respect to the soil moisture-based strategy and over a 55% with respect to the fixed interval management. For wheat, crop yield ranges from 7 to 9 ton ha^{-1}. Rainfed strategy achieved in 5 years crop yield values over 7 ton ha^{-1}, due to having enough water coming from the rain when wheat needed. Similarly to the results obtained for maize and sugar beet, soil moisture-based strategy shows high values of crop yield using around 400 mm, lower than the fixed interval management which presented a mean value of 600 mm. GET-OPTIS strategy, however, could use 250 mm to get high values of crop yield.

4.3.2 Results for all soil types

Maximum dry yield, water used to obtain maximum dry yield and water use efficiency for maize, sugar beet and wheat using different irrigation strategies for all soil types described in Table 4.2 are presented in Figure 4.4. According to the results obtained for maize (first column), GET-OPTIS reached the highest crop yield values (Figure 4.4.a) and applied less water (Figure 4.4.b) than the other irrigation management. WUE reached the maximum considering GET-OPTIS (Figure 4.4.c). Regarding the sugar beet (second column), were obtained similar results. As far as the wheat (third column), GET-OPTIS reached the highest crop yield values but applied less water in some soil types (clay loam 2, loam 2, loam 3, silty loam 2 and silty loam 3). WUE shared the maximum value among rainfed, soil moisture-based and GET-OPTIS.

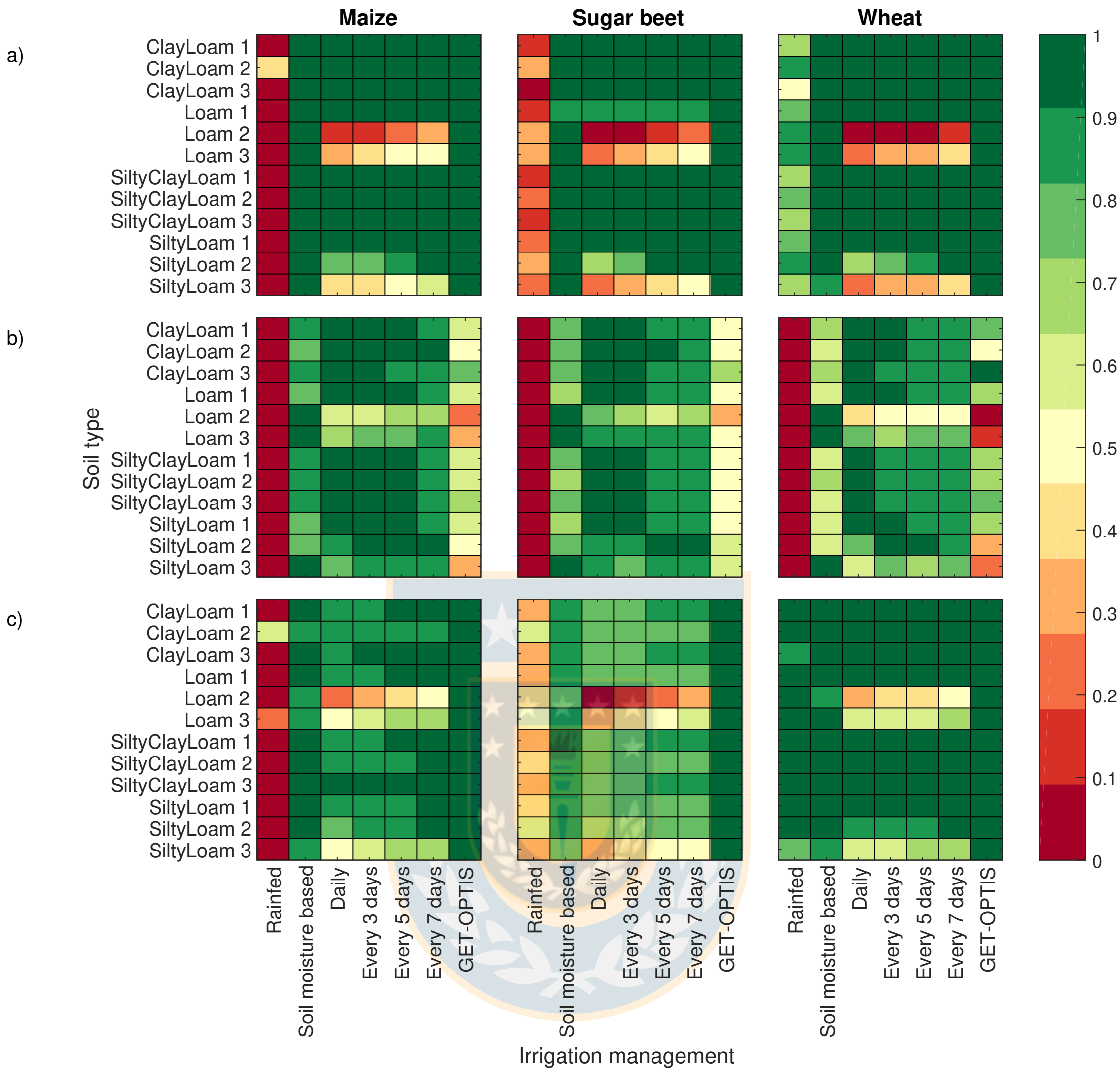

Figure 4.4: Maximum dry yield (a), water used to obtain maximum dry yield (b) and water use efficiency (c) for maize, sugar beet and wheat using different irrigation strategies. All values were divided by the maximum obtained for each soil type and for each crop to get numbers from 0 to 1 (Source: Own elaboration)

4.4 Conclusions

A methodology was developed to estimate crop yield depending on different irrigation management, using an LCA-based methodology, calculating maximum crop yield, water used to get maximum crop yield and water use efficiency considering local conditions of crops, soils, weather, sowing date and management. This methodology was assessed by 52 years of weather database (from 1965 to 2016) and seven irrigation management (rainfed, soil moisture-based, a fixed interval every 1, 3, 5 and 7 days, and a problem-specific algorithm for optimal irrigation scheduling with limited water supply (GET-OPTIS). According to our results, GET-OPTIS was the methodology with the best performance (highest crop yield values, lowest water used and highest WUE), followed by the soil moisture-based management. Regarding wheat, there were 5 years where rainfed strategy achieved in 5 years crop yield values over 7 ton ha^{-1}, due to having enough water coming from the rain when the crop needed. Future studies should focus on the validation of AquaCrop-OS under local conditions in order to include GET-OPTIS to produce “more crop per drop”.

Part VI

Conclusions

Through this thesis has been considered the concept of multiperiod optimisation, starting with the development of a monthly crop yield equation (Chapter 1) which presented low values of RMSE and RD (below to 0.03 and 6.75%, respectively) when was compared to the daily approach proposed by Raes et al. (2006). This Chapter supported the development of Chapter 2.

Chapter 2 aimed to develop a monthly optimisation model to obtain an optimum cropping pattern and monthly water allocation for irrigated agriculture under Chilean conditions. The model included the monthly crop yield equation which was developed in Chapter 1 and improvements in water resource management such as water storage and water transactions, being the latter a monthly decision variable that can increase farmer's profits. Results showed that optimizing resources on a monthly basis attained higher profits as it allowed farmers to tailor their management practices and manage costs to cope with less available resources. Moreover, monthly scenarios, which include improvements in water resource management (such as water transactions and water storage), the model not only attains higher profits but also decreases uncertainty and improves risk management.

The development of Chapter 3 started also from Chapter 1, carrying out a methodology to estimate the yield response factor under local conditions and how much the crop yield values differ when are taken into account the coefficients proposed by the literature, e.g., CROPWAT 8.0 (FAO, 2017). Results showed differences among both sources (local estimated using AquaCrop-OS and literature), being the local-estimated whose with the best agreement (over 85% of the results for each crop presented NRMSE values below to 20%). The main reason is that the listed *Ky* values reported by the literature are not specific for a particular soil type or management. The principal advantage of considering local-estimated values of *Ky* is a more realistic option when different scenarios for management are considered.

Finally, some results generated in Chapter 3 were included in Chapter 4, which analysed the estimation of crop yield depending on different irrigation management using an LCA-based methodology, calculating maximum crop yield, water use to get maximum crop yield and water use efficiency under local conditions. Results showed that there were differences among irrigation management, being GET-OPTIS the strategy with the best performance (highest crop yield, lowest water use and highest WUE), followed by the soil moisture-based management.

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