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Optimización de huertos frutales y proyecciones climáticas en cultivos anuales: Un enfoque estratégico para la agricultura del Valle Central de Chile

Optimization of fruit orchards and climate projections in annual crops: A strategic approach for agriculture in Chile's Central Valley

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Resumen

La sostenibilidad de los sistemas agrícolas enfrenta presiones crecientes derivadas del aumento en la demanda alimentaria, la escasez de recursos hídricos y los impactos acelerados del cambio climático. Estos desafíos se manifiestan con especial intensidad en el Valle Central de Chile, donde la agricultura bajo riego constituye una actividad clave. En este contexto, la planificación agrícola predial requiere herramientas que integren de forma sistemática variables técnicas, económicas y climáticas, permitiendo decisiones estratégicas y adaptativas en escenarios de alta incertidumbre. Esta tesis propone el uso de modelos de optimización y simulación como instrumentos para fortalecer la planificación agrícola, aplicados en huertos frutales y cultivos anuales bajo distintas condiciones de manejo y horizontes temporales.

Con el fin de optimizar la planificación frutícola en el largo plazo, se desarrolló un modelo de optimización no lineal para determinar el patrón óptimo en huertos frutales con un horizonte de planificación de 20 años. El modelo considera la distribución anual de agua disponible, la volatilidad de precios, la disponibilidad de mano de obra y otras restricciones operativas, con el objetivo de maximizar las utilidades netas prediales. Los resultados muestran que el modelo permite identificar combinaciones de especies más rentables y adaptadas a las restricciones del predio, concluyendo que la disponibilidad de agua y mano de obra son factores críticos en la planificación de largo plazo.

Posteriormente, el modelo fue aplicado a una empresa agrícola, donde se evalúan tres patrones de establecimiento utilizados en distintos periodos, integrando datos

reales sobre superficie plantada, especies cultivadas y escenarios operativos. Además, se analizó cómo distintos niveles de eficiencia en el uso del agua afectan la rentabilidad y sostenibilidad del sistema. El patrón optimizado propuesto aumentó las utilidades netas en un 32.7% respecto al patrón del año 2000. El análisis de sensibilidad mostró que variables como la disponibilidad hídrica y las condiciones de mercado pueden alterar significativamente la rentabilidad, lo que evidencia la necesidad de analizar los patrones de establecimiento bajo distintos escenarios. Estos resultados confirman el potencial del modelo como herramienta de apoyo a la toma de decisiones para mejorar la planificación predial en huertos frutales.

Finalmente, se utilizó el modelo de simulación AquaCrop para evaluar los impactos proyectados del cambio climático (escenario RCP8.5) en, la demanda hídrica y el rendimiento de los cultivos de maíz, remolacha azucarera y trigo en la cuenca del río Itata para el periodo 2035–2065. Los resultados evidenciaron una marcada heterogeneidad espacial y temporal en los requerimientos netos de riego, siendo la remolacha el cultivo más demandante de agua. Las proyecciones indicaron incrementos en el rendimiento y en la productividad del agua de riego para trigo y remolacha, mientras que el maíz mostró una respuesta menos favorable, afectada por la reducción en la duración del ciclo fenológico y su menor sensibilidad fisiológica al incremento de CO_2. El adelanto en la fecha de siembra permitió extender el ciclo de los cultivos, mejorar el rendimiento y reducir el requerimiento neto de riego, lo cual demuestra su eficacia como medida de adaptación agroclimática. En conjunto, la tesis entrega herramientas robustas que permiten apoyar decisiones productivas resilientes frente a escenarios de cambio climático y operativa creciente.

Abstract

The sustainability of agricultural systems is under increasing pressure due to rising food demand, water resource scarcity, and the accelerating impacts of climate change. These challenges are particularly acute in Chile's Central Valley, where irrigated agriculture plays a key role. In this context, on-farm agricultural planning requires tools that systematically integrate technical, economic, and climatic variables, enabling strategic and adaptive decision-making in scenarios marked by high uncertainty. This thesis proposes the use of optimization and simulation models as instruments to strengthen agricultural planning, applied to fruit orchards and annual crops under different management conditions and time horizons.

To optimize long-term fruit production planning, a nonlinear optimization model was developed to determine the optimal crop pattern in fruit orchards over a 20-year planning horizon. The model accounts for the annual distribution of available water, price volatility, labor availability, and other operational constraints, with the objective of maximizing farm net profits. Results show that the model can identify combinations of species that are more profitable and better adapted to site-specific constraints, concluding that water and labor availability are critical factors for long-term planning.

Subsequently, the model was applied to an agricultural company, where three crop patterns used in different periods were evaluated using real data on planted area, cultivated species, and operational scenarios. Additionally, the study analyzed how different levels of water use efficiency affect system profitability and sustainability. The optimized crop pattern increased net profits by 32.7% compared to the year 2000 baseline. Sensitivity analysis showed that variables such as water availability and market conditions can significantly alter profitability, underscoring the need to evaluate planting patterns under different scenarios. These results confirm the potential of the model as a decision-support tool to improve on-farm planning in fruit orchards.

Finally, the AquaCrop simulation model was used to evaluate the projected impacts of climate change (RCP8.5 scenario) on water demand and yield for maize, sugar beet, and wheat crops in the Itata River basin for the 2035–2065 period. Results revealed marked spatial and temporal heterogeneity in net irrigation requirements, with sugar beet being the most water-demanding crop. Projections indicated increases in yield and irrigation water productivity for wheat and sugar beet, while maize showed a less favorable response, affected by the shortened phenological cycle and its lower physiological sensitivity to elevated CO_2. Advancing sowing dates helped extend crop cycles, improve yields, and reduce net irrigation requirements, demonstrating its effectiveness as an agroclimatic adaptation strategy. Altogether, this thesis provides robust tools that support resilient production decisions in the face of climate change and increasing operational challenges.

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Introducción

La agricultura enfrenta desafíos crecientes dado que es el principal consumidor de agua dulce a nivel mundial, utilizando cerca del 70% del recurso disponible para el riego de cultivos (Galán-Martín et al., 2017). Esta alta demanda se ve intensificada por el crecimiento demográfico y los cambios en los patrones de consumo alimentario, que requieren aumentar de forma sostenida la producción agrícola (Ibarrola-Rivas et al., 2017). Las proyecciones indican que la población mundial superará los 9.000 millones de personas hacia 2050, lo que implicará una presión cada vez mayor sobre los recursos hídricos y la superficie cultivable (de Fraiture & Wichelns, 2010). En paralelo, el cambio climático está modificando profundamente las condiciones agroclimáticas, reduciendo la disponibilidad de agua, alterando los ciclos fenológicos y aumentando la frecuencia de eventos extremos (Malek et al., 2018; Wu et al., 2023). En este contexto, la escasez hídrica y la variabilidad climática se han consolidado como factores limitantes críticos para la productividad agrícola, especialmente en regiones que dependen del riego (Nie et al., 2021). Frente a este escenario, fortalecer la planificación agrícola es clave para mejorar la eficiencia en el uso de los recursos, asegurar la rentabilidad predial y aumentar la resiliencia frente a condiciones cambiantes.

En Chile, estos desafíos se manifiestan con particular intensidad en el Valle Central, donde se concentra una parte significativa de la producción agrícola nacional y existe una alta dependencia del riego (Arumí et al., 2013). En este contexto, los patrones de cultivo han cambiado de forma considerable en las últimas décadas, con un aumento del 43% en la superficie frutícola entre 2003 y 2018, acompañado por una disminución en la disponibilidad de mano de obra (ODEPA, 2019a). Estos cambios se han producido, en muchos casos, sin una planificación predial adecuada que considere la disponibilidad hídrica, la demanda de mano de obra y los riesgos asociados a la variabilidad climática y económica (Quezada et al., 2025). Esta situación pone de relieve la necesidad de desarrollar herramientas y estrategias de gestión que permitan un uso eficiente y sostenible de los recursos.

En este contexto, los modelos de optimización y simulación han adquirido un rol central en la planificación agrícola. Los modelos de optimización son una de las herramientas científicas que ayudan a los investigadores a obtener los mejores resultados en problemas como la programación, la planificación, la asignación de recursos, entre otros (Jain et al., 2021; Varade & Patel, 2019). En el ámbito agrícola, se han aplicado para maximizar la rentabilidad predial (Kuschel-Otárola et al., 2018), aumentar el rendimiento (Li et al., 2020a) o minimizar el uso de agua (Richter et al., 2023) y la aplicación de fertilizantes y pesticidas (Mardani Najafabadi et al., 2019), considerando múltiples restricciones de tipo técnico, económico y ambiental. Cuando el objetivo del modelo incluye la estimación de rendimientos o utilidades agrícolas, es necesario incorporar una función de producción que relacione el rendimiento con el volumen de agua aplicada (Singh, 2012). Una formulación común es aquella que vincula la pérdida relativa de rendimiento con la pérdida relativa de evapotranspiración, dando lugar a una función cóncava que representa la respuesta del rendimiento cosechable al agua efectivamente aplicada (Carvallo et al., 1998).

A diferencia de los modelos de optimización, los modelos de simulación permiten representar de forma detallada el comportamiento dinámico de cultivos frente a diferentes condiciones climáticas, de manejo o disponibilidad hídrica, sin buscar una solución óptima, proporcionando escenarios valiosos para evaluar impactos y respuestas. En este sentido, la Organización de las Naciones Unidas para la Alimentación y la Agricultura (FAO) desarrolló el modelo AquaCrop, diseñado para simular el rendimiento de cultivos en función del consumo de agua (Steduto et al., 2009). Este modelo considera distintos regímenes hídricos, incluyendo condiciones de secano, riego suplementario, riego deficitario y riego pleno, y ha sido ampliamente utilizado para estimar el rendimiento de cultivos como maíz (Heng et al., 2009; Paredes et al., 2014), trigo (Andarzian et al., 2011; Toumi et al., 2016) y remolacha (Garcia-Vila et al., 2019). Asimismo, ha demostrado su utilidad en simulaciones realizadas bajo condiciones actuales, en reconstrucciones de condiciones pasadas (Kuschel-Otárola et al., 2020) y, especialmente, en proyecciones que incorporan escenarios futuros de cambio climático (Alvar-Beltrán et al., 2025; Zhao et al., 2025). Su capacidad de simular respuestas fisiológicas y productivas bajo distintos regímenes hídricos y condiciones climáticas lo convierte en una herramienta útil para analizar medidas de adaptación y evaluar la sostenibilidad agrícola frente a nuevas condiciones ambientales.

Esta tesis busca contribuir al desarrollo de herramientas que fortalezcan la toma de decisiones a nivel predial, orientadas a mejorar la rentabilidad, el uso eficiente del recurso hídrico y la resiliencia del sistema productivo agrícola frente a escenarios de creciente complejidad. Para ello, se plantea el uso de modelos de optimización y de simulación, cada uno enfocado en problemáticas específicas asociadas a distintos tipos de cultivos y horizontes de análisis. Esta doble aproximación permite abordar tanto decisiones estratégicas de planificación predial como respuestas adaptativas frente a escenarios de cambio climático, entregando fundamentos técnicos para una planificación agrícola más robusta y contextualizada.

La estructura de esta tesis consiste en cuatro capítulos:

En el Capítulo 1 desarrolla un modelo de programación no lineal que optimice la asignación de superficies para huertos frutales a lo largo de un período de 20 años, incluyendo una distribución anual de agua, con el fin de maximizar las utilidades netas de empresa agrícola. El modelo incorpora restricciones operativas y analiza aspectos clave de la planificación predial, tales como la combinación óptima de especies frutales, el impacto de la volatilidad de precios en la rentabilidad y el papel determinante de factores como la disponibilidad de mano de obra y de agua. Este enfoque busca aportar una herramienta para apoyar decisiones estratégicas en la gestión de huertos frutales, integrando componentes técnicos, económicos y de riesgo.

En el Capítulo 2 se aplica el modelo de optimización desarrollado en el capítulo anterior para evaluar los patrones de establecimiento implementados por una empresa agrícola frutícola en tres periodos distintos. El análisis incorpora condiciones reales del predio, como la superficie disponible y las especies plantadas, además evalúa cómo distintos niveles de eficiencia en el uso del agua impactan en el desempeño económico y operativo. Sobre esta base, se propone un nuevo patrón frutal optimizado que maximiza los beneficios económicos y mejora la eficiencia en el uso de los recursos.

En el Capítulo 3 se utiliza el modelo de simulación AquaCrop para evaluar los impactos del cambio climático sobre el rendimiento, la demanda hídrica y la utilidad neta agrícola de los cultivos de maíz, trigo y remolacha en la cuenca del río Itata, durante el periodo 2035–2065. El análisis incorpora siete modelos climáticos globales bajo el escenario RCP8.5, y considera una estrategia de adaptación basada en el adelanto de la fecha de siembra, con el fin de identificar prácticas que mejoren la eficiencia hídrica y la resiliencia productiva ante condiciones climáticas futuras.

El Capítulo 4 presenta las conclusiones generales obtenidas a partir del desarrollo de la tesis. Además, se proponen líneas de investigación futuras orientadas a profundizar y complementar los enfoques presentados.

Hipótesis

- La aplicación de un modelo de optimización para el establecimiento de huertos frutales bajo riego mantiene la viabilidad económica, limitando las pérdidas de utilidad a menos del 8% incluso ante reducciones de hasta un 30% en agua y un 24% en mano de obra. Asimismo, en el contexto de una empresa frutícola, dicho modelo permite definir un patrón productivo óptimo que eleva las utilidades hasta en un 33% respecto al patrón de referencia.
- Los requerimientos netos de riego aumentarían hasta un 5% en comparación con las condiciones actuales bajo el escenario RCP8.5.

Objetivo General

Evaluar estrategias de planificación agrícola mediante un modelo de optimización para establecer huertos frutales en un horizonte de largo plazo y un modelo de simulación para proyectar los impactos del cambio climático en cultivos anuales, con el fin de mejorar la eficiencia en la asignación de recursos, la rentabilidad predial y la resiliencia del sistema agrícola frente a restricciones operativas y climáticas.

Objetivos Específicos

- Desarrollar un modelo de optimización para definir el patrón óptimo de especies frutales en un horizonte de 20 años a nivel predial de acuerdo con el ciclo de vida productivo maximizando los beneficios económicos del predio.
- Evaluar el desempeño productivo y económico de una empresa agrícola frutícola mediante un modelo de optimización que optimice la asignación de superficies y agua para huertos frutales.
- Evaluar el impacto y posibles medidas de adaptación del cambio climático en la demanda hídrica y rendimiento en trigo, maíz y remolacha en el Valle Central de Chile utilizando AquaCrop bajo el escenario RCP 8.5 para el periodo 2035-2064.

Chapter 1

Optimization of Water and Land Allocation in Fruit Orchards over a 20-Year Period

Quezada, L., Holzapfel, E., Kuschel-Otárola, M., Lillo-Saavedra, M., Rivera, D., Souto, C., Lagos, O., & Palma, D. (2025). Optimization of Water and Land Allocation in Fruit Orchards over a 20-Year Period. *Water, **17**(1)*, 8. https://doi.org/10.3390/w17010008

Abstract

This study proposes a nonlinear programming model for the optimization of water and land allocation in a 1000 ha orchard over a 20-year period to maximize farmers' net profits. Different scenarios were evaluated, including equitable and unrestricted land allocation, and the risks associated with fruit production were considered. Additionally, a sensitivity analysis that focused on the variability of labor and water availability was conducted. The results reveal that with equitable land allocations and no constraints on the cultivated area, cherry emerges as the most profitable crop, although there are large risks associated with its price volatility. The introduction of risk and land allocation constraints highlights the importance of crop diversification in mitigating

economic risks. A sensitivity analysis indicated that reductions in water and labor availability significantly affect the optimal cropping pattern of an orchard, suggesting that the efficient and adaptive management of resources is required. The proposed optimal cropping pattern maintains the economic viability of the orchard even with 70% and 24% reductions in water and labor, respectively. This approach underscores the importance of implementing resilient and sustainable agricultural strategies to ensure food security and increase economic stability in the face of changing climatic and labor conditions

1.1 Introduction

Agriculture is the primary use for water worldwide, with an estimated 70% of freshwater used for crop irrigation (Galán-Martín et al., 2017; Mancosu et al., 2015). This demand for water is expected to continue to rise due to increasing pressure to produce more food, which is the result of population growth and changing diets (Ibarrola-Rivas et al., 2017). In fact, the world population is projected to reach 9 billion by 2050, which will lead to a significant increase in food production and water consumption (de Fraiture & Wichelns, 2010), posing challenges to the sustainable use of water in agriculture, particularly in water-scarce regions where competition for water resources is high (Hanjra & Qureshi, 2010). Agricultural production is fundamental to improving nutrition and serves as the main source of income for farmers, and it also plays a crucial role in food security, economic stability, and society (Ritchie et al., 2023).

Global fruit production has experienced a remarkable increase in recent decades (Retamales, 2011) due to population growth, changing dietary preferences, and improved agricultural techniques (Alexander et al., 2015; Mason-D'Croz et al., 2019). On a global scale, the cultivated area fruit crops covered increased by 55% between 2000 and 2020, and fruit production reached 887 million tons in 2020, reflecting both the expansion of the sector and the use of new technologies and improved agricultural practices (FAO, 2022).

Currently, Chile has established itself as the leading producer and exporter of fruits in the Southern Hemisphere, dominating in the export of cherries, blueberries, table grapes, avocados, and walnuts to markets in North America, Asia, and Europe (ODEPA, 2020b). The O'Higgins Region stands out as one of the country's principal agricultural areas, contributing significantly to its fruit production and exports. However, in recent years, this region has been affected by a megadrought that has negatively impacted agricultural production. Additionally, the area devoted to fruit cultivation increased by 43% between 2003 and 2018, without proper planning, with a simultaneous decline seen in the availability of labor (ODEPA, 2019a). These challenges emphasize the need to develop management tools and strategies that enable the efficient and sustainable use of resources.

In this sense, optimization techniques, which are mathematical and computational methods used to find the best possible solution within a set of feasible alternatives (Gatzke, 2022), are being employed in water resource management to ensure food security as well as the availability and sustainability of water resources (Mortada et al., 2018). Determining optimal cropping patterns can improve water use efficiency, increase farmers' incomes, and help mitigate the adverse impacts of climate change and droughts (Abdi-Dehkordi et al., 2018). Several studies have developed models that can maximize profits by determining optimal cropping patterns. For instance, Bhatia and Rana (2020) used linear programming to determine optimal crop combinations, significantly increasing farm incomes. Chen et al. (2022) developed a multi-objective programming model that combines an economic profit function and a water quality model to optimize cropping patterns under climate uncertainty, achieving a reduction in pollutant emissions without significantly affecting economic benefits. Richter et al. (2023) reported a reduction of 28-57% in the use of water for irrigation by optimizing crop combinations while maintaining or improving the net revenues of agricultural land. Varade and Patel (2019) applied particle swarm optimization (PSO) algorithms and teaching–learning-based optimization (TLBO) to determine optimal cropping patterns in areas with limited water resources, reporting increases in net profits and reductions in water use. Mardani Najafabadi and Ashktorab (2023) developed a robust fractional linear programming model to determine sustainable cropping patterns, achieving a reduction in the use of inputs such as fertilizers and pesticides while maintaining profitability. Similarly, Abdi-Dehkordi et al. (2017) developed a mathematical model to maximize profits and found that proper management and adequate cropping patterns can increase revenues, even with a reduced supply of and increased demand for water. Dariane et al. (2021) proposed a method that could be used to determine optimal short-term cropping patterns in a four-reservoir system in the Karun Basin, Iran. Another study conducted by Varade and Patel (2018) used advanced optimization algorithms, such as Jaya and PSO, to determine an optimal cropping pattern to maximize annual net returns, conserve groundwater resources, and achieve optimal land use in a region with scarce surface water resources and uncertain rainfall. Zeng et al. (2017) developed a stochastic model in order to optimize water management in arid regions, using ecological and economic variables to promote sustainability in agricultural and ecological systems under conditions of high climatic variability and water scarcity. Zeng et al. (2018) also proposed a hybrid stochastic–fuzzy model for planning irrigated agricultural production and forest protection in scenarios marked by water and land stress. This approach enables the generation of integrated strategies that maximize socioeconomic benefits while mitigating environmental impacts. Additionally, Kuschel-Otárola et al. (2018) developed a multi-period optimization model to obtain an optimal cropping pattern for annual crops under different water availability conditions in order to generate monthly allocations of resources such as water, labor, and capital and maximize profits while considering the phenological stages of the crops. However, it is important to note that all these aforementioned studies are based on conceptual or theoretical models, which makes a direct evaluation and comparison of their proposed cropping patterns with real field results difficult. In fact, while these models can contribute to decision making in a significant way, they may not fully reflect the complexities of the agricultural sector.

Despite the numerous studies conducted on the optimization of cropping patterns, there are still significant gaps in the research on long-term land allocation, especially for extended periods of more than 15 years. Most of these studies focus on irrigation over a single season, which limits their applicability in long-term planning. To the best of our knowledge, no previous studies have proposed an optimal cropping pattern for fruit orchards while considering the volatility of fruit prices. Therefore, the main objective of this study is to develop a nonlinear programming model that optimizes land allocation for fruit orchards over a 20-year period and allocates water on an annual basis in order to maximize net profits in crop production. Our specific objectives are (1) to evaluate the impact of different fruit crop combinations on water use and crop productivity; (2) to analyze the risk associated with price volatility at the time of the orchard's establishment; and (3) to evaluate the impact of labor and water availability on orchard planning and management.

1.2 Materials and Methods

Given the current and potential challenges encountered during fruit production, a model was developed to optimize land and water allocation for different fruit crops. This approach seeks to maximize profits within different resource availability scenarios, thus serving as a tool for informed decision making. This model includes factors such as water availability and labor shortages, which are critical for sustainable fruit production. A 20-year planning period has been chosen based on several studies indicating that many fruit orchards can maintain optimal production levels during this period before facing challenges that compromise their productivity and economic viability (Day et al., 2005; Herrera, 1995; Sharif et al., 2009; Vinyes et al., 2015). Due to its theoretical nature, this model provides an approximate estimate of the yield using production functions. In this sense, the model evaluates how fluctuations in resource availability impact profitability and sustainability, determining optimal land and water allocations for each fruit crop based on economic returns and resource requirements.

1.2.1 Production Functions

An extensive bibliographic review was undertaken. Crop water production functions were obtained from studies or analyses carried out on field experiments conducted under different soil and climatic conditions and using different agricultural practices. Some of these functions were obtained from research conducted at the study site (described in Section 1.2.3), while others were obtained from different works on the topic. The analysis of the impact of the climate on fruit crop productivity focuses on real and potential evapotranspiration at the study site. This approach enables a more accurate estimation of the water available to plants and its relationship to the crop yield. To achieve this, a relative representation of yields and evapotranspiration with respect to the maximum potential of the fruit crop is used, making the comparison and parameterization of heterogeneous data more expeditious (Carvallo et al., 1998).

The crop water production function shows that there is a concave relationship between the water applied and the harvestable yield, leading to diminishing returns. This means that once the maximum production value is reached, any further increase in irrigation leads to lower yields (Foster & Brozović, 2018; Varzi, 2016). The mathematical expressions that model these functions are commonly defined as follows (Holzapfel et al., 1990; Li et al., 2020a):

$$Y_{rel} = \alpha \cdot (ET_{rel})^2 + \beta \cdot ET_{rel} + \gamma \tag{1.1}$$

$$Y = \left[\alpha \cdot \left(\frac{ET_a}{ET_c} \right)^2 + \beta \cdot \left(\frac{ET_a}{ET_c} \right) + \gamma \right] \cdot Y_m \tag{1.2}$$

where α, β, and γ are empirical parameters obtained from the studies; Y_{rel} is the relative yield; ET_{rel} is the relative evapotranspiration; Y is the crop yield (t ha^{-1}); ET_a is the actual evapotranspiration of the fruit crop (mm); ET_c is the potential evapotranspiration of the fruit crop (mm); and Y_m is the maximum yield of the fruit crop (t ha^{-1}).

1.2.2 Model Formulation

A nonlinear programming model has been developed, with a focus on optimal land allocation to maximize the net profits of fruit orchards over a 20-year period. This model takes a holistic approach that includes considering the proper management of water and land use, operating costs, and labor, as well as the risks associated with the volatility of sale prices. The key decision variables are land allocation and the annual allocation of water for each fruit crop.

This model adapts and extends the methodologies previously developed for annual crops by Carvallo et al. (1998) and Kuschel-Otárola et al. (2018) according to the specific conditions favored by the fruit crops evaluated.

Objective Function

The objective function is designed to maximize the total profits of the farm, which are calculated as the difference between sales revenues and the associated production costs. Revenue is calculated by multiplying the market price by the area and the crop yield, which is determined by the total amount of water applied. Production costs include direct costs such as labor, water use, and other agricultural inputs. The equation is represented as follows:

$$\max U = \sum_{i=1}^{n} \sum_{k=1}^{t} P_{i,k} A_i Y_{i,k} - \sum_{i=1}^{n} \sum_{k=1}^{t} A_i C_{i,k} \tag{1.3}$$

where U is the profit of the farm, expressed in millions of CLP (M CLP), where CLP corresponds to Chilean pesos; P_i is the price per ton of the fruit crop i in the year k (M CLP t^{-1}); A_i is the area the fruit crop i is to be cultivated in (ha); Y_i is the yield generated by the crop i in year k (t ha^{-1}); and $C_{i,k}$ represents the production costs per unit area of the crop i in year k (M CLP ha^{-1}). Some of the components of $C_{i,k}$ are soil preparation, planting (the initial stage only), pruning, harvesting, fertilizers, and pesticides. The costs vary depending on how many years k it has been since the crop was planted.

Irrigation costs (IC) are associated with drip or microjet irrigation systems and correspond to the equipment's amortization per hectare. The costs related to soil preparation, planting, irrigation, and general orchard management during the first three years of the orchard's establishment, in which fruit crops do not produce significant yields, were also considered. To estimate these costs, a 17-year amortization period was considered. The capital recovery factor (CRF) (Steiner, 1973) was calculated to equitably distribute the initial costs throughout the amortization period, resulting in annual payments that the company needs to make.

$$CRF = \frac{(1+i)^t \cdot i}{(1+i)^t - 1} \tag{1.4}$$

where i is the annual real interest rate (%) and t is the number of years over which the capital is amortized. The extended function is as follows:

$$\begin{aligned} \max U = \sum_{i=1}^{n}\sum_{k=1}^{t} P_{i,k}A_i \left[\alpha_i \cdot \left(\frac{ET_a}{ET_c}\right)^2 + \beta_i \cdot \left(\frac{ET_a}{ET_c}\right) + \gamma_i\right] Ym_i \\ - \sum_{i=1}^{n}\sum_{k=1}^{t} A_i NL_{i,k} LC_{i,k} - \sum_{i=1}^{n}\sum_{k=1}^{t} A_i OC_{i,k} \\ -10\, Csw \sum_{i=1}^{n}\sum_{k=1}^{t} A_i \frac{ET_a}{EA_i} - \sum_{i=1}^{n}\sum_{k=1}^{t} A_i IC_{i,k} \end{aligned} \tag{1.5}$$

where LC is the cost of the labor required for the fruit crop i in the year k (M CLP person-day^{-1}); $NL_{i,k}$ is the labor required per unit area (person-day ha^{-1} year^{-1}); $OC_{i,k}$ corresponds to costs such as fertilizers, pesticides, and others; and Sw_k is the amount of surface water required in the year k (m^3 year^{-1}), with its corresponding cost being Csw (M CLP m^{-3}).

Model Constraints

The model includes constraints that guarantee the operational viability and sustainability of the orchard:

- Land availability: This constraint ensures that the total cultivated area does not exceed the total area available in the farm and is expressed as

$$\sum_{i=1}^{n} A_i \leq A_T \tag{1.6}$$

where A_T is the total land area (ha).

- Water availability: This constraint ensures that the sum of the gross water requirements of the fruit crops i in the year k does not exceed the farm's total water availability (W_T).

$$Wr_{i,k} = 10 \sum_{i=1}^{n} \frac{A_i ETa_{i,k}}{AE_i} \tag{1.7}$$

$$\sum_{k=1}^{t} [SW_k - Wr_{i,k}] \leq W_T, \quad \forall k \tag{1.8}$$

  where $Wr_{i,k}$ is the gross water requirement for each fruit crop i in the year k (m^3) and AE_i is efficiency of the irrigation system for the fruit tree i ($0 < AE < 1$). This variable is multiplied by 10 to convert mm to m^3.

- Minimum water applied: This constraint ensures that each crop receives the minimum amount of water required for crop development and productivity. The criterion used to determine the minimum amount of water applied to each crop in the year k is that it should not be less than 55% of the potential evapotranspiration of that crop, adjusted for the cultivated area. This value was obtained by analyzing the production functions presented in Table **??**. This threshold is essential for preventing significant water stress, which could compromise both the crop yield and the sustainability of the agricultural system. Mathematically, this constraint is expressed as

$$ETa_{i,k}\, A_i \geq 0.55 \ \cdot ETc_{i,k}\, A_i, \quad \forall i, k \tag{1.9}$$

- Labor availability: Given that the labor force can change from one year to the next, this constraint is expressed as

$$\sum_{i=1}^{n} A_i\, NL_{i,k} \leq La_k, \quad \forall k \tag{1.10}$$

where La_k is the total annual availability of labor per year k (person-day year^{-1}).

- Price risk constraint: This constraint aims to mitigate the financial impact of the volatility of market prices on the farm. It guarantees that the sum of the cultivated areas, weighted by a risk factor associated with the price volatility of each crop, does not exceed the acceptable risk limit for the farm. Mathematically, it is expressed as

$$\sum_{i=1}^{n} A_i r_i \leq R_{\text{Total}} \tag{1.11}$$

where r_i is the risk factor associated with the fruit crop i (adimensional). r_i is calculated as the ratio between the standard deviation of the price of the fruit crop and the maximum standard deviation observed among all fruit crops (Equation (1.12)).

$$r_i = \frac{DesvStd(i)}{DesvStd_{\text{max}}} \tag{1.12}$$

In our model, the 'risk level' represents the uncertainty associated with the market price of fruit crops. The total risk limit, R_{Total} (ha), is determined by the farm manager and is expressed as a percentage of the total area (δ):

$$R_{\text{total}} = \delta \cdot A_{\text{Total}}; \quad R_{\text{total}} \geq r_i \text{ min} \tag{1.13}$$

This limit is conceptualized in terms of 'equivalent hectares of risk', a metric that quantifies the risk in relation to the size of the farm, facilitating risk management based on market price volatility and the farmer's risk tolerance.

- Crop area considerations: Agricultural, market, and productive diversity management criteria need to be considered in order to restrict maximum and minimum crop areas based on possible market or agricultural limitations. These constraints are expressed as follows:

$$min\, S_i \leq A_i \leq max\, S_i, \quad \forall k \tag{1.14}$$

where $min\ Si$ and $max\ Si$ correspond to the minimum and maximum crop area assigned to a farm producing fruit crop i, respectively (both in ha).

- Complementary considerations: A constraint is required to force the crop water requirement to assume a value greater than or equal to zero when the cultivated area is also zero, and this is expressed as

$$K \cdot A_i - \sum_{k=1}^{t} ETa_{i,k} \geq 0, \quad \forall k \tag{1.15}$$

where K is a positive constant (K = 10.000 mm ha^{-1}). In addition, to prevent the application of more water than the crop requires, the following constraint is added:

$$ETa_{i,k} \leq ETc_{i,k}, \quad \forall i, k \tag{1.16}$$

- Finally, there is a non-negativity constraint, which is expressed as

$$A_i, ETa_{i,k} \geq 0 \tag{1.17}$$

To aid readers in their understanding of the structure and functioning of the proposed model, Figure 1 contains a schematic diagram illustrating the relationships between the different components, including the model's objective function, constraints, input parameters (such as prices, costs, production functions, and potential evapotranspiration), and decision variables (the land and water allocation for each fruit crop).

1.2.3 Study site

The model was applied to the O'Higgins Region, which is located in the central valley of Chile (latitude 34°15′ S and 35°58′ S and longitude 70°30′ W and 72°00′ W) and covers an area of approximately 16,387 km^2 (Figure 15). The region's climate is predominantly Mediterranean, characterized by rainy winters and dry summers. The average annual precipitation in the region is approximately 652 mm, with concentrated rainfall mainly seen from May to August. The average annual temperature is 14 °C, reaching a maximum of up to 30 °C in summer and a minimum of up to 3 °C in winter (MMA, 2023).

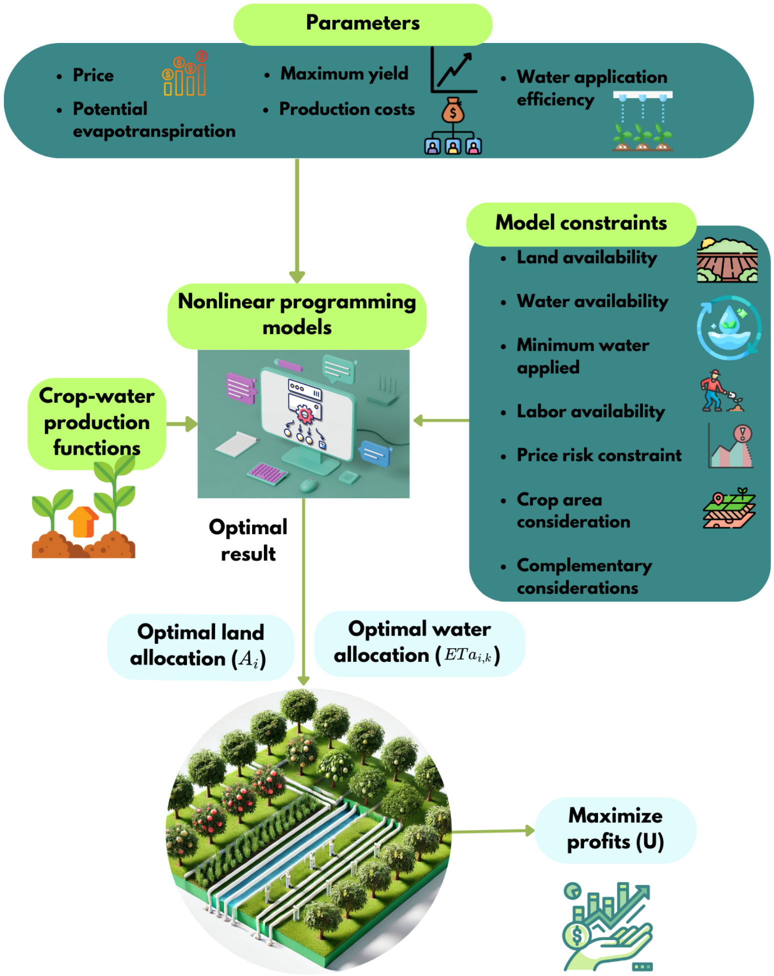

Figure 1: A schematic diagram of the nonlinear programming model developed for establishing the optimal cropping pattern for fruit orchards.

The O'Higgins Region plays a key role in Chile's agricultural production, accounting for 26.9% of the total surface area of the country that is planted with fruit crops, including 24.2, 13.4, and 13.9% of cherries, table grapes, and citrus fruits (mandarins, oranges, and lemons), respectively. Other important crops are apples, pears, and avocados, for which they produce 4.6, 3.9, and 3.8% of the country's total, respectively. The region also contains 30% of the area covered by vineyards in Chile, making it the second most important region for wine after the Maule Region (ODEPA, 2022; ODEPA and

CIREN, 2021). Since 2003, the area cultivated with cherries has increased by 799.3%, while table grapes have shown only a marginal increase of 0.5%. In addition, crops such as citrus fruits, apples, pears, and avocados have recorded changes of 20.0%, -35.3%, 14.0%, and 80.9%, respectively (ODEPA and CIREN, 2021). These variations in the cultivated area directly reflect the dynamics of the demand for and price of these crops in international markets, resulting in the expansion of the most profitable crops and a decrease in the planted area of the least profitable crops. Currently, the cultivation of crops such as kiwi and peach is rising, indicating farmers' continuous adaptation to market trends.

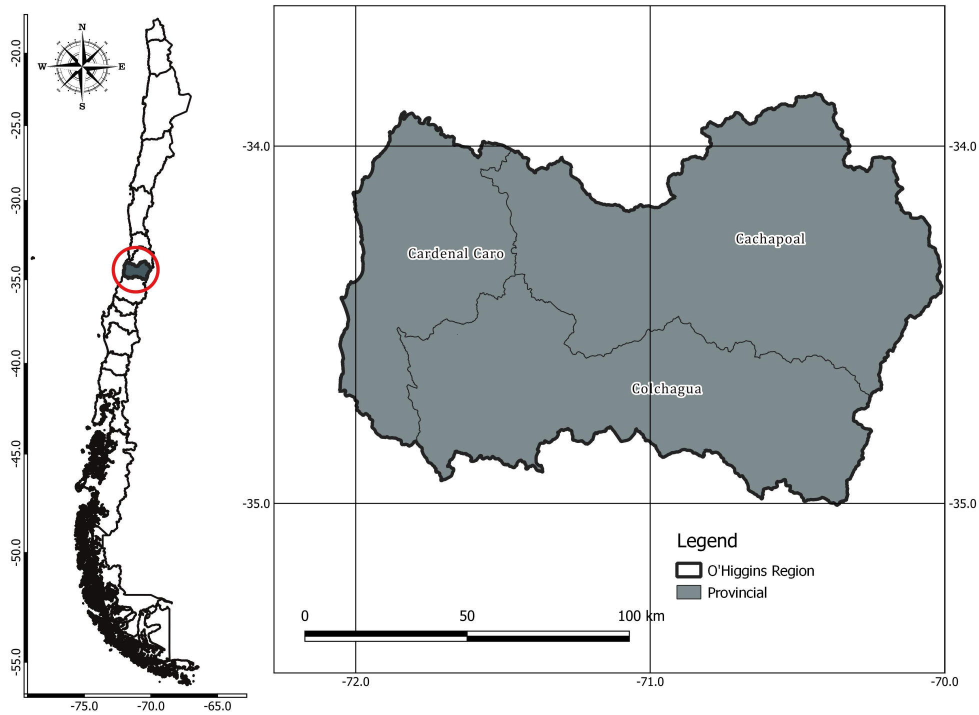

Figure 2: Map showing the location of the study site in the O'Higgins Region, located in the Central Valley of Chile (latitude 34°15′ S to 35°58′ S and longitude 70°30′ W to 72°00′ W).

1.2.4 Model Input Data

The fruit crops selected for this study are shown in Table 1, along with the empirical parameters of their production functions. Additionally, data on the maximum yields for each crop, compiled from various research studies, are presented in Table 2. These values represent the potential productive capacity of these crops under ideal agronomic conditions and optimized water management and serve as fundamental parameters in the crop water production function (Equation (1.2)). Yield estimates are adjusted based on applied water deficits or surpluses, allowing the model to simulate yield reductions in scenarios where the water applied deviates from the crop's optimal water requirements.

Table 1: Relative crop water production functions for the fruit crops analyzed using our model.

Fruit Crop	α	β	γ	Source
Blueberry	-0.6306	1.7716	-0.1204	Holzapfel et al. (2004)
Cherry	-2.4364	3.1661	-0.0286	Carrasco-Benavides et al. (2020)
Citrus fruit	-0.4664	1.0754	0.3962	Holzapfel et al. (2001)
Peach	-1.3714	2.6952	-0.3238	Darshana et al. (2012)
Kiwi	-0.7875	1.6847	0.1149	Holzapfel et al. (2000)
Apple	-1.0448	2.0595	-0.0147	Darshana et al. (2012)
Wine grape	-0.6604	1.1676	0.5060	Jara et al. (2017)
Table grape	-0.5760	1.2360	0.2827	Zúñiga-Espinoza et al. (2015)
Pear	-2.3378	4.2551	9.9660	Gomes et al. (2023)
Avocado	-0.4462	1.1205	0.3257	Holzapfel et al. (2017)

Table 2: Maximum yield values used for the fruit crops included in the model.

Fruit Crop	Maximum Yield (t ha^{-1})	Source
Blueberry	20	Holzapfel et al. (2020)
Cherry	20	Blanco et al. (2019)
Citrus fruit	70	Holzapfel et al. (2001)
Peach	40	INIA (2017a)
Kiwi	45	Holzapfel et al. (2000)
Apple	70	Lecaros-Arellano et al. (2021)
Wine grape	25	Jara et al. (2017)
Table grape	28	INIA (2017b)
Pear	50	ODEPA and CIREN (2021)
Avocado	25	Holzapfel et al. (2017)

This analysis covers the 2000–2020 period, and export prices in US dollars (USD) for this period were obtained from the Office of Agrarian Studies and Policies (ODEPA) (ODEPA, 2024) (Figure 3). To convert these prices to Chilean pesos (CLP), the official exchange rate provided annually by the Central Bank of Chile was applied (Banco Central de Chile, 2024). It should be noted that the exchange rate has experienced variations over time; however, in 2020, USD 1 was equivalent to CLP 792. Production costs were extracted from ODEPA's technical–economic reports (CNR, 2014) and were adjusted annually using the Consumer Price Index (CPI), which was provided by the National Institute of Statistics (INE). The annual water demand for each crop was calculated from local evapotranspiration references (Alvarez-Garreton et al., 2018). Potential evapotranspiration was then calculated using the crop potential factor (CPF) and based on the percentage cover model or leaf area index (Holzapfel et al., 2015; Holzapfel et al., 2020). This measurement is crucial for estimating the exact water demand required by each crop under optimal conditions.

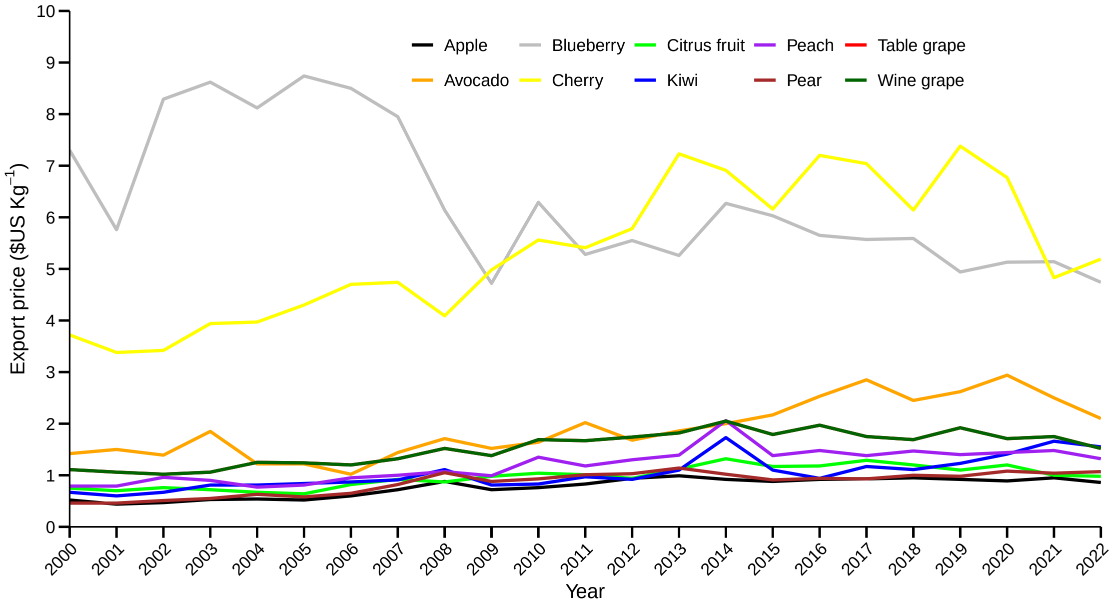

Figure 3: Trends in fruit export prices in the 2000 − 2022 period.

1.2.5 Model Evaluation

The optimization model was initially implemented without considering water and labor constraints, using *General Algebraic Modeling System* (GAMS) software, version 45, and solved using the SCIP solver. The GAMS is a robust and versatile tool used for solving optimization problems, renowned for its ability to handle complex nonlinear models and its flexibility in algebraic problem formulation (Pintér, 2007). Its architecture facilitates its integration with various solvers, allowing for the selection of optimal algorithms tailored to the specific nature and constraints of each scenario (Ćalasan et al., 2019), thereby enhancing its efficiency and accuracy in the optimization process (Duraiappah, 2003).

This initial configuration allowed for the identification of the maximum potential yield of the fruit crops, allowing for the addition of more objective constraints at later stages. The model was configured for a fixed area of 1000 ha, with irrigation and labor costs adjusted for inflation in order to reflect the projection of economic conditions over a 20-year period. For the year 2020, these costs were 10.17 CLP m^{-3} of water (Kuschel-Otárola et al., 2018) and CLP 20,000 per working day (CNR, 2014). Drip irrigation (AE = 0.9) was used for blueberries, cherries, oranges, peaches, kiwis, apples, wine grapes, table grapes, and pears, while microjet irrigation (AE = 0.85) was used for avocados.

An equitable surface distribution was carried out, allocating 100 ha to each type of fruit crop in order to assess their water and labor requirements, as well as their profitability. Subsequently, a detailed analysis was carried out on the risk associated with price volatility and the farmer's risk tolerance by applying the previously established risk constraint. Initially, the model did not limit the maximum area allocated to each fruit crop. However, an additional constraint was considered, limiting the maximum area per fruit crop to 350 ha to simulate how variations in risk level (100%, 80%, 60%, and 40%) influence the optimal cropping pattern. This approach is crucial to adapt the model to the farmer's preferences and mitigate possible economic losses, thus ensuring sustained profits amid market fluctuations.

Additionally, a detailed sensitivity analysis was conducted to assess how labor and water availability affect orchard management. A limit of 250 ha was established as the maximum area for each fruit crop. A progressive reduction in labor was simulated at intervals of 12.5%, 25%, 37.5%, 50%, and 67.5% to model different levels of labor shortage. Simultaneously, water availability levels were reduced by 12.5%, 25%, 37.5%, and 50% to represent different water restriction scenarios. This analysis allowed us to quantify the impact of the scarcity of these critical resources on land allocation and crop profitability, enabling us to adapt the agricultural strategies used in order to optimize crop management in the face of resource limitations.

To maximize profitability and ensure adequate crop diversification, several scenarios were analyzed, with both economic viability and resilience to variations in resource availability and market prices considered. The goal is for the results of the model to help inform decision making in critical situations such as water deficits, labor shortages, and price fluctuations. Although these variations may have affected profits, our findings can contribute to the adaptation of farming strategies, maintaining the viability and sustainability of orchards.

1.3 Results and Discussion

1.3.1 Homogeneous Fruit Crop Distribution Pattern

This section discusses the analysis of the profits from and water and labor requirements for each fruit crop over a 20-year period, considering a total surface area of 1000 ha equally distributed among the fruit crops. Figure 4A shows the different water requirements of each fruit crop throughout the study period. To conduct a detailed analysis of their water requirements, the 2019–2020 season was selected, as this was the period in which the highest water demand was recorded during the study. Figure 4B illustrates the specific water needs of each fruit crop evaluated during that season. This approach not only enables the identification of differences in water requirements among various fruit species but also provides a robust foundation for the optimal planning of fruit orchards based on water availability. In addition, Figure 5 presents the profits obtained and the labor required per crop.

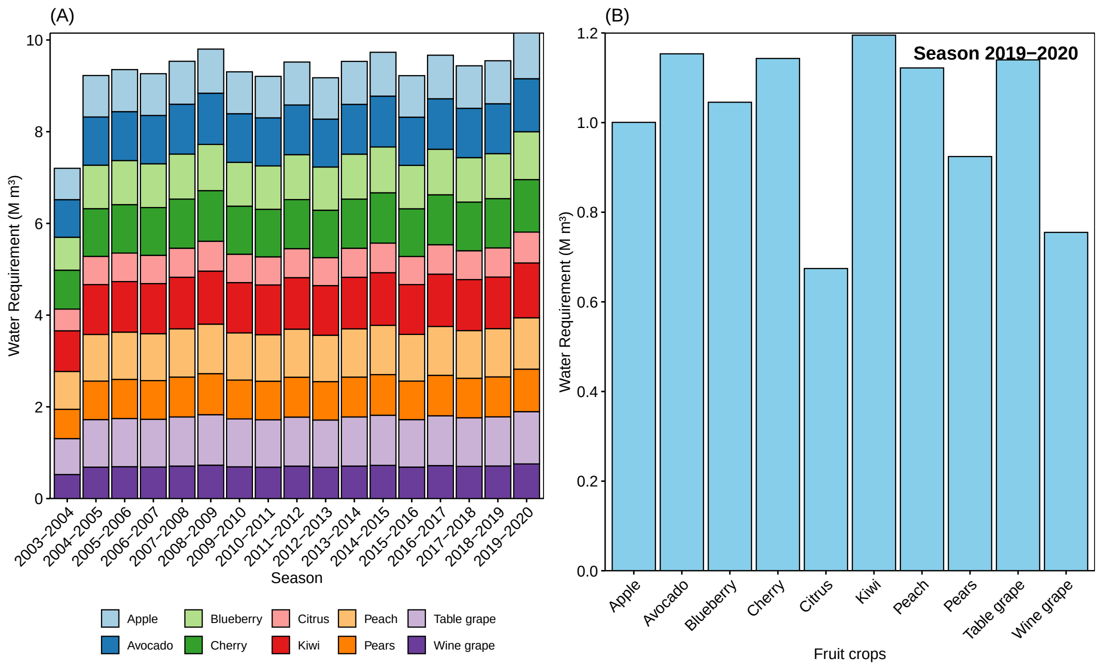

Figure 4: The water demand per season for each fruit crop when grown in homogeneous 100 ha areas (A) and their water requirements for the 2019–2020 growing season (B).

The analysis of how the water requirements changed over time revealed that the crops had a lower water demand during the 2003–2004 season, which was largely influenced by the plants' development under incomplete vegetation cover conditions. From the 2005–2006 season onwards, water consumption began to become more influenced by evapotranspiration, indicating that the crops had matured and there was an increase in water requirements. The highest water demand was recorded in the 2019–2020 season due to climatic conditions in the region (Figure 4B). Kiwis and avocados stand out for their high water requirements, which is in contrast to citrus fruits and wine grapes, which require significantly lower amounts of water. Understanding these differences is fundamental to implementing efficient water management, particularly in areas affected by water scarcity.

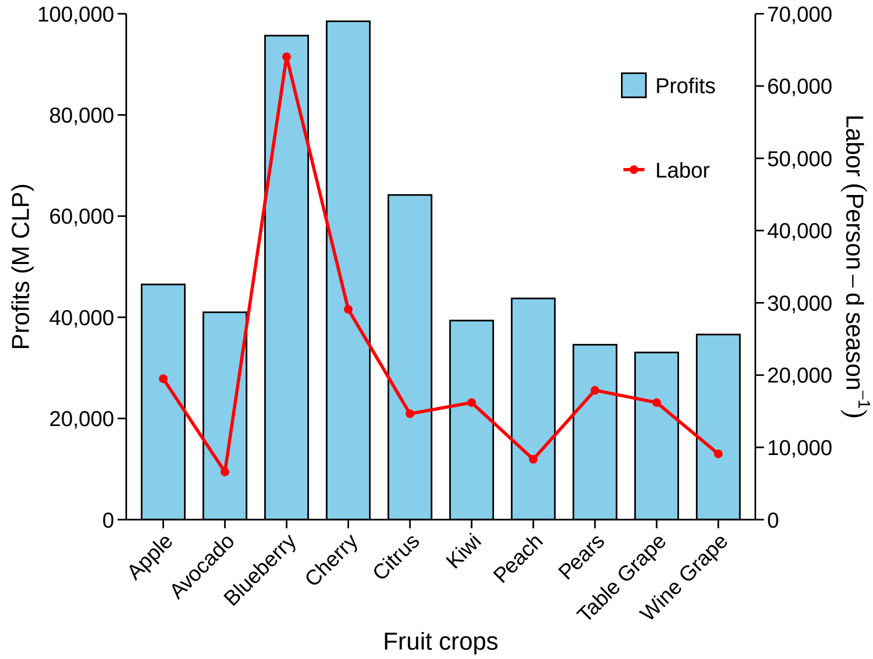

Figure 5: Profits generated and labor required for each fruit crop when grown in homogeneous 100 ha areas.

The analysis of the profits generated by fruit crops cultivated in equal areas of 100 ha (Figure 5) reveals significant differences between the crops over the study period. Cherries stand out as the most profitable fruit crop, followed by blueberries and citrus fruits. Peaches, apples, avocados, and kiwis show smaller profits, while the lowest profitability is observed in table grapes and pears. These data show the variability in the profitability associated with each type of fruit and highlight the importance of a strategic selection of crops to maximize economic benefits.

With respect to labor (Figure 5), blueberry stands out as the crop that required the highest number of labor days per 100 ha in the 2019–2020 season. Apples and pears are also labor-intensive, whereas peaches and avocados require significantly less labor. These findings underscore the importance of considering the availability of labor when allocating land for fruit orchards, particularly in places where labor is a limiting factor. Table 3 summarizes the average labor and water requirements for each fruit crop, as well as the profits generated when they are cultivated in equal areas of 100 ha.

Table 3: Profits generated and labor required for the analyzed fruit crops, considering an area of 100 ha.

Avg Labor Requirement (person-d/season)	Avg Water Requirement (m^3/season)	Profit (M CLP)
192,943	9,480,158	533,143

1.3.2 Analysis of the Land Distribution Associated with Price Risk

Figure 6 shows the variation in the export prices of the fruit crops analyzed over the 2000–2020 period. The analysis of the standard deviation of their prices revealed that cherries and blueberries are the crops with the greatest fluctuations, although they generally correlate with higher economic returns. In contrast, apples, citrus, pears, and kiwis exhibit smaller fluctuations in prices, indicating their relative stability in the market. These results are crucial for adjusting diversification and risk management strategies in the allocation of land for fruit production.

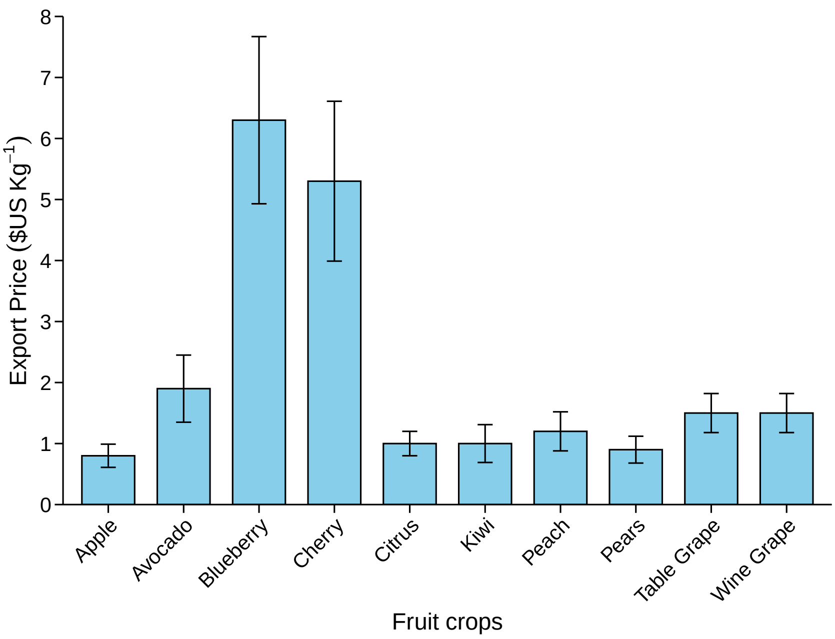

Figure 6: Export prices of the fruit crops studied.

Figure 7 presents the results of analyzing the area allocated to different fruit crops when no maximum area constraint is applied but their associated risk level is considered. This figure allows us to observe how the allocation of land varies in response to the different levels of risk assumed by the farmer. As the farmer opts to assume less risk, the size of the area allocated to cherry trees decreases, while the area dedicated to citrus trees increases. This phenomenon is mainly explained by the fact that although cherry trees offer high economic returns, they also exhibit the second highest price variability. In contrast, citrus trees, despite being third in terms of economic return, have lower price variability, which makes them a less risky option for the farmer.

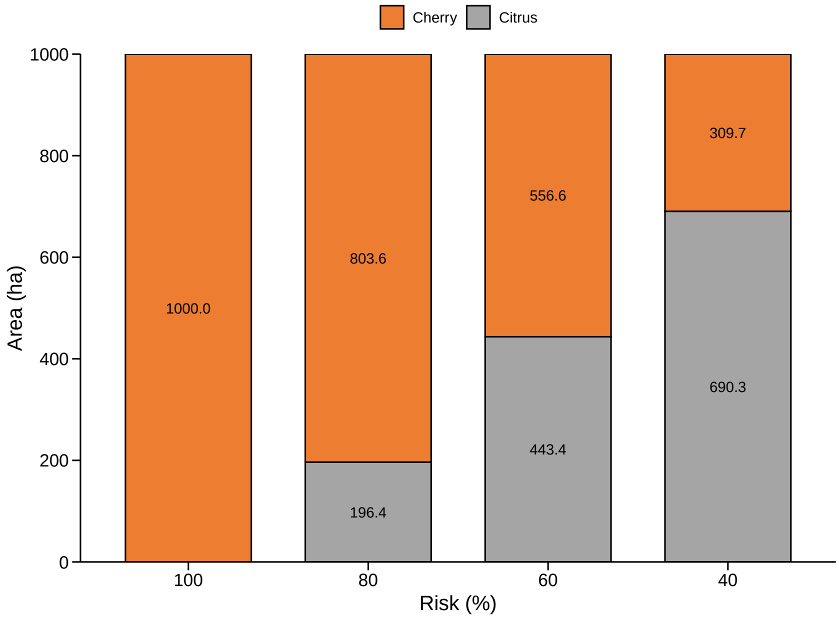

Figure 7: Land allocation in scenarios where different levels of risk are assumed by the farmer.

Table 4 shows the maximum labor and water requirements for this orchard, along with the profits generated under different risk levels. As the risk level is reduced, a decrease in water and labor demand is observed, as citrus fruits have lower water and labor requirements than cherries. However, these requirements are accompanied by a decrease in profits due to the lower economic return of citric fruits. Specifically, profits are reduced by 6.8%, 15.5%, and 24.1% when moving from a risk level of 100% to risk levels of 80%, 60%, and 40%, respectively.

Table 4: Labor and water requirements and profits generated at different risk levels.

Risk (%)	Avg Labor Requirement (person-d/season)	Avg Water Requirement (m^3/season)	Profit (M CLP)
100	273,694	10,676,152	985,130
80	247,586	9,816,545	917,708
60	214,752	8,735,484	832,916
40	181,919	7,654,423	748,123

Establishing a maximum land allocation constraint of 35% of the total farm area has a marked effect on the risk level, as Figure 8 shows. This constraint provides a different perception of risk, as it forces diversification in order to mitigate the farmer's dependence on fruit crops with highly volatile prices. Specifically, assuming a risk level of 100% or 80% does not produce alterations in the cropping pattern. However, a risk level of 60% reduces the cultivation of blueberries and increases that of apples. Additionally, a risk level of 40% reduces the cultivated area of blueberries to an almost imperceptible value of only 4.8 ha, while the area planted with apples and peaches increases. This compensatory diversification is due to the low volatility of citrus fruit, apple, and peach prices, which balance the high risk derived from the high volatility of cherry and blueberry prices.

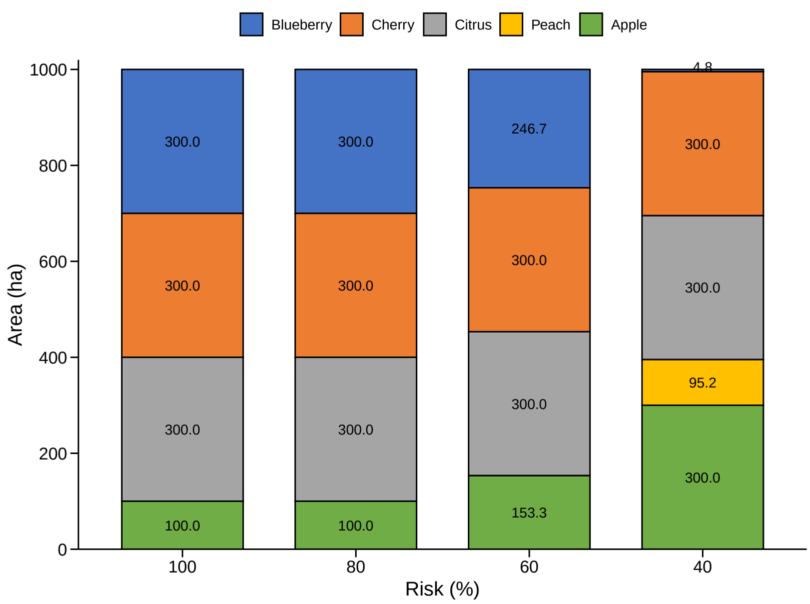

Figure 8: The land distribution of fruit crops when different risk levels are assumed by the farmer, with an area constraint of 35% of the total farm area for all fruit crops.

Table 5 shows the labor and water requirements of the orchard, as well as its corresponding profit outcomes, under the constraint of allocating a maximum of 35% of the total farm area to each crop and across varying risk levels, as defined in the 'Crop Area Considerations' (Equation (1.14)). As the risk level is reduced from 100% to 40%, there is a considerable tendency towards a decrease in labor requirements. This reflects a transition towards fruit crops with lower volatility and labor intensity, such as peaches and apples, which replace those with greater volatility and labor requirements, such as blueberries.

Despite changes in the cropping pattern, water consumption remains stable. This is attributed to the fact that the analyzed crops have similar water requirements, which facilitates efficient water management under the established constraints. In terms of profits, a consistent and significant reduction is observed. From the risk level 100% to 60%, profits decrease by 3.2%, while a more marked decrease of 18.0% is recorded from a risk level of 100% to 40%. These changes indicate that the selection of fruit crops with less volatile market prices has an important economic impact, resulting in lower returns but higher financial stability and predictability. This analysis confirms that although different risk levels modify the distribution of fruit crops, an adequate selection of crops can maintain an efficient water balance, which is essential for sustainable crop production in water scarcity scenarios.

Table 5: Labor and water requirements, and profits per crop, based on different risk levels, under the constraint that crops do not exceed 35% of the total farm area.

Risk (%)	Avg Labor Requirement (person-d/season)	Avg Water Requirement (m^3/season)	Profit (M CLP)
100	325,149	8,955,335	821,609
80	325,149	8,955,335	821,609
60	302,660	8,932,573	795,403
40	200,773	8,937,287	673,780

When analyzing the allocation of land without a constraint on the maximum area for each fruit crop, there was a tendency to select one or two main fruit crops depending on the risk level. For example, cherries (high profitability and high volatility) and citrus fruits (good profitability and low volatility) dominated land allocation results, leading to significantly higher profits than those obtained under maximum area constraints. Specifically, the profits obtained at a 60% risk level without the constraint exceeded those at a 100% risk level with the constraint. However, the impact on profit was considerably lower under the constraint scenario, demonstrating that the effective diversification and distribution of fruit crops can reduce risk and protect against market volatility, promoting long-term financial stability and more efficient and sustainable risk management.

Furthermore, our analyses revealed that the water requirements seen at different risk levels and without a maximum area constraint vary widely due to the concentration of specific fruit crops. However, area constraints led to a notable stabilization in the demand for water, which resulted from broader diversification in the allocation of fruit crops adapted to different risk levels, thus preventing large fluctuations in water demand. This is crucial for the sustainability of agricultural operations, as it guarantees the efficient and predictable management of water resources, which is a determining factor in the long-term viability of agricultural practices under water scarcity scenarios.

1.3.3 Labor Sensitivity Analysis

The sensitivity analysis of labor availability reveals significant changes in land allocation and net profits, highlighting the importance of adequate crop planning. Figure 9 shows how the areas allocated to different fruit crops are adjusted as labor availability rates vary. The cultivation area of blueberries, which had an initial allocation of 250 ha, is reduced to zero as the labor available decreases to 37.5%, demonstrating the large amount of labor required by the crop. Regardless of their high labor requirements, cherries manage to maintain a constant allocation of 250 ha until the labor available drops to 50%, at which point their land allocation is reduced to 113 ha; this reduced but persistent allocation is explained by their high profitability. Citrus fruits maintain their full allocation of 250 ha at all labor availability rates, demonstrating that they have an optimal balance between labor requirements and profitability.

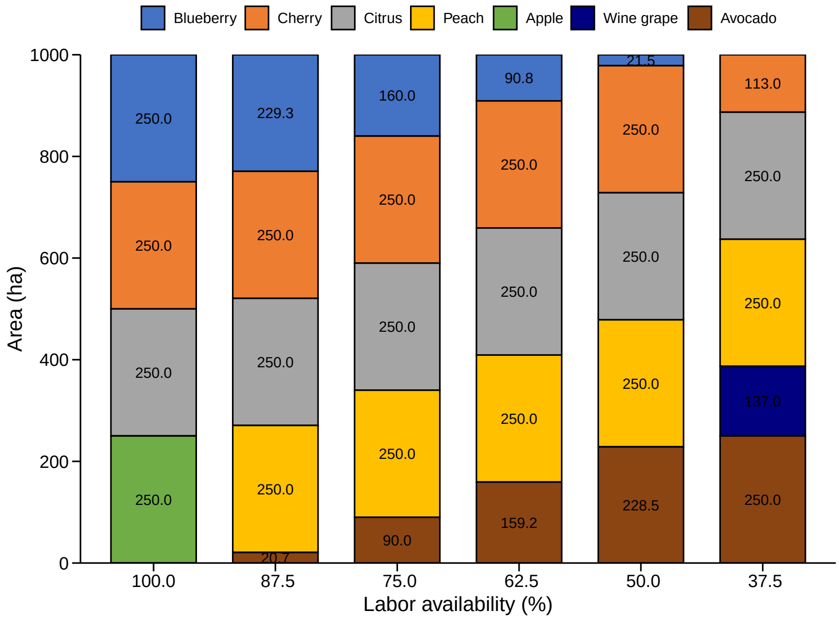

Figure 9: Land allocation of each crop under different labor availability rates.

The land allocated to apples is reduced to zero when the labor available reaches 87.5%, with peaches favored instead, as they have the second lowest labor requirements and offer only slightly lower returns. Simultaneously, the land allocated to avocados, which presents the lowest labor requirements, increases from 20.7 ha at 87.5% availability to 250 ha at 37.5%, highlighting their lower dependence on intensive labor. Wine grapes are third in terms of having a low labor requirement and are allocated 137 ha at the minimum labor availability. This allocation shows tactical adaptation, as crops with lower labor requirements and good returns are prioritized to optimize the use of available resources in response to labor constraints.

Table 6 shows how variations in labor availability directly affect labor, water use, and profits in fruit production. As the labor available decreases from 100 to 37.5%, a progressive reduction from 318,250 to 119,344 people per season is observed, resulting in changes in the land allocation of less labor-intensive fruit crops. Water consumption increases markedly when 87.5% of labor is available. At this point, the land allocated to apples, which require less water, is reduced to zero, while that allocated to peaches, which have higher water requirements, increases. As the labor available continues to decrease to 50%, a further increase in water consumption is observed, coinciding with an increase in the land allocated to avocados and a reduction in that allocated to blueberries. From the 87.5% level of labor availability, avocados, which require more water than blueberries, begin to occupy more area, increasing the water consumed. However, there is a decrease in water requirements when the labor available reaches 37.5%. This reduction is due to the decrease in the land allocated to cherries and the increase in that allocated to wine grapes, the fruit with the second lowest water requirements. The direct correlation between the decrease in labor availability and changes in land allocation reveals how changes in labor availability can cause significant variations in water requirements. This phenomenon not only directly affects the operation and sustainability of orchards under variable conditions, but also reflects that the strategic management of water resources should align with fluctuations in labor availability. This allocation pattern highlights the importance of the efficient integration of water resource management and labor planning to optimize the sustainability of agricultural operations, demonstrating that effective crop diversification and adequate planning can mitigate the impacts of labor and water availability issues.

Table 6: Maximum labor and water requirements and net profits under different levels of available labor.

Labor Availability (%)	Max Labor Requirement (person-d/season)	Avg Labor Requirement (person-d/season)	Avg Water Requirement (m^3/season)	Profit (M CLP)	Reduction of Profits (%)
100.0	318,250	301,869	9,018,882	762,162	0.0
87.5	278,469	264,683	9,323,579	743,920	2.4
75.0	238,688	226,893	9,393,474	706,050	7.4
62.5	198,906	189,102	9,463,369	668,181	12.3
50.0	159,125	151,312	9,533,263	630,311	17.3
37.5	119,344	114,521	9,057,336	533,676	30.0

In terms of net profits, our analysis shows that labor availability significantly influences profitability; the higher the amount of labor available, the less pronounced the reduction in profits. With full labor availability, profits are found to be CLP 762,162

M, and they decrease to CLP 533,676 M when the labor available is reduced to 37.5%, a 30% drop. This decrease illustrates the direct impact of labor constraints on the profitability of the fruit sector. Therefore, proactive land allocation planning that anticipates labor shortages can protect both the operation and profits of orchards.

The integration of advanced technologies into agriculture, such as automated harvesting and other farm management practices, can significantly alter fruit cropping patterns. These innovations compensate for labor constraints and allow for the cultivation of labor-intensive but profitable fruit crops (e.g., blueberries and cherries) under labor shortage conditions. By reducing farmers' dependence on labor, these technologies not only improve operational efficiency but also strengthen the economic viability and sustainability of farms. This approach highlights the need to reevaluate farm optimization models to incorporate the impact of automation, ensuring that agricultural practices can adapt to future challenges.

1.3.4 Water Sensitivity Analysis

The water availability analysis reveals an interesting pattern in land allocation, highlighting the strategic variations made in response to the availability of water. As shown in Figure 10, blueberries, cherries, and citrus fruits maintain a constant allocation of 250 ha for all levels of water availability. This indicates that regardless of water restrictions, these crops are prioritized due to their profitability.

The adjustment in the allocation of land between apples and grapes is particularly significant. With a reduction in water availability to 75%, the land allocated to apples decreases dramatically, from 250 to 91 ha, and eventually decreases to zero at 62.5% availability. Furthermore, the land allocated to wine grapes increases to 250 ha at 62.5% availability, before decreasing to 28 ha at 50%, indicating that their water requirements are lower than those of apples. This strategic adaptation is a response to the lower amount of water available, highlighting the importance of the efficient use of all available land area. While other fruit crops may offer higher returns than wine grapes, the crop that allows for a more complete use of the land under water restrictions is preferred, even if that crop is less profitable. With a water availability of 50%, only 778 of the 1000 ha is used. This demonstrates that the available water is insufficient to cultivate the entire farm.

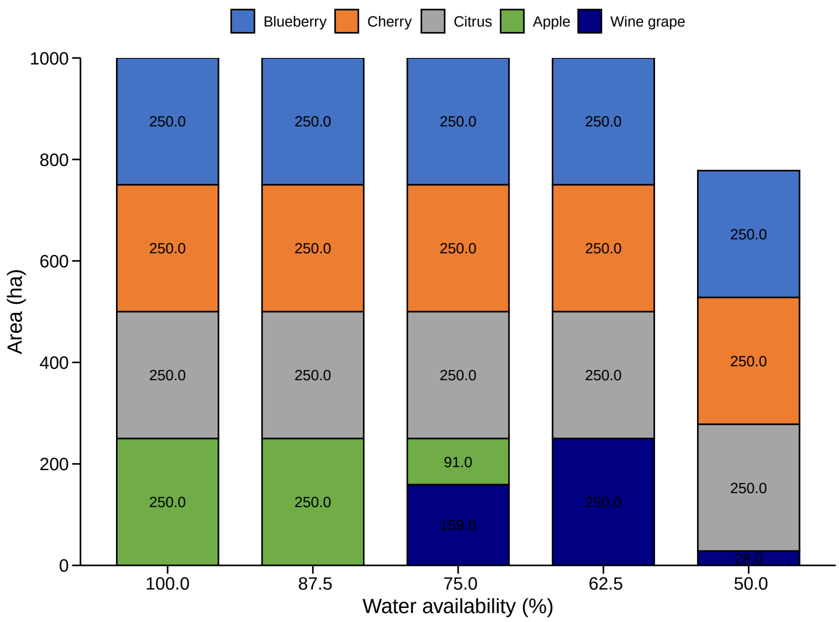

Figure 10: Land distribution under different levels of water availability.

The analysis of water use reveals interesting water management patterns in the face of water availability variations (Figure 11). At 87.5% availability, cherries are allocated more water than blueberries. Likewise, apples have higher water needs than citrus fruits. As the availability of water is reduced to 75%, the water allocated to blueberries increases compared to that of cherries, and an overall decrease in water volume is observed in citrus fruits. Simultaneously, the reduction in the water allocated to apples allows for the increased irrigation of wine grapes.

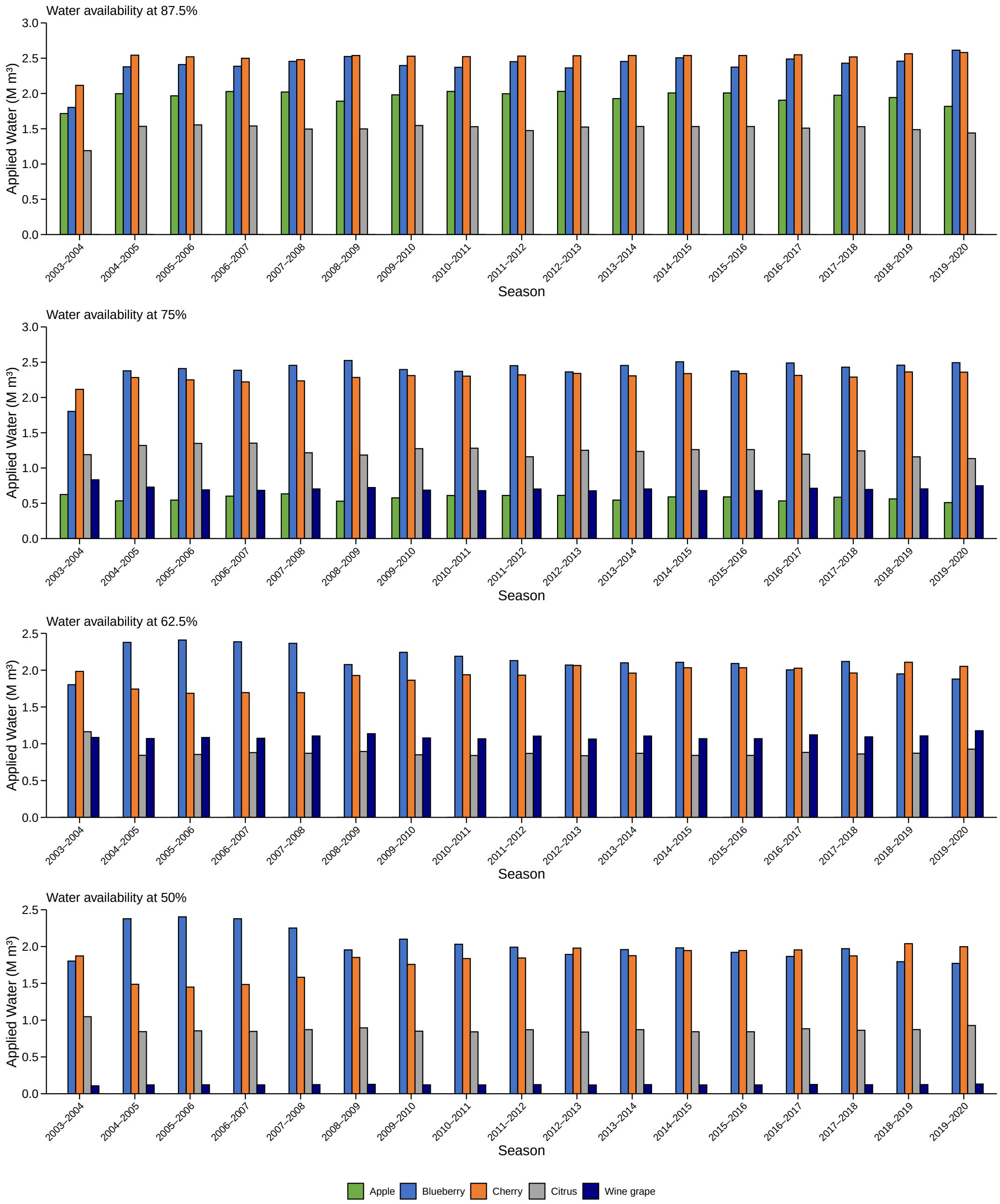

Figure 11: Water applied to fruit crops, given different levels of water availability, throughout the study period.

When reducing the availability of water to 62.5% and 50%, blueberries show an increase in their water allocation, particularly in the 2004–2005 and 2007–2008 seasons. This is explained by their high profitability and yield, which is directly related to the high market prices of blueberries recorded in those periods. As the water available decreases, a progressive reduction in the water allocated to cherries and citrus fruits is observed. In parallel, the water allocated to wine grapes initially increases when the water availability is 62.5% due to an increase in their cultivated area, but this then decreases as their area is reduced. This analysis underscores the importance of using adaptive water management to maximize the efficiency and profitability of the water used in the fruit sector under water deficit conditions.

After evaluating water management over several seasons and under different levels of water availability, our analysis focuses on the 2019–2020 season, the period with the highest recorded water demand, to thoroughly evaluate the allocation of water resources to fruit crops during peak demand. Figure 12 shows the amount of water applied per hectare for each fruit crop, considering the previously defined cropping pattern. It can be observed that even in the context of a progressive reduction in the water available, the high water requirements of certain crops such as blueberries and cherries are still met, highlighting their economic value and priority in water resource management.

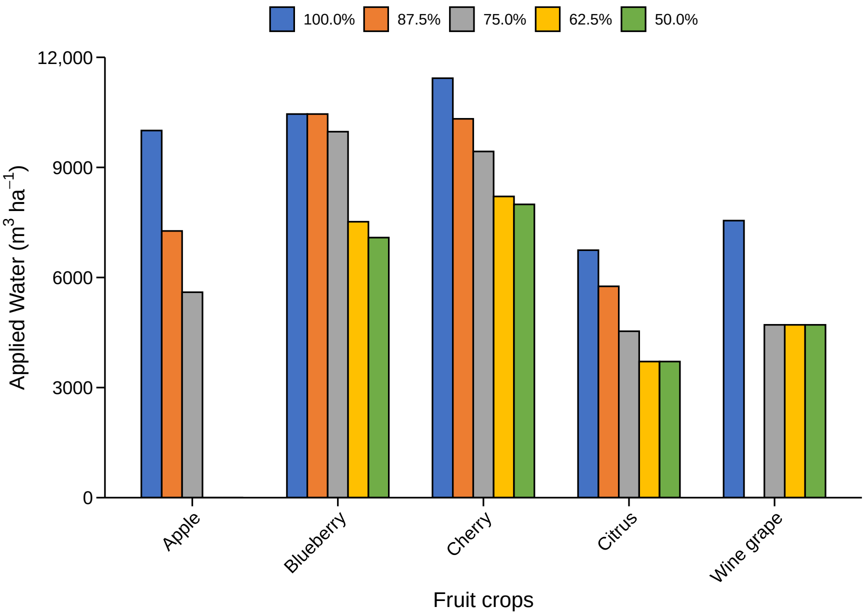

Figure 12: Water applied per hectare to select fruit crops in the 2019–2020 season.

The water allocated to citrus fruits is only reduced to 55% of their usual requirement at a water availability of 62.5%. Similarly, the water allocated to apples is reduced as the water available decreases until their land allocation decreases to zero. When the availability of water reaches 75%, land begins to be allocated to wine grapes and, despite variations in water availability, the amount of water they receive remains constant up to a water availability of 50%, reflecting the effort to optimize water use in less demanding crops when limited water is available.

Table 7 summarizes the combined effects of water availability and labor requirements on revenues in fruit production. As the water available decreases from 100 to 50%, we observe a proportional reduction in both labor and water requirements; labor decreases from 301,869 to 258,053 workers per season, while the maximum water requirement is significantly reduced from 9,658,391 m^3 to 4,829,196 m^3 per season. This is reflected in the profits, which fall from CLP 762,162 M to CLP 565,379 M, resulting in a reduction of 25.8%. It is important to note that the greatest diversification in the orchard was observed at 75% water availability, while the reduction in profits was relatively moderate, reaching 5.8%. This indicates that adequate management strategies can mitigate negative economic impacts even under significant reductions in water and labor availability. Finally, these results underscore the high sensitivity of fruit production to water, emphasizing the importance of the integrated and efficient management of labor and water resources. This adaptive capacity is essential in order for the sector to respond to fluctuations in resource availability and maintain profitability, ensuring that agricultural operations remain sustainable under uncertain conditions. The segmentation of land allocation is part of the strategic management of water resources, allowing farmers to prioritize crops with better adaptability to or higher economic returns under water stress scenarios. Their capacity to adjust the area allocated to crops according to the water available is crucial to maintaining economic viability under conditions of water uncertainty.

Table 7: Maximum labor and water requirements and net profits under different levels of available labor.

Water Availability (%)	Avg Labor Requirement (person-d/season)	Max Water Requirement (person-d/season)	Avg Water Requirement (m^3/season)	Profit (M CLP)	Reduction of Profits (%)
100.0	301,869	9,658,391	9,018,882	762,162	0.0
87.5	301,869	8,451,092	8,451,092	754,801	1.0
75.0	286,851	7,243,794	7,243,794	717,885	5.8
62.5	278,252	6,036,495	6,036,495	656,624	13.8
50.0	258,053	4,829,196	4,829,196	565,379	25.8

1.3.5 Optimum Cropping Pattern

In this section, we present the results obtained from the analysis of land and water allocation patterns that maximize water and labor use efficiency under potential scarcity conditions. Figure 13 illustrates the optimal amount of land to allocate to each crop, with the aim of maximizing profits and effectively managing the risk associated with price volatility and water and labor availability. This optimal pattern was determined after an exhaustive evaluation of different availability conditions, and it was selected because of its higher profitability and operational resilience. This strategy is designed to fit within the limits of the resources available. Table 8 presents both the average labor and water requirements for a cropping pattern with a 52% risk; this risk is due to the variability of fruit crops and the maximum availability of these resources. This comparison reveals that the operational requirements of this cropping pattern are substantially lower than the actual availability of these resources, which shows that the proposed pattern is highly efficient and sustainable.

Table 8: The availability and requirements of different resources, the risk level, and the profits generated by the optimal cropping pattern.

Max Labor Availability (person-d/season)	Max Water Availability (m^3/season)	Max Labor Requirement (person-d/season)	Max Water Requirement (m^3/season)	Risk (%)	Profit (M CLP)
301,869	9,658,391	240,880	9,648,769	52	719,070

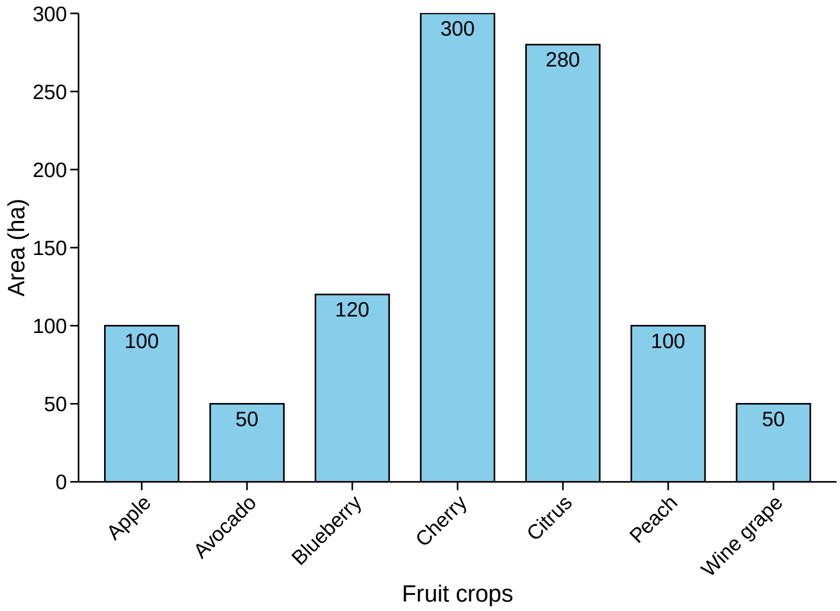

Figure 13: Optimum allocation of land to establish a cropping pattern in a fruit orchard.

A sensitivity analysis focusing on water availability was performed to determine the resilience of the optimum land allocation pattern to water variations. The established pattern can operate effectively when the availability of water is reduced to 70%, highlighting its remarkable capacity to adapt to water deficits of up to 30%. Additionally, a comprehensive evaluation of the amount of water applied per hectare for each fruit crop was carried out according to the optimum cropping pattern. Figure 14 shows how water is distributed per hectare during the 2019–2020 season, considering various levels of water availability, which allows us to observe the adaptability of the system to different water availability conditions.

As the water available decreases, a general reduction in water consumption is evident for all fruit crops, which move from optimal supply levels to a threshold of 70%. This pattern is essential to preserving the economic viability of the orchard; the water supply to high-yield fruit crops such as blueberries and cherries is prioritized, while the water consumption of less profitable crops or those more tolerant to water deficits, such as wine grapes, is reduced. Specifically, the reduction in the water supplied to cherry, citrus fruit, peach, and apple occurs gradually as the water available decreases, while the reduction is more pronounced in avocado, which becomes stable when the availability of water falls below 77.5%. This analysis highlights the urgent need to establish cropping patterns that efficiently adapt to the variability of water availability, ensuring the long-term sustainability of agricultural operations in areas susceptible to water deficits.

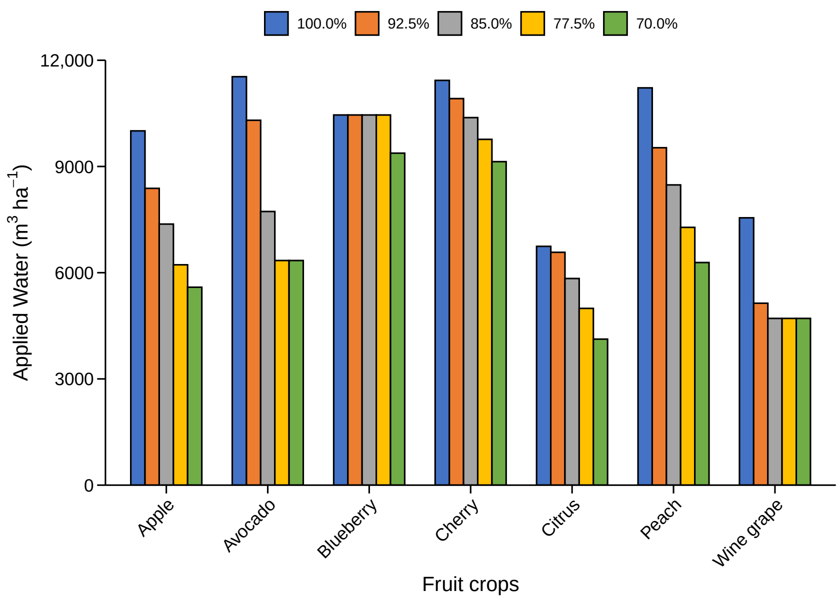

Figure 14: Water applied per hectare to selected fruit crops in the 2019-2020 season.

Table 9 shows how variations in the availability of water impact orchard profits, while also presenting the maximum labor and water required under different water availability conditions. When using the optimal pattern, the decrease in water availability does not affect labor requirements, which is attributed to the fact that this pattern employs 24% less labor than the maximum available. This strategy is adopted to minimize the orchard's dependence on labor, which is increasingly scarce, and to increase its long-term sustainability. In terms of profits, with a water availability of 85%, the reduction in the orchard's profits is only 1.4%. However, when this availability decreases to 70%, a more pronounced reduction in profits is observed, as these fall from CLP 719,070 M with full availability to CLP 661,443 M, representing a 7.8% decrease in profits. This analysis highlights the importance of efficiently managing water and labor resources when there are large changes in their availability.

Table 9: Labor and water requirements and net profits for the optimal pattern when different levels of water are available.

Water Availability (%)	Avg Labor Requirement (person-d/season)	Avg Water Requirement (m^3/season)	Profit (M CLP)	Reduction in Profits (%)
100.0	228,810	9,009,919	719,070	0.0
92.5	228,810	8,872,055	717,917	0.2
85.0	228,810	8,209,633	708,961	1.4
77.5	228,810	7,485,253	690,910	3.9
70.0	228,810	6,760,874	662,853	7.8

These analyses demonstrate that the optimal cropping pattern can respond effectively to variations in water and labor availability, maintaining its economic viability in different scenarios. Despite significant variations in the resources available, the stability in its profits highlights the strength and effectiveness of the proposed model. These results validate the implementation of agricultural strategies that respond to current conditions and proactively prepare for future challenges, ensuring the efficient and resilient management of fruit crops.

1.4 Conclusions

The proposed model determines optimal fruit cropping patterns in orchards over a 20-year period and includes a risk dimension to evaluate price volatility. This allows farmers to manage and select the most appropriate risk level for their orchards, with the annual allocation of water adapted to the specific conditions of irrigated agriculture in Chile between 2000 and 2020. The objective function of the model is based on production functions, which were used to estimate fruit yields. The model includes critical variables such as the maximum evapotranspiration recorded in the region, labor requirements, production costs, and annual sale prices.

However, this model is limited due to its theoretical nature, which prevents it from capturing the full complexity of agricultural reality. Even though resource allocation is optimized, the model does not consider factors such as pests and soil fluctuations, which can affect actual yields. Furthermore, the equations apply to annual periods and ignore short-term variations and changes occurring in the cropping area during the study period. These limitations indicate that this model is a complementary tool rather than an accurate representation of agricultural reality.

The initial analysis conducted, with 100 ha allocated to each crop, revealed significant differences in the crops' water and labor requirements, as well as their profitability, highlighting the importance of strategically selecting crops to maximize profits. The results showed that without maximum area constraints, allocating the entire area to one crop such as cherry can be highly profitable but also risky, due to the orchard's dependence on a single market and the volatility of fruit prices. The risk assessment revealed that by reducing risk, the land allocated to stable crops such as citrus fruit and apple increases, while that allocated to volatile crops such as cherry and blueberry decreases. Therefore, farming practices need to be adapted to respond to different market uncertainty scenarios. Furthermore, sensitivity analyses of labor and water availability showed that potential variations in these areas have substantial impacts on the planning and sustainability of orchards. The adaptability of cropping patterns to these variations is vital to maintaining the economic viability of an orchard. The optimal cropping pattern showed an ability to adapt to reductions in water availability of up to 70% and reductions in labor availability of 24%, ensuring economic sustainability under various scenarios. The stability of its profits, despite these variations in resources, underlines the effectiveness of this cropping pattern and the proposed allocation of water for sustainable management.

In conclusion, the implementation of agricultural strategies that efficiently integrate water use and labor management is crucial for the economic and environmental sustainability of fruit production. The findings of this study indicate that proactive approaches, including crop diversification and balanced resource allocation, need to be implemented to prepare for future challenges and mitigate the risks associated with price volatility and the fluctuating availability of essential resources. Future research should consider integrating the developed model into decision support systems (DSSs) to assist farmers and agricultural managers in the optimal planning of crops and resource allocation. These systems can provide tailored recommendations based on the specific conditions of each farm, helping to maximize profits and efficiently manage water and land resources. Furthermore, researchers should explore optimal cropping patterns at the basin scale, integrating annual and perennial crops into this assessment and extending the study period, thus allowing for the more strategic and sustainable management of agricultural resources. In water deficit scenarios, the prioritization of the water allocated to fruit crops is recommended, given their perennial nature and the long-term investment they represent, and also as annual crops have shorter and more flexible life cycles. The land allocated to annual crops serves as a buffer area, providing additional flexibility and resilience in resource management.

Finally, it is important to note that the incorporation of advanced technologies such as irrigation and harvest automation could redefine these patterns by optimizing operational efficiency and mitigating labor shortages. This would allow for the more strategic and sustainable management of water resources, ensuring the economic and environmental viability of agricultural practices in regions susceptible to water supply constraints. This approach addresses current needs while also preparing for future challenges in agricultural management.

Chapter 2

Optimization in fruit orchards to maximize profitability and sustainability: A case study

Quezada, L., Holzapfel, E., Kuschel-Otárola, M., Lillo-Saavedra, M., Rivera, D., Rivera-Ruiz, D., Pérez, A., & Souto, C. (2025). Optimization in fruit orchards to maximize profitability and sustainability: A case study. *Submitted to Agricultural Water Management.*

Abstract

Agriculture faces critical challenges due to the increasing food demand and the scarcity of water resources caused by climate change. While there are various studies on water and land optimization in annual crops, there is a significant gap in research regarding the optimal allocation of these resources in fruit orchards considering long-term horizons. This study applied a nonlinear optimization model to maximize the net profit of a fruit agricultural enterprise in Chile over a long term horizon (2000-2020). The model optimizes land allocation and annual water distribution by integrating variables such as irrigation efficiency, operational costs, and labor requirements. Crop patterns corresponding to the years 2000, 2010, and 2020 were evaluated under total

distribution efficiency scenarios of 90% and 70%. The results showed that a 90% efficiency reduces economic losses associated with water deficits, thereby improving the sustainability of the farm. The proposed optimal pattern increased profits by 32.7% compared to the 2000 pattern. The sensitivity analysis revealed that the pattern is robust against moderate variations in water availability (up to 20%), labor, and operational costs. However, reductions greater than 30% in water availability or drops of 50% in export prices require adjustments in crop distribution. Consequently, the model provides a valuable decision-support tool capable of simulating diverse scenarios, offering strategic guidance for the board when selecting crop patterns for fruit orchards.

2.1 Introduction

The increasing demand for food, combined with the effects of climate change, pressures water resources for agriculture (de Fraiture & Wichelns, 2010; Nikolaou et al., 2020), affecting water availability, yields, and profits (Srivastav et al., 2021; Wang et al., 2016). Therefore, efficient management of water resources supports the sustainability of agricultural activities, especially in regions with limited water availability and fluctuations in water supply (Masia et al., 2021). The availability of water affects both strategic and operational planning, while (Aliyari et al., 2021; Zhao & Boll, 2022) strategies that optimize water use help long-term economic viability (Bonetti et al., 2022; Evans & Sadler, 2008).

Increasing the efficiency of irrigation systems can mitigate the negative impacts of water scarcity (Touil et al., 2022). However, despite advances in water management, many farms operate at suboptimal efficiency levels (Kourgialas et al., 2018), increasing their vulnerability during periods of water scarcity (Chai et al., 2015). Optimization models enable efficient allocation of water and cultivable area, while facilitating the selection of the most suitable crops in different scenarios of water availability (Li et al., 2019; Shirshahi et al., 2020). Proper allocation of resources helps reduce the volume of applied irrigation water and increases profits (Wang et al., 2019).

There are different tools and approaches to optimize the allocation of water and land in agriculture. Li et al. (2020b) applied a multiobjective non-linear optimization model for the allocation of water and land, balancing economic, environmental, and social considerations. Xie et al. (2018) proposed a fuzzy stochastic programming model for irrigation water allocation and land use, taking into account uncertainties in precipitation and crop water requirements. Ren et al. (2019) developed a multiobjective stochastic optimization model to allocate water and land, prioritizing the maximization of net benefits and water productivity, achieving optimal irrigation schemes under multiple uncertainties. Bulukazari et al. (2022) combined a nonlinear optimization model with AquaCrop to determine the optimal allocation of water and land under saline and deficit irrigation conditions, achieving a 20% reduction in irrigation water without affecting profits. Jiang et al. (2016) developed an optimization model to allocate land area and water in order to maximize the efficiency of water use and economic benefits in irrigated agricultural systems. Kuschel-Otárola et al. (2018) developed a non-linear optimization model to identify the optimal crop pattern that maximizes profits through efficient allocation of water, labor, and capital on a monthly basis. Thilagavathi et al. (2021) applied Ant Colony Optimization (ACO) to optimize agricultural land allocation, achieving a significant increase in profits through improved strategic planning. Mardani Najafabadi and Ashktorab (2023) developed a robust fractional linear programming model to optimize sustainable cropping patterns, reducing the use of fertilizers and pesticides without compromising agricultural profitability. Despite advances in agricultural optimization, most studies focus on annual crops with one-year analysis, limiting their applicability in more complex systems such as fruit orchards, as they require a long-term perspective to capture multiyear dynamics. Furthermore, analyses are often conducted at broad scales (e.g., watershed levels), making it challenging to implement them at more specific scales, such as individual farms, where operational decisions must be adapted to local conditions.

Currently, there is a research gap regarding the optimal allocation of area and water in farms with fruit orchards aimed at promoting sustainable fruit production over a 20-year planning horizon (Day et al., 2005; Vinyes et al., 2015). This case study aims to evaluate the conditions of a fruit-growing agricultural company using a non-linear optimization model that optimizes orchard area allocation over a 20-year timeframe. The model includes annual water distribution to maximize the net profits of the agricultural enterprise. In addition, we evaluate the impact of efficiency on farm sustainability while proposing an optimal crop pattern that maximizes profits and optimizes available resources.

2.2 Materials and methods

2.2.1 Optimization Model: Relative yield

The methodology used in this chapter is based on that described in Chapter 1, maintaining the same production function framework (Section 1.2.1) and model formulation (Section 1.2.2). Initially, the yield of fruit crops is determined using the production functions presented in Table 1, considering that, for citrus crops, a general function is applied in this study to oranges, mandarins, lemons, and grapefruits, due to their productive similarity. Regarding the formulation, the original structure is preserved, with the objective function of maximizing net profit and the constraints of land availability, water availability, minimum water application, labor availability, crop area consideration, and complementary considerations. However, unlike the model in Chapter 1, the price variability risk constraint is not included, since the main purpose of this chapter is to faithfully represent the company's actual production pattern and assess its water use efficiency under the observed conditions.

2.2.2 Study site

The study site is an agricultural farm in the O'Higgins region of Chile's Central Valley, between coordinates 34 ° 32 'S and 71 ° 24 'W, with an approximate area of 2,137 ha (Figure 15). The climate is Mediterranean, characterized by very dry summers and rainy winters. Most precipitation occurs between May and August, with an annual average of 652 mm. The average annual temperature is 14 °C, with highs reaching 30 ° C in summer and lows of about 3 ° C in winter (MMA, 2023).

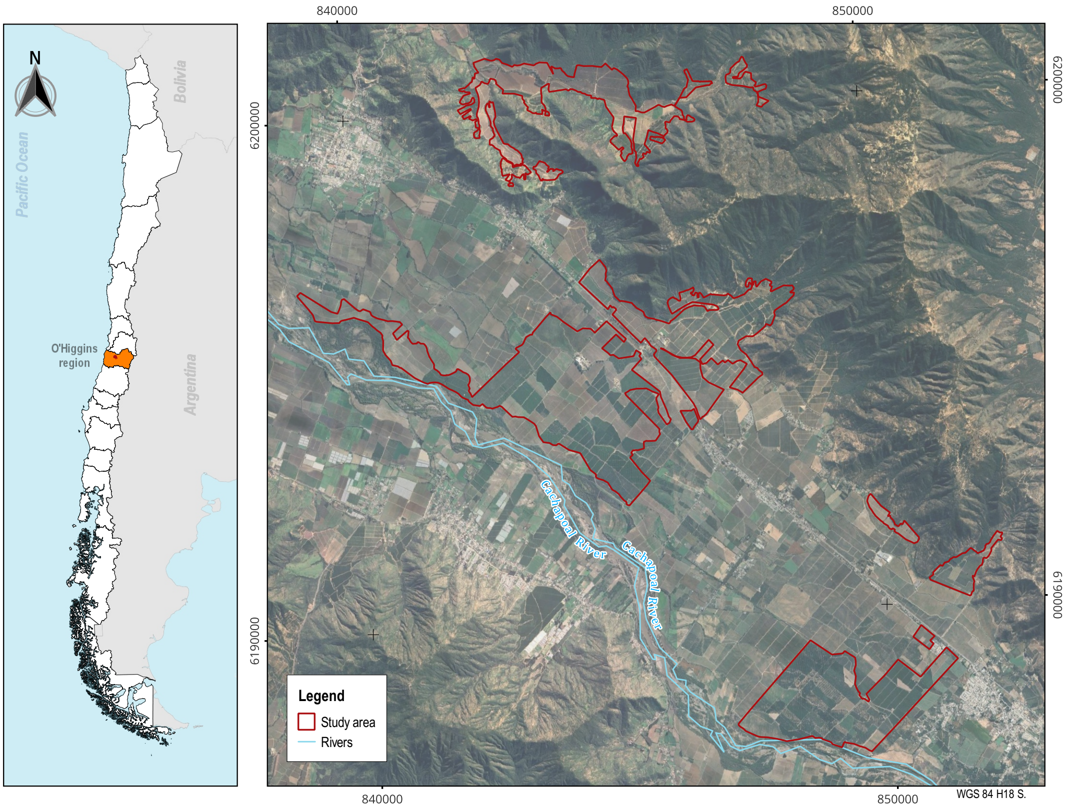

Figure 15: Location of the study area.

The input data comes from various sources to represent the productive, water-related, and economic conditions of the farm during the 2000–2020 period. The main fruit crops are citrus (orange, mandarin, lemon, grapefruit), peaches, kiwi, apples, wine grapes, table grapes, pears, avocados, and european plums. Additionally, cherries and blueberries—although not cultivated on the farm—were included in the analysis due to their high relevance in the study area according to statistics provided by the Office of Agricultural Studies and Policies (ODEPA) (ODEPA and CIREN, 2021). Fruit export prices were obtained from (ODEPA, 2024) (Figure 16). The official exchange rate provided annually by the Central Bank of Chile (Banco Central de Chile, 2024) was used to convert these prices to Chilean pesos (CLP). It should be noted that the exchange rate has varied over time; however, in 2020, 1 USD was equivalent to 792 CLP. Based on historical harvest data provided by the farm's management board, maximum yield values were obtained for each fruit crop for the period 2003 to 2021. For blueberry and cherry, yield values were taken from Quezada et al. (2025). These values are detailed in Table 10. Production costs were derived from technical and economic reports (CNR, 2014) and adjusted annually using the Consumer Price Index (CPI) to account for inflation.

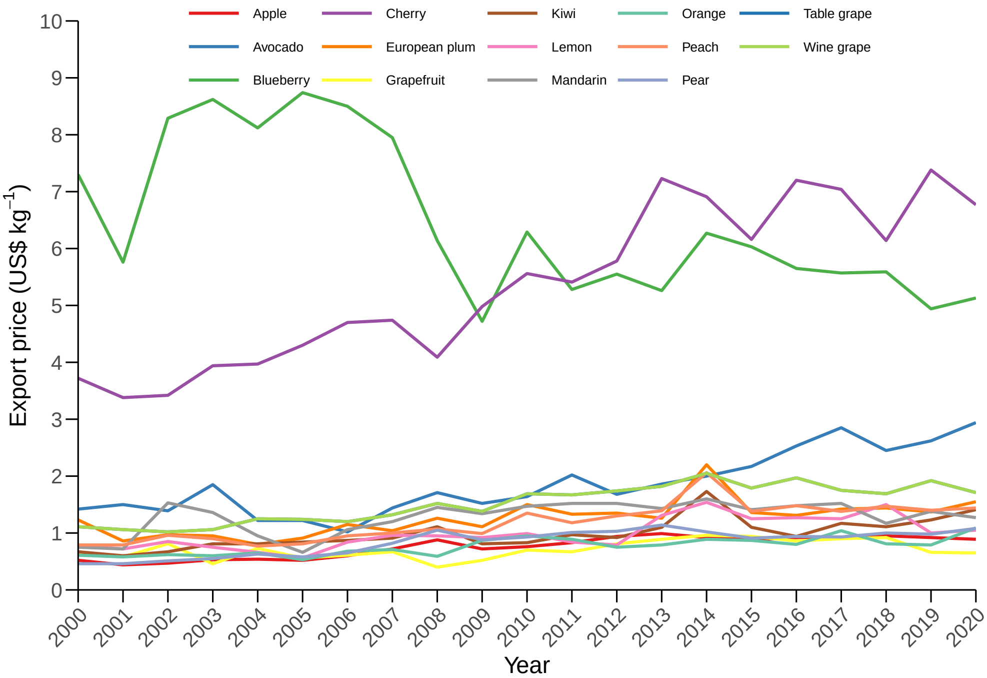

Figure 16: Export prices from Chile for the analyzed fruit crops during the 2000–2020 period.

Regarding water availability, the farmer holds 170.8 (13 L s^{-1}) and 26.7 (11 L s^{-1}) water shares of surface water sources. In addition, the farmer has water rights of 549 L s^{-1} from groundwater. In 2020, the costs for the use of surface and groundwater were 5.02 and 61.31 CLP per cubic meter, respectively. Likewise, the labor cost was estimated at 20,000 CLP per working day in 2020 (ODEPA, 2020a). Later, both water and labor costs were adjusted to reflect inflation effects throughout the analysis period.

To estimate the water requirements for each crop, the reference evapotranspiration for the area was calculated, followed by the determination of the potential evapotranspiration of each fruit using the crop coefficient factor (FPC) (Holzapfel et al., 2020; Lecaros-Arellano et al., 2021). Figure 17 shows the water demand for fruit crops, taking the 2019–2020 season as a reference, and the labor requirements for each fruit crop in its mature stage per hectare.

Table 10: Maximum yields for the analyzed fruit crops, corresponding to the 2003–2021 period.

Fruit crop	Maximum yield (t ha^{-1})
Apple	70.0
Avocado	26.4
Blueberry	20.0
Cherry	20.0
European plum	31.5
Grapefruit	46.1
Kiwifruit	45.6
Lemon	56.1
Mandarin	47.7
Orange	68.7
Peach	40.0
Pear	57.8
Table grape	34.0
Wine grape	20.1

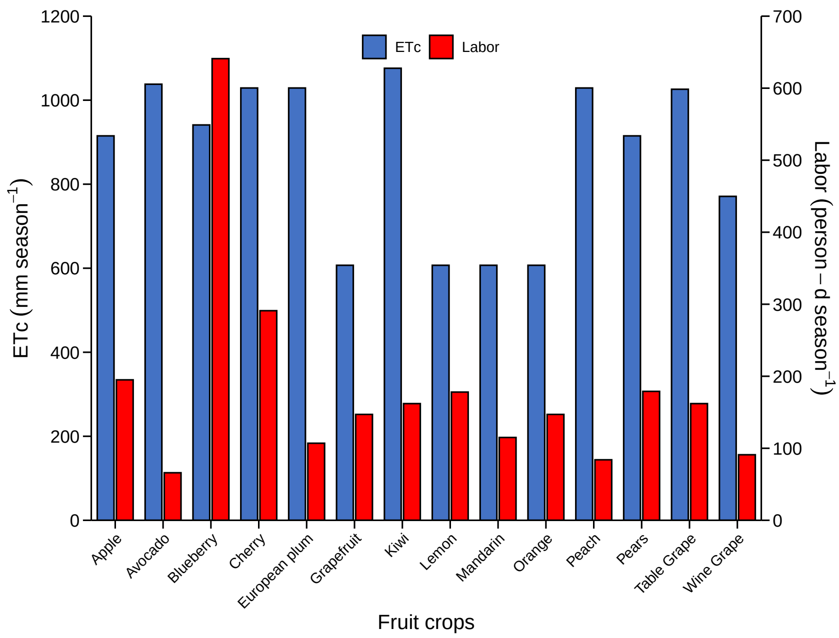

Figure 17: Crop evapotranspiration (ETc) and labor required for the analyzed fruit crops in the 2019–2020 season.

2.2.3 Model runs

The availability of water in the study case was estimated for the period 2000-2020, considering the land use patterns for the years 2000, 2010 and 2020, called CP2000, CP2010, and CP2020, respectively . The model was implemented using the $General\ Algebraic\ Modeling\ System$ (GAMS), version 45, and the MINOS solver. To perform an analysis exclusively focused on optimal water allocation, the cultivated area of the model was restricted to match the actual area of the farm, thus allowing the estimation of potential profits under optimal conditions, that is, without water deficits.

For this study, "efficiency" specifically refers to the Total Distribution Efficiency (TDE). Optimal management conditions consider setting the TDE at 90% to evaluate farm water availability under highly efficient irrigation management (Pannunzio et al., 2016) and thus analyze its impact on farm profits. An alternative scenario with a 70% TDE simulates farmer management practices during the study period (Levidow et al., 2014), as it mimics more realistic but nonoptimal management conditions that can cause inefficiencies and water waste , such as errors in estimating crop water demand and incorrect scheduling of irrigation cycles (Latorre et al., 2020). Furthermore, practices such as inadequate irrigation in fruit crops, especially when automated irrigation technologies are not used, can lead to inefficient water use (Millán et al., 2019), as well as improper use or lack of maintenance of irrigation systems, negatively affecting water distribution efficiency. A detailed comparison of water allocation for the CP2000 allows determining how different efficiency levels affect required and applied volumes, especially in years with water deficits. The optimal land use pattern for orchard management considers conditions in 2000 and TDE a 90%.

A sensitivity analysis allows one to evaluate the impact of various factors on the economic returns of the farm, such as changes in water availability (reductions of 20, 30, and 40%), increases in labor costs (10, 50 and 100%) and increases in water (500%) and operational (100%) costs. A reduction in export prices 50% was also analyzed for key crops such as cherries, mandarins, and avocados.

2.2.4 Collection of qualitative information through interviews

In-depth interviews with the board were conducted to collect detailed information on key aspects such as water monitoring, irrigation scheduling, irrigation system maintenance, and crop selection criteria. These qualitative insights complemented the quantitative analysis of the optimization model by clarifying the practical and strategic decision-making processes. Furthermore, the proposed optimal crop pattern was presented to the management team during focused group discussion sessions, where systematic feedback was gathered to pinpoint areas for improvement and to assess the pattern's applicability within the farm's operational context.

2.3 Results and Discussion

2.3.1 Water availability and crop patterns

Figure 18 shows the annual availability of surface water and groundwater resources for irrigation. Water availability exhibits significant interannual variability, with the highest levels recorded from the 2001–2002 to the 2007–2008 season, reaching maximums of 28.54 million m^3 and 26.98 million m^3 in the 2002–2003 and 2003–2004 seasons, respectively. However, from 2008 onwards, a pronounced decline in surface water availability is evident, leading to variations in water shares due to reduced streamflows and groundwater level fluctuations. Thus, the continuous decline in surface water reduced the overall availability of water for irrigation. This decline was particularly critical during the 2013–2014 and 2014–2015 seasons, demonstrating severe water scarcity. Fluctuations in surface water availability and recurrent scarcity require the implementation of irrigation optimization strategies and the establishment of crop patterns tailored to water-scarce conditions. The observed trends support the application of optimization models to maximize water use efficiency and ensure long-term farm sustainability and profitability.

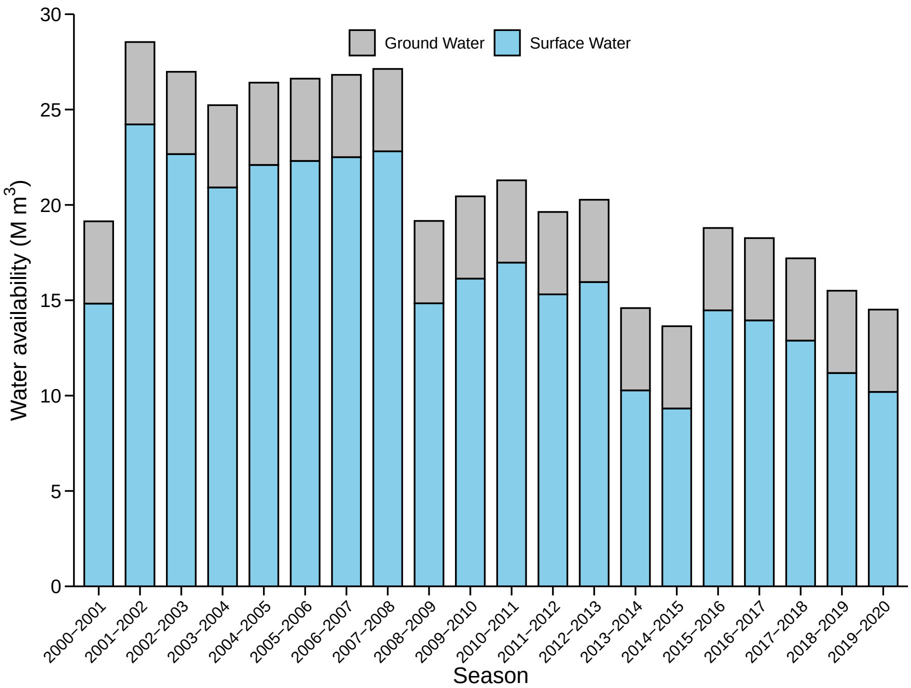

Figure 18: Total surface and groundwater availability of the orchard from 2000 to 2020.

Table 11 shows these changes in the cultivated area, allowing the identification of trends and patterns that may have influenced profitability, water demand, labor needs, and long-term farm sustainability. In CP2000, wine grapes (696 ha) and oranges (660 ha) dominated the total orchard area of the farm, combining 1,350 ha out of 2,124 ha. In CP2010, wine grapes consolidated as the main crop (781.5 ha), while avocado area grew to 236.3 ha, bringing the total area to 2,231.5 ha. In CP2020, avocados and mandarins had notable increases, reaching 423.4 and 231.6 ha, respectively, while wine grapes and oranges adjusted downward. In CP2020, the total area was settled at 2,137 ha, reflecting changes in farm production priorities.

To evaluate the economic performance of the land use patterns, as well as water and labor requirements Table 12 shows the variation in resource requirements and profits. Although potential profits were calculated under ideal conditions without water constraints, they provide a baseline reflecting the maximum income-generating capacity of the farm under optimal scenarios. CP2000 yielded the lowest economic return, along with water and labor requirements reflecting the crop structure of that period. By contrast, CP2010 required more water and labor yet produced higher profits than the earlier pattern, partly due to increased acreage. CP2020 delivered the highest profit, while requiring less water and labor than in 2010 and using a smaller total area.

Table 11: Cultivated area (ha) by fruit crop on the farm during 2000, 2010, and 2020.

	Crop pattern (ha)		
Fruit crop	CP2000	CP2010	CP2020
Apple	40.2	17.7	0.0
Avocado	164.2	236.3	423.4
European plum	220.0	387.9	199.0
Grapefruit	37.9	27.0	22.9
Kiwi	89.7	84.5	83.6
Lemon	37.4	44.0	42.9
Mandarin	18.6	25.4	231.6
Orange	605.0	374.4	311.1
Peach	68.6	17.7	12.3
Pear	147.0	127.1	169.9
Table grape	0.0	108.0	38.5
Wine grape	696.0	781.5	601.8

Table 12: Average water requirements, peak labor requirements per season, and profits generated by the crop patterns in different years.

Crop Pattern	Avg Water Requirement (M m^3/season)	Max Labor Requirement (person-d/season)	Profit (M CLP)
CP2000	16.43	255,028	816,923
CP2010	18.21	256,499	825,389
CP2020	17.34	238,444	850,929

2.3.2 High TDE: 90% Efficiency

In this scenario, the impact of operating with efficiency 90% in water management was evaluated for the land use patterns of CP2000, CP2010 and CP2020 during the period 2000-2020. Unlike scenarios with lower efficiency, this analysis focuses on how optimizing irrigation reduces the volume of applied water and improves crop profitability. In addition, higher efficiency is closer to best practices in water management, reducing pressure on water resources, and providing a model for economic sustainability under climatic variability.

Figure 19 shows the potential water requirements of the three crop patterns with efficiency 90% compared to the actual availability of water during the study period. In the early years (up to the 2007-2008 season), the availability of water on the farm exceeded the potential requirements of the patterns by 45 to 60%, except in 2003-2004, when the availability exceeded the requirements by 80 to 99% due to the lower demand for water from fruit trees then in the development stages. However, we observe three seasons with notable deficits: 2013–2014 (13% for CP2000, 21% for pattern 2010, and 18% for pattern 2020), 2014–2015 (20 % for CP2000, 28% for CP2010, and 27% for CP2020) and 2019-2020 (19% for CP2000, 24% for CP2010, and 23% for CP2020). Thus, although efficiency 90% mitigates deficits in most seasons, patterns with higher water demand continue to be affected in years of limited supply.

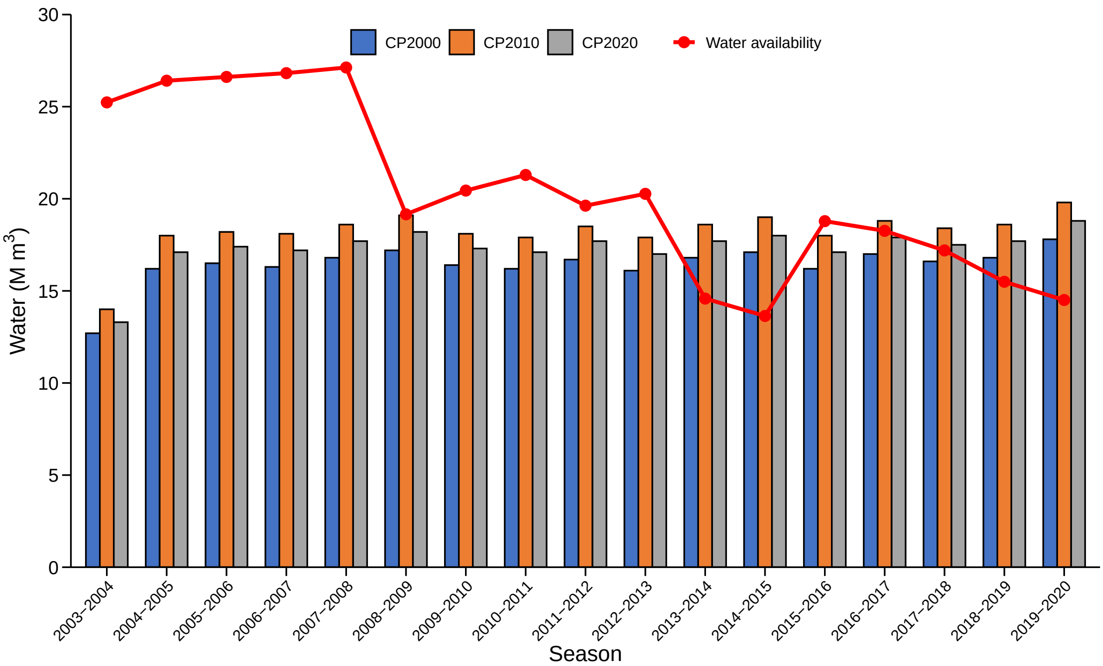

Figure 19: Water requirements of the crop patterns (CP2000, CP2010, and CP2020) at 90% efficiency compared to actual water availability from 2003 to 2020.

Table 13 shows the economic impact of operating with 90% efficiency. Under this scenario, all patterns show reduced water demand and lower profit losses compared to the less efficient scenario. The CP2000 maintained the lowest water requirement and showed the smallest reduction in profits (1.0%), showing resilience to water deficits. The CP2010, although requiring the most water, improved profit losses to 2.2%. The CP2020, with intermediate water requirements, exhibited a 1.7% reduction in profits and is regarded the best economic performer.

Table 13: Average water applied, profits generated, and profit reduction at 90% efficiency for the crop patterns CP2000, CP2010, and CP2020.

Crop Pattern	Avg Water Applied (m^3 $season^{-1}$)	Profit (M CLP)	Reduction of Profits (%)
CP2000	15,805,379	809,145	1.0
CP2010	17,018,309	807,360	2.2
CP2020	16,425,829	836,429	1.7

Achieving a total distribution efficiency of 90% provides substantial benefits, including mitigation of the economic impacts derived from water deficits. This level of efficiency also contributes to reducing the vulnerability of land use patterns to fluctuations in water availability, particularly during critical years with limited supply. In a context of increasing water scarcity and climatic variability, optimizing water use through efficient irrigation systems is crucial not only for better management of water resources, but also for strengthening economic sustainability.

2.3.3 Low TDE: 70% Efficiency

Figure 20 shows the potential water requirements compared to actual water availability throughout the study period considering a TDE of 70%. This scenario increases the water volume necessary to maintain crops, thus exacerbating water deficits in critical years. In particular, the CP2010 and CP2020 consistently require more water than the CP2000, especially from the 2009–2010 through the 2012–2013 seasons. During these years, the CP2010 and CP2020 present slight water deficits, whereas the CP2000 experiences almost no shortages. The most pronounced deficits occurred in the 2013–2014 and 2014–2015 irrigation seasons, with deficits of 32% and 39% for the CP2000, 39% and 44% for the CP2010, and 36% and 41% for the CP2020, respectively. Subsequently, from the 2016–2017 season onward, a growing trend in water deficits was observed, reaching levels similar to those recorded in the 2014–2015 season.

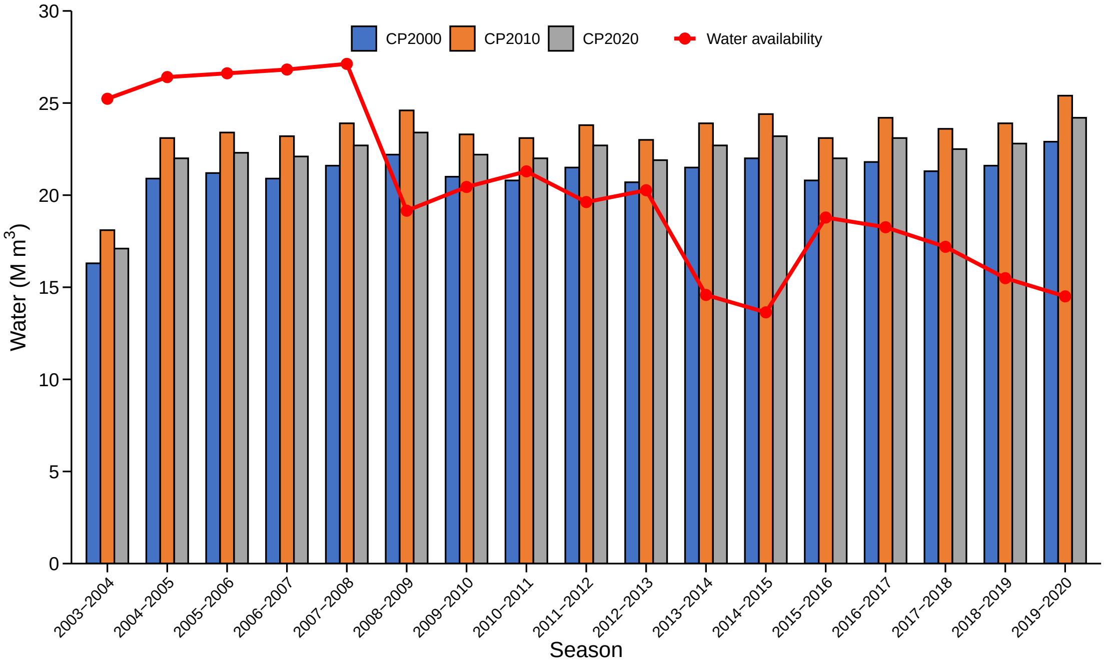

Figure 20: Potential water requirements of the crop patterns CP2000, CP2010, and CP2020 at 70% efficiency compared with actual water availability during the study period.

Table 14 quantifies the economic impact of reduced system efficiency. Land use patterns that require larger water volumes are more vulnerable to fluctuations in resource availability. In the case of CP2010, the largest reduction in profits, with an 8.5% decrease, reflecting its high water demand and lower adaptability to low-efficiency conditions. Meanwhile, CP2020 showed a 6.3% profit reduction, despite having slightly higher water requirements than those of the 2000 pattern. In contrast, CP2000 experienced the smallest profit decrease (4.7%), due to its lower water requirements and greater resilience to deficits compared to the other patterns. Lower efficiency in the irrigation system increases water requirements and directly impacts crop profitability, highlighting the need to adopt more efficient irrigation practices and adjust crop patterns to minimize economic losses from water deficits.

Table 14: Profit reductions caused by water deficits in the crop patterns CP2000, CP2010, and CP2020 (70% efficiency).

Crop Pattern	Avg Water Applied (m^3 season^{-1})	Profit (M CLP)	Reduction of Profits (%)
CP2000	18,445,352	778,256	4.7
CP2010	19,554,287	755,257	8.5
CP2020	18,798,687	796,981	6.3

2.3.4 Water allocation

For the CP2000, we ran different TDE scenarios to compare how two levels of irrigation efficiency (90% and 70%) affect the amount of water applied, highlighting the discrepancies between crop water requirements and applied volumes in each scenario. Figure 21 shows the amount of water applied to fruit crops in efficiency 70% and 90% from 2003-2004 to 2019-2020. In general, the results indicate that irrigation efficiency significantly affects the amount of water to meet crop demand. With 90% efficiency, the applied volumes are consistently lower in all seasons, reflecting a better capacity to reduce water losses and optimize available resources.

The fruit crops that receive the largest total volumes of applied water are wine grapes, oranges, European plums, and avocados. Although these crops differ in their water needs, their extensive cultivated areas strongly influence the total volume of applied water. In contrast, fruit crops with smaller cultivated areas, such as mandarins, lemons, grapefruits, and apples, require less applied water volumes.

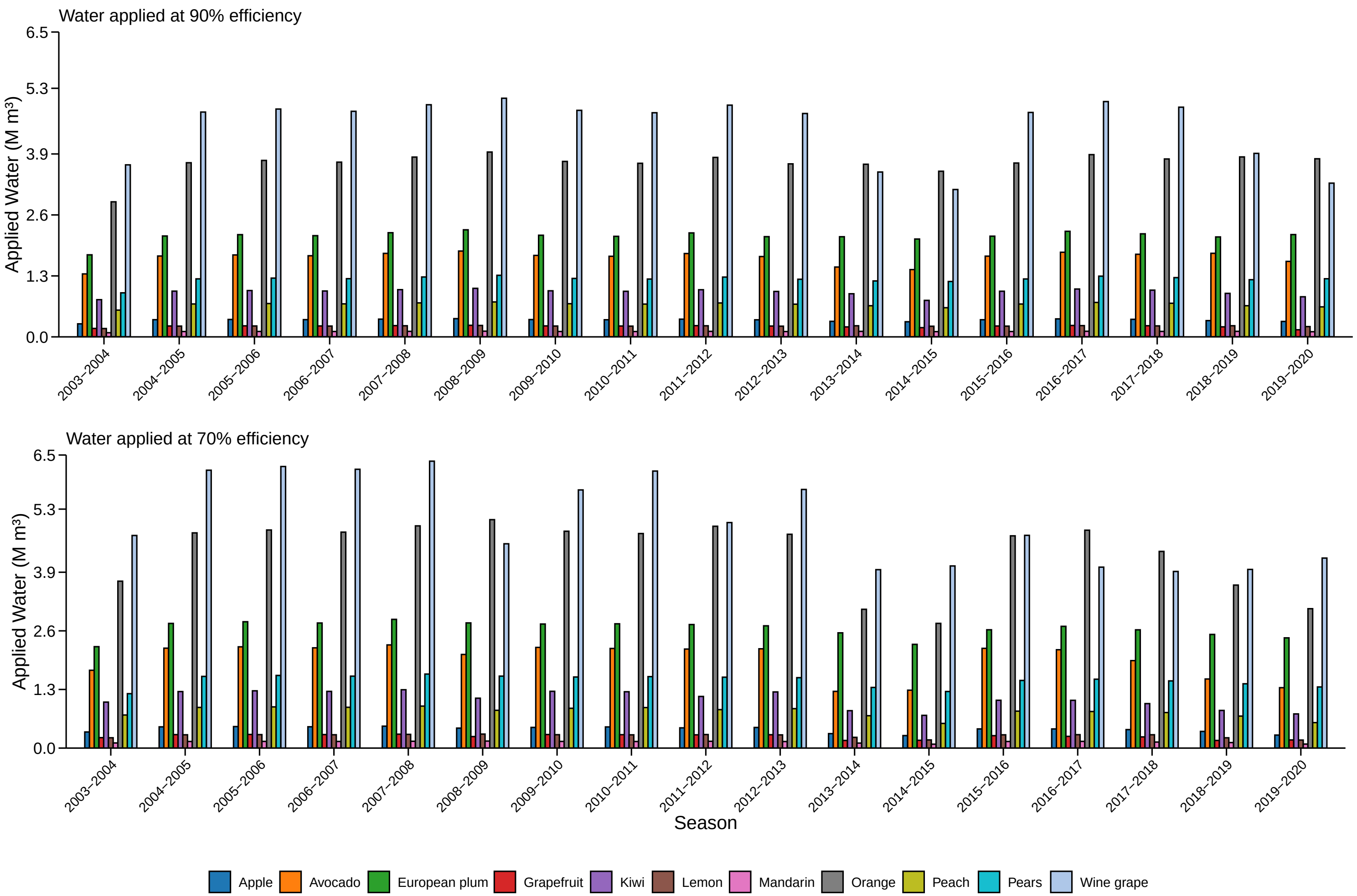

Figure 21: Water applied to different fruit crops from the 2003–2004 to the 2019–2020 growing seasons under two irrigation efficiency scenarios (90% and 70%) for the CP2000 land use pattern.

In the 90% efficiency scenario, the volumes of applied water met the crop requirements during most of the study period (see Fig. 19). However, in seasons with water deficits, the amount of applied water decreased, which affected wine grapes the most, particularly in 2013–2014, 2018–2019, and 2019–2020. In the 70% efficiency scenario, there were more seasons with water deficits (Fig. 20). Wine grapes were the most affected, with large reductions in 2008–2009, 2011–2012, and continuously from 2013-2014 to 2019-2020. Oranges and avocados also experienced notable reductions in water application, especially in the most deficit-prone seasons, such as 2013–2014, 2018–2019, and 2019–2020.

After evaluating multiple seasons and various levels of efficiency, the 2014-2015 season was chosen for a closer examination, as it presented the largest water deficit. Fig. 22 shows the volume of water required and applied per hectare for each fruit crop, using the CP2000. At 90% efficiency, fruit crops that received less water were wine grapes, receiving only 62% of the required water, followed by avocados (71%) and kiwi (80%). However, this reduction in water availability did not show a noticeable impact on yields. In contrast, fruit crops with mild deficits, that is, receiving more than 90% of the water demand, such as oranges, mandarins, lemons, European plums, and pears. When the efficiency decreased to 70%, the required water volumes increased and the water deficits became more pronounced. In this scenario, the crops most affected were oranges, avocados, grapefruits, kiwis, mandarins, and apples, each receiving only 55% of the necessary water (see Equation (**??**)), while wine grapes reached 62%. In contrast, pears and European plums were the least affected, with 75% and 79% of the required water, respectively. The model used for water allocation incorporates both the production function - which estimates the impact of water supply on yield - and the sale price of each fruit crop. This integration optimizes the distribution of the resource based on profitability and productive response. Moreover, previous studies have shown that efficient water use substantially improves crop performance in areas with limited water resources, optimizing the relationship between applied water and yield (Pascale et al., 2011).

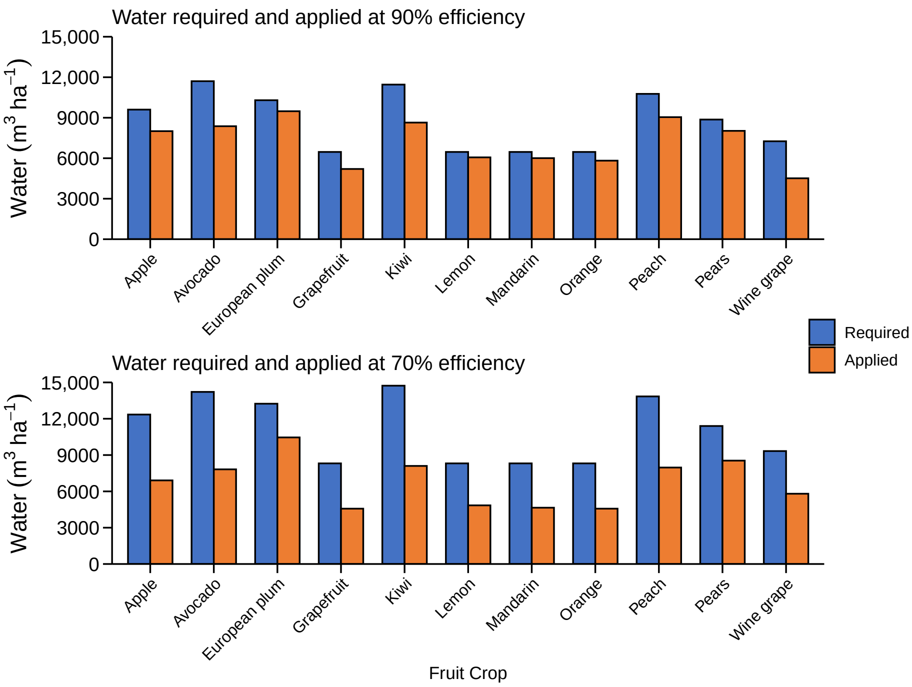

Figure 22: Water applied per hectare to fruit crops during the 2014–2015 season for the CP2000.

The capacity of irrigation systems to mitigate the impacts of water deficits is highly dependent on optimizing water use efficiency. Implementing advanced irrigation techniques and improving water management in agriculture improves sustainability and strengthens resilience to climate change (Chaves & Davies, 2010).

In agricultural contexts where water resources are increasingly limited, it is crucial to evaluate the best use of water by improving water management efficiency. This approach minimizes water losses and increases farm economic sustainability by reducing the costs associated with water application and increasing the stability of agricultural yields (Tejero et al., 2011). Water efficiency has also been identified as a key factor in enhancing crop resilience in water-scarce conditions, as corroborated by various studies on improved water use in deficit irrigation systems (Gao et al., 2017).

For this case study, improving irrigation efficiency not only mitigates the effects of water deficits, but also promotes more sustainable water management, thus ensuring long-term crop profitability amid growing climatic uncertainties.

2.3.5 Optimal pattern

An optimal land use pattern considers labor conditions for the year 2000 and the TDE of 90% to compare it to the pattern implemented in the study area, evaluating profits, water requirements and allocation, as well as labor needs, and fluctuations in water availability. We seek to identify more sustainable strategies from both a water and economic point of view, taking the initial conditions of the orchard in 2000 as a baseline and projecting its evolution until 2020. Table 15 shows the optimal distribution of the orchard area under these conditions and presents the seasonal labor requirements for each fruit crop.

Table 15: Optimal distribution of fruit crop area and labor requirements under year 2000 conditions and 90% TDE.

Fruit Crop	Area (ha)	Labor (person-d season^{-1})
Avocado	641.1	42,313
Cherry	213.7	62,187
Lemon	94.8	16,912
Mandarin	641.1	73,983
Orange	213.7	31,307
Peach	107.8	9,001
Wine grape	212.5	19,338

Figure 23 shows the potential water requirements corresponding to the proposed optimal crop pattern, comparing them with the actual water availability during the study period. The results indicate that, in general, water requirements remained stable over the years, averaging 18.5 million cubic meters (M m^3) per season. However, from the 2008-2009 season, a decrease in water availability was observed, leading to water deficits in several key seasons, particularly 2013-2014, 2014-2015, 2018-2019 and 2019-2020, with a maximum deficit of 28% relative to water requirements. Figure 24 compares the applied water per area to optimal levels despite fluctuations in water availability. However, in the most severe deficit seasons (2013-2014, 2014-2015 and 2019-2020), a moderate reduction in applied water was observed. The level of efficiency 90% partially mitigated the negative impacts, although avocados, wine grapes, and peaches were the crops most affected. In particular, avocados experienced reductions in applied water of 34.9, 42.3 and 32. 7% during these seasons.

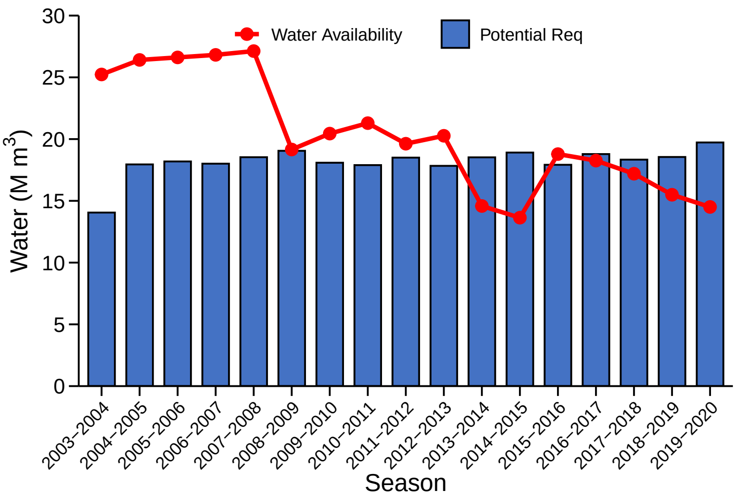

Figure 23: Potential water requirements of the optimal crop pattern at 90% efficiency, compared with actual water availability from 2003 to 2020.

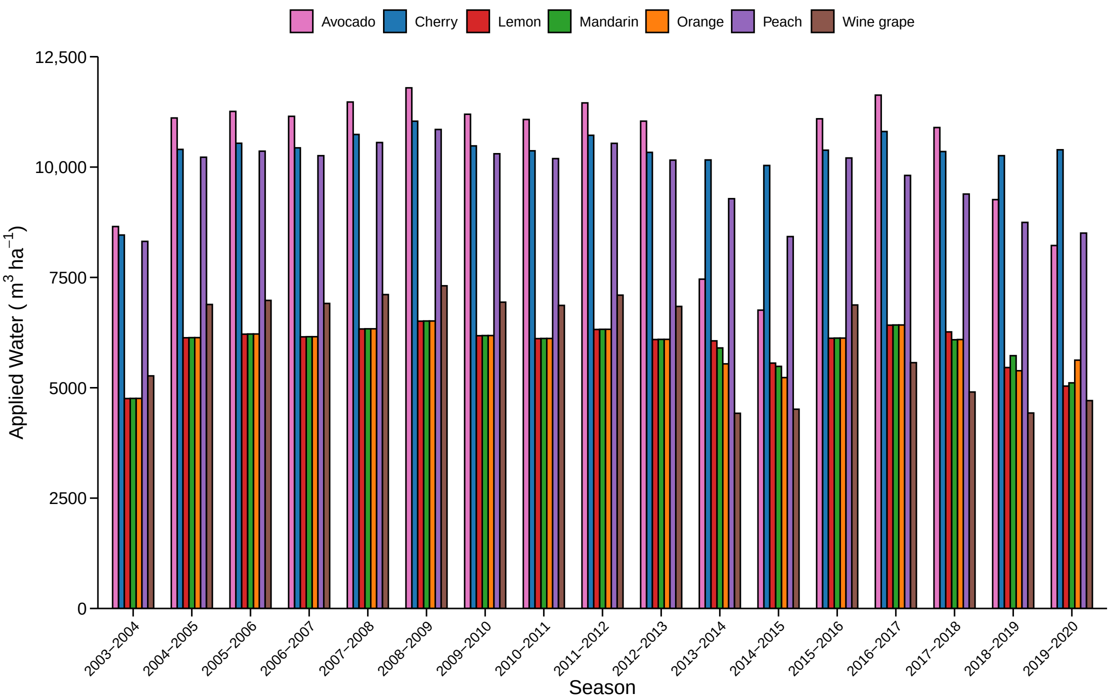

Figure 24: Optimal water allocation for the proposed pattern.

The optimal land use pattern is resistant up to a deficit 30% in water requirements and up to 47.2% relative to the theoretical water use rights. During the last seven seasons, from 2013-2014 to 2019-2020, the optimal allocation pattern maintains profits and yields under a 41.5% deficit in potential requirements and a 53.2% deficit in relation to theoretical water rights. Table 16 summarizes the simulation of implementing the optimal land use pattern, including labor requirements, the average water volume applied per season, profits, and the percentage increase in these profits compared to the CP2000. Regarding labor requirements, peak labor availability was reached once fruit crops entered the mature stage, making labor one of the main limiting factors in selecting the optimal pattern. Although some fruit crops, such as cherries, blueberries, and apples, deliver high economic returns, their significant labor demands influenced a reduction or exclusion of their allocated area in this pattern. For this reason, 30% of the total area are avocados as their lower labor requirements.

Table 16: Summary of labor requirements, water volume applied, and profits generated by the optimal cropping pattern.

Max Labor Availability (person-d season^{-1})	Avg Labor Requirement (person-d season^{-1})	Avg Water Applied (m^3 season^{-1})	Profit (M CLP)	Increase in Profits (%)
255,028	225,437	16,905,148	1,073,574	32.7

The average volume of water applied under the optimal pattern reached 16,905,148 m^3 per season, representing a 7% increase compared to the 15,805,279 m^3 required under CP2000. Despite the increase in water use, the proposed pattern remained within acceptable efficiency levels thanks to optimized water management. In terms of profits, the optimal pattern generated a total of 1,073,574 million CLP (M CLP), a 32.7% increase over the original 2000 pattern. This improvement comes from strategically selecting fruit crops that are better suited to the conditions of the farm and efficiently managing resources.

Our results are consistent with previous research that states that water use efficiency and optimal labor management are key factors in improving sustainability and profitability in irrigated agriculture. Li et al. (2020c), for example, show that efficient water distribution can improve sustainability and reduce water scarcity. Zhang et al. (2020)

showed that optimizing water use not only mitigates economic losses but also fosters sustainability in arid regions, a crucial aspect of boosting profitability, as evidenced by the 32.7% profit increase found here. In addition, Montazar (2013) highlighted how integrated planning tools can maximize economic benefits by optimizing water allocation, and Tan and Zhang (2018) argue that improving the efficiency of water use can improve agricultural resilience to uncertainty in water availability and partially offset the limitations posed by water deficits, as observed in this study.

2.3.6 Sensitivity analysis

The sensitivity analysis aimed to evaluate the optimal pattern in various scenarios that involve changes in water availability, labor costs, operational costs, and fluctuations in export prices for key crops. Table 17 summarizes the results for each scenario, in order to assess how these factors affect the cultivated area, labor demand, water consumption and profits.

The optimal pattern is robust against moderate variations in water availability, as well as increases in labor, water, and operational costs. A 20% reduction in water leads to a 4.7% decrease in profits, while a 40% reduction cuts profits by 16.4% and reduces land allocation for crops of high water demand such as avocados. Increasing labor costs by up to 300% causes a 13.7% reduction in profits, but does not affect land allocation. Meanwhile, a 500% increase in water costs and a 100% increase in operational costs show a reduction in profit of 2.3% and 4.6%, respectively, indicating limited impacts on overall profitability. Reducing the export price of a specific fruit by 50% causes that crop to be removed from land allocation. In this scenario, cherries cause the greatest drop in profits (8.0%), illustrating the sensitivity of the model when dealing with key export prices. These results highlight the ability of the optimal pattern to adapt to moderate water deficits and increased operational costs, keeping the cultivated area stable in most scenarios. However, when water reductions exceed 30% or export prices fall, adjustments in crop allocation become necessary, affecting both profitability and resource use. This analysis underscores the importance of water use efficiency and diversification of export crops to mitigate economic risks posed by external fluctuations and climate change.

2.3.7 Qualitative interview

From the interviews, the farm management team regularly monitors water consumption and soil moisture, and irrigation scheduling varies depending on the type of soil and root characteristics of each crop. However, uniformity in water distribution is not regularly evaluated, representing a limitation in achieving higher irrigation efficiency. Improving this practice could help optimize resource use and mitigate water losses during the growing season.

Regarding crop selection and management, decisions rely largely on economic variables, such as profits and water availability, prioritizing water allocation for crops with the highest economic return during shortages. This focus differs from the optimal pattern, which integrates multiple criteria for water allocation, such as production-function curves, market prices, and operating costs. More comprehensive strategies should be considered that balance profitability maximization with long-term sustainability.

The optimal pattern was presented to the farm management team, who acknowledged it as a significant advance in the strategic planning and economic development of the farm. They noted its potential to evaluate long-term scenarios, but emphasized that final decisions are influenced by additional factors, such as the preferences of the board of directors, which do not always align with the optimal results of the model. This underscores the need to balance scientific approaches with practical farm dynamics, promoting integration that maximizes both profitability and sustainability in specific contexts. It is worth noting that the management team identified limited labor availability during critical seasons and fluctuations in water supply as a top priority challenge.

Table 17: Sensitivity analysis of the optimal cropping pattern under scenarios of variation in water availability, labor cost, water cost, other costs (OC), and export prices.

		Decrease water			Increase labor cost			Increase water cost	Increase OC	Decrease export price -50%		
	Optimal	-20%	-30%	-40%	10%	100%	300%	500%	100%	Cherry	Mandarin	Avocado
Blueberry (ha)	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Cherry (ha)	213.7	213.7	213.7	213.7	213.7	213.7	213.7	213.7	213.7	0.0	213.7	213.7
Orange (ha)	213.7	213.7	213.7	213.7	213.7	213.7	213.7	213.7	213.7	213.7	534.3	313.2
Mandarin (ha)	641.1	641.1	641.1	641.1	641.1	641.1	641.1	641.1	641.1	641.1	0.0	641.1
Lemon (ha)	94.8	94.8	173.0	213.7	94.8	94.8	94.8	94.8	83.8	320.6	97.5	0.0
Grapefruit (ha)	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Peach (ha)	107.8	107.8	0.0	0.0	107.8	107.8	107.8	107.8	129.9	0.0	425.6	641.1
Kiwi (ha)	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Apple (ha)	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	190.6	0.0	0.0
Wine grape (ha)	212.5	212.5	212.5	395.8	212.5	212.5	212.5	212.5	213.7	212.5	212.5	213.7
Table grape (ha)	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Pear (ha)	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Avocado (ha)	641.1	641.1	566.0	203.2	641.1	641.1	641.1	641.1	641.1	546.2	641.1	0.0
European plum (ha)	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Total area (ha)	2124.6	2124.6	2020.0	1881.2	2124.6	2124.6	2124.6	2124.6	2137.0	2124.6	2124.6	2022.8
Avg labor need (person-d season^{-1})	225,437	225,437	223,247	223,650	225,437	225,437	225,437	225,437	225,437	220,375	235,357	230,115
Avg water applied (M m^3 season^{-1})	16.91	15.08	13.41	11.44	16.91	16.91	16.91	16.91	16.91	16.01	17.67	15.74
Profit (M CLP)	1,073,574	1,025,618	973,125	900,079	1,068,665	1,024,480	926,291	1,049,249	1,045,047	986,270	1,011,347	1,031,070
Reduction of profit (%)	0.0	4.5	9.4	16.2	0.5	4.6	13.7	2.3	2.7	8.1	5.8	4.0

2.4 Conclusions

This study evaluated the conditions of an agricultural farm using a non-linear optimization model with the aim of maximizing net profits Quezada et al. (2025). The model allocates land and annually distributes water in fruit orchards over a long-term period, as should be the case for orchard farms. The results showed that water availability is a critical factor for the sustainability of the farm. Furthermore, comparing land use patterns for years 2000, 2010, and 2020 changes in crop distribution have a direct impact on both the profitability and sustainability of the enterprise.

Efficient water management has become a key factor in mitigating the impact of water deficits and enhancing the sustainability of the agricultural system. Efficiency operation 90% proved to be more effective in reducing water shortages and economic losses compared to the efficiency scenario 70%. These findings underscore the importance of implementing efficient irrigation practices that optimize water use in the face of increasing water scarcity and climatic variability, thus ensuring long-term profits.

Analyzing the optimal crop pattern under a 90% efficiency scenario demonstrated that net profits can be maximized through strategic and efficient management of orchard resources. This approach yielded a 32.7% increase in profits compared to the pattern CP2000, achieving an optimal allocation of available resources. The sensitivity analysis further confirmed the robustness of the optimal pattern to moderate variations in water availability (up to 20%) and to increases in labor, water, and operational costs. However, significant reductions in water availability or abrupt declines in the export prices of key crops require adjustments in land allocation to preserve farm profitability.

We stress the importance of combining advanced scientific tools, such as optimization models, with a deep understanding of practical farm dynamics. Surveys and interviews confirmed that operational decisions are driven not only by technical or economic considerations but also by subjective factors, such as producer preferences and board of directors' priorities.

However, while our optimization model effectively allocates resources at the farm scale, it does not capture potential downstream impacts. Improved water use at the farm level could reduce water availability for downstream users within the basin. Future research should therefore focus on developing an integrated optimization framework that incorporates both farm-level efficiency and basin-scale hydrological dynamics to ensure sustainable water management throughout the entire watershed.

Finally, improving and innovating labor practices associated with fruit crops can significantly influence crop distribution patterns. Implementing techniques that reduce labor requirements, particularly for high labor-demand fruit crops such as cherries, blueberries, and apples, would facilitate their inclusion in the optimal crop pattern. By optimizing and automating critical tasks, one of the main limiting factors of the study can be mitigated, allowing more efficient resource allocation and boosting farm profitability.

Chapter 3

Impacts of climate change on the productivity and water demand of annual crops in south-central Chile

Abstract

Climate change poses a critical challenge to agricultural sustainability due to alterations in water demand and crop yields. This study evaluates the projected agroclimatic, hydrological, productive, and economic impacts on maize, sugar beet, and wheat crops in the Itata River basin for the period 2035–2065, using simulations with the AquaCrop model under the RCP8.5 climate scenario. In addition, the effect of an adaptation strategy based on earlier sowing dates was analyzed. The results revealed marked spatial heterogeneity in net irrigation requirements (NIR), with higher demands for sugar beet (735–917 mm), followed by maize (566–733 mm) and wheat (503–636 mm). Compared to the historical period (1980–2010), projected reductions in precipitation and the duration of the phenological cycle limited the accumulation of both potential and actual evapotranspiration. Yields increased for sugar beet (16.2%) and wheat (19.5%), while maize showed a slight decrease (0.77%). Irrigation water productivity (IWP) increased for sugar beet (18.5%) and wheat (26.6%), and decreased for maize (4.8%), reflecting different physiological sensitivities to elevated CO_2 levels. Economically,

wheat and sugar beet exhibited increased profitability across all scenarios, whereas maize profitability was constrained by its lower productive response and inflationary effects. Finally, earlier sowing extended the crop cycle, increasing yields and reducing NIR for wheat and maize, confirming that the use of longer-cycle varieties constitutes an effective adaptation measure.

3.1 Introduction

Climate change represents one of the main challenges to the sustainability of agricultural systems worldwide (Mohapatra et al., 2024; Yang et al., 2024). Projections indicate that rising average temperatures, altered precipitation patterns, and increased frequency of extreme events are significantly affecting crop dynamics (Alotaibi, 2023; Islam et al., 2012). Among the most relevant impacts are changes in water demand and crop yields, both critical variables for the viability of agriculture, especially in regions that rely on supplemental irrigation (Masia et al., 2021). Water demand tends to increase in many areas due to higher potential evapotranspiration and lower water availability; however, the magnitude and direction of this effect vary depending on the crop, its phenological stage, and local climatic conditions (Li et al., 2017; Wakjira et al., 2025). Understanding how these changes will affect productivity and water requirements under different agroclimatic contexts is key to anticipating risks, optimizing water management, and designing regional adaptation strategies. Moreover, in some cases, reductions in water demand may occur, reinforcing the need for localized assessments (Xiao et al., 2020).

In Chile, the Central Valley hosts a significant portion of the country's agricultural production and is experiencing a progressive decline in water resource availability (Fuentes et al., 2021). Over recent decades, this region has undergone a sustained decrease in water availability, linked to rising temperatures and a marked reduction in precipitation, exacerbated by phenomena such as the megadrought (Garreaud et al., 2020; Jaque et al., 2023). These conditions threaten the future viability of agricultural activity, particularly for annual crops such as maize, sugar beet, and spring wheat, whose productivity is highly dependent on supplemental irrigation (Donoso, 2021).

Given this context of increasing water vulnerability in south-central Chile, the RCP 8.5 scenario—which represents a high-emission pathway of the IPCC, projecting a radiative forcing of $8.5\,\mathrm{W\,m^{-2}}$ by 2100, associated with CO_2 concentrations exceeding 900 ppm and a mean global temperature increase of approximately 4 °C above pre-industrial levels (Araya-Osses et al., 2020; van Vuuren et al., 2011)—is used as a reference for evaluating long-term climate impacts, as it reflects extreme conditions that demand robust adaptive responses in agricultural production (Alvar-Beltrán et al., 2021; Moya et al., 2024). Assessing impacts under this scenario allows for the establishment of safety margins for planning and prioritizing adaptation measures (Ricalde et al., 2022). Within this framework, crop simulation models are essential tools for analyzing the response of agricultural systems to future conditions (Ahmadi et al., 2024; Alvar-Beltrán et al., 2023). Among them, AquaCrop, developed by the FAO, has been specifically designed to evaluate crop yield response to water availability, taking into account the influence of climate, soil, and agronomic management.

Numerous studies have used AquaCrop in different regions worldwide to assess the impacts of climate change on crop yields and water requirements. For instance, Bouras et al. (2019) estimated the effects of climate change on irrigated wheat under RCP4.5 and RCP8.5 scenarios in Morocco, showing that the shortening of the phenological cycle significantly reduces water requirements, while increased CO_2 levels can offset yield losses. Irmak et al. (2022) evaluated 18 climate models to simulate maize yield in Nebraska under RCP4.5 and RCP8.5, observing lower yields, particularly under rainfed conditions, and an increase in water demand to maintain productivity under RCP8.5. Shirazi et al. (2022) analyzed the yield and water balance of wheat and maize in the Huang-Huai-Hai plain under RCP4.5 and RCP8.5 using AquaCrop, finding that wheat yields would increase, while maize yields would progressively decrease under RCP8.5 (2.1% by 2080), along with a slight reduction in evapotranspiration. Zhao et al. (2025) evaluated how changes in sowing dates could affect yield and irrigation demand in Canada, finding that earlier sowing improves yields and reduces water requirements under high-emission scenarios. Busschaert et al. (2022) projected changes in net irrigation requirements in Europe under a high-emission scenario, estimating increases of up to 35% by 2100, particularly in central and southern regions of the continent. Hadri et al. (2022) integrated AquaCrop and WEAP to simulate scenarios in Morocco, detecting a 50.5% reduction in net precipitation and a 22% increase in unmet demand by 2050 under the RCP8.5 scenario. Collectively, these studies highlight the value of AquaCrop for simulating crop responses to climate change and underscore the importance of applying this approach in specific agricultural contexts.

The overall objective of this study is to comprehensively assess the agroclimatic, productive, hydrological, and economic impacts of climate change on maize, sugar beet, and wheat crops in the Itata River basin during the 2035–2065 period, using simulations with the AquaCrop model under the RCP8.5 climate scenario. Additionally, the study analyzes the effect of an adaptation strategy based on advancing the sowing date, with the aim of identifying practices that enhance water use efficiency and support the profitability of agricultural systems in a context of increasing aridity and climatic uncertainty.

3.2 Materials and methods

3.2.1 Study Site

This study was conducted in the Itata River basin, located in south-central Chile, in the regions of Ñuble and Biobío, and bounded by coordinates 36°30’ to 37°30’ south latitude and 71°30’ to 72°45’ west longitude (Figure 25). The basin covers an approximate area of 11,294 km^2 and extends from the Coastal Range to the Andes Mountains, exhibiting notable topographic and climatic variability. The climate is Mediterranean, characterized by a prolonged dry season during summer and marked seasonality in precipitation, which is concentrated between June and August. Mean annual precipitation in the lower, middle, and upper basin is approximately 827 mm, 1,217 mm, and 2,160 mm, respectively, decreasing from the mountains toward the coast. Average maximum temperatures vary around 18.8°C in the lower basin, 20.3°C in the middle, and 14.5°C in the upper area, reflecting the altitudinal gradient typical of the basin (Méndez-Freire et al., 2022).

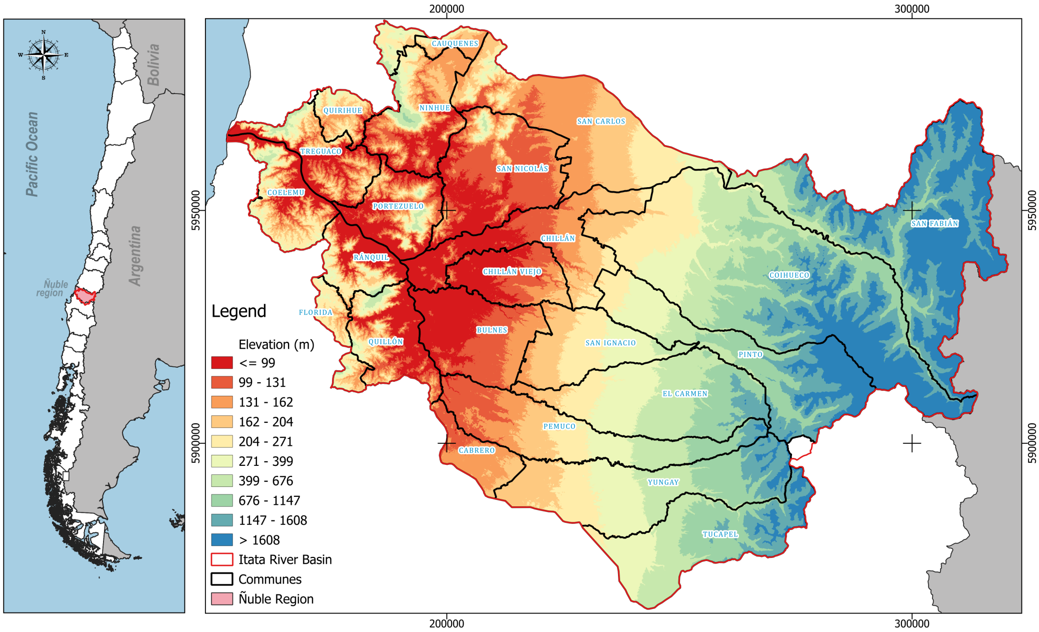

Figure 25: Location of the Itata River basin.

The selected area includes municipalities (the Chilean local administrative unit) with significant production of wheat (*Triticum aestivum L.*), maize (*Zea mays L.*), and sugar beet (*Beta vulgaris L.*), which are strategic crops for both food security and the regional agricultural economy. The Ñuble region accounts for 36.7% of the national wheat production, while sugar beet represents 45.3% and maize 14.5% of national output, respectively (ODEPA, 2019b). These agricultural activities are primarily concentrated in the middle and lower parts of the basin, where the availability of surface and groundwater is critical to productivity.

3.2.2 Input Data

Daily meteorological data were obtained from the Climate Risk Atlas for Chile (ARClim, https://arclim.mma.gob.cl). This database was constructed using statistical downscaling of daily outputs from 25 global circulation models (GCMs) from the CMIP5 ensemble, reduced to a spatial resolution of 5 × 5 km through downscaling methods.

The data were downloaded at the municipal scale, with the platform providing a daily time series for each municipality, derived as the spatial average of the high-resolution grid corresponding to each area. Two climate periods were considered: a historical period (1980–2010) and a future period (2035–2065), under the RCP8.5 scenario. For each municipality within the Itata River basin, daily data were compiled for maximum and minimum air temperature (°C), precipitation (mm), relative humidity (%), wind speed at 2 m (m/s), surface atmospheric pressure (hPa), and specific humidity (g/kg). Reference evapotranspiration (ETo) was calculated following the standardized methodology proposed by the American Society of Civil Engineers (ASCE) (Walter et al., 2000), as it provides a consistent and widely accepted framework for estimating reference evapotranspiration under different climatic conditions, including Mediterranean climates, and has been previously applied in the study area (Lagos et al., 2024). Only those GCMs with all necessary variables for ETo estimation were used, reducing the initial set to seven GCMs and ensuring methodological consistency.

In the Central Valley, soils are predominantly derived from both recent and ancient volcanic ash, resulting in high edaphic heterogeneity even over small areas (Von Buch, 1967). These soils are characterized by high water retention capacity, attributed to their elevated porosity and organic matter content (Beck-Broichsitter et al., 2016; Martínez et al., 2024).

To characterize soil properties in the Itata River basin, a vector-based cartographic product provided by the Center for Natural Resources Information (CIREN) was used, detailing the spatial distribution of soil series within the basin. As analyses were conducted at the municipal scale, the predominant soil series in terms of area was selected for each municipality. The spatial distribution of the selected soil series is presented in Figure 26.

Physical and hydraulic properties of each soil series were extracted from the Ñuble Region Agrological Study (CIREN, 2014), including texture, saturation moisture content, permanent wilting point, field capacity, and bulk density for each soil profile horizon. Based on these properties, saturated hydraulic conductivity was estimated using pedotransfer functions via the Rosetta model integrated within HYDRUS-1D software (Šimůnek et al., 2016).

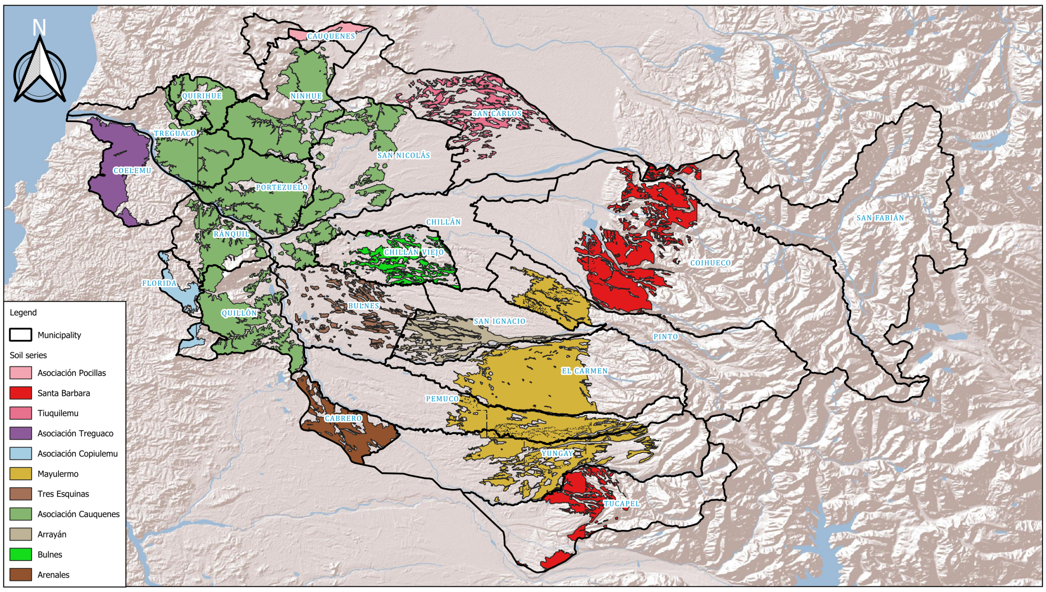

Figure 26: Spatial distribution of the dominant soil series in each municipality of the Itata River basin.

The crop parameters used in AquaCrop to simulate wheat and maize were taken from previous local studies conducted in Chile's Central Valley (Peña, 2013; Sepúlveda, 2022). For sugar beet, parameters were obtained from a combination of the study by (Garcia-Vila et al., 2019) and a technical report from the IANSA company (IANSA, 2014). The sowing dates used in the model correspond to typical regional planting periods: July 31 for wheat, October 15 for maize, and August 7 for sugar beet. The specific values for the most influential crop parameters are presented in Table 18; for parameters not included in this table, the model's default values for each crop were retained, as they have been validated in previous applications and are less sensitive to local calibration compared to those explicitly listed.

Table 18: Crop parameters used for AquaCrop simulations.

Parameter	Maize	Sugar beet	Wheat
Base temperature (°C)	8	5	0
Upper temperature (°C)	30	30	26
Initial Canopy Cover (CC_0)	0.5	0.1	3.8
Plant density (plants/ha)	69167	100000	2513333
Canopy Growth Coefficient (CGC) (%/day)	9.4	15.5	19.2
Maximum Canopy Cover (CC_x)	96	1	95
Canopy Decline Coefficient (CDC)	1.1	0.5	0.4
Time from sowing to emergence (GDD)	104	46	136
Time between sowing and flowering (GDD)	849	–	882
Time between sowing and start tuber formation (GDD)	–	473	–
Duration of flowering stage (GDD)	494	0	165
Time between sowing and senescence initiation (GDD)	1485	2245	1934
Time between sowing and maturity (GDD)	1758	2673	2375
Effective minimum root depth (m)	0.3	0.3	0.1
Effective maximum root depth (m)	2.3	1.0	1.5
Crop transpiration coefficient (KcTr,x)	1.1	1.1	1.1
Crop water productivity (WP) (g m^{-2})	33.7	17	15
Reference Harvest Index (HI_o) (%)	70	48	50
Dry matter content of fresh yield (%)	85	20	90

3.2.3 AquaCrop Model

AquaCrop is a simulation model developed by the Food and Agriculture Organization of the United Nations (FAO), designed to estimate the productivity of herbaceous crops based on available water. The model explicitly represents the interaction between components of the soil–plant–atmosphere system, allowing for the estimation of water balance and crop growth. AquaCrop separates total crop evapotranspiration into soil evaporation (E) and crop transpiration (Tr), enabling a more accurate evaluation of the volume of water effectively used for biomass production. Biomass generation is estimated from crop transpiration using a normalized water productivity coefficient based on evaporative demand and CO_2 concentration. The model also explicitly incorporates the effects of water stress, salinity, soil fertility, and temperature on crop growth and phenology (Raes et al., 2009; Steduto et al., 2009). Final biomass (B) and crop yield (Y) are calculated according to the following relationship:

$$B = WP^* \sum \frac{T_r}{ET_o} \tag{3.1}$$

$$Y = B \cdot HI \tag{3.2}$$

where WP^* is the normalized water productivity (g m^{-2}), Tr is crop transpiration (mm), ETo is reference evapotranspiration (mm), and HI is the harvest index (%), whose evolution may be affected by the timing, intensity, and duration of water stress during the reproductive phase, particularly if it occurs during flowering or yield formation (Vanuytrecht et al., 2014). AquaCrop uses stress coefficients (Ks) to simulate their effect on key processes such as canopy expansion, stomatal conductance, leaf senescence, and root development.

Crop vegetative development is represented through green canopy cover (CC), defined as the fraction of the soil surface covered by photosynthetically active foliage. In the absence of water and temperature constraints, the increase in CC is modeled using the Canopy Growth Coefficient (CGC), from an initial value CC_0 after emergence to a maximum canopy cover CCx, which may approach 100% in cases of full canopy closure (Raes et al., 2023). Subsequently, the decline in cover during the maturation phase is described by the Canopy Decline Coefficient (CDC). Both CGC and CDC are defined as functions of accumulated thermal time, expressed in growing degree days (GDD).

Temperature variations influence phenological development through GDD, either accelerating or delaying growth stages. Extreme temperatures can reduce photosynthetic efficiency or affect reproductive viability, directly impacting biomass accumulation or the HI. Furthermore, elevated CO_2 concentrations induce partial stomatal closure, reducing transpiration while maintaining photosynthesis, thereby increasing water productivity (Gardner et al., 2023; Pazzagli et al., 2016).

3.2.4 Simulations and scenarios

Management conditions assumed unrestricted water supply, allowing estimation of the Net Irrigation Requirement (NIR) as the difference between actual crop evapotranspiration (ETa) and effectively usable precipitation during the crop cycle. An irrigation strategy was assumed that maintains soil moisture around 50% of the readily available water (RAW).

To quantify the benefit of irrigation on yield under climate change scenarios, irrigation water productivity (IWP) was calculated as the yield increase between irrigated and rainfed conditions, relative to the total volume of water applied. This indicator was estimated for each simulation using the following formula:

$$IWP = \frac{Y_{\text{Irrigated}} - Y_{\text{Rainfed}}}{NIR} \tag{3.3}$$

where $Y_{\text{Irrigated}}$ is the yield under irrigated conditions (kg ha^{-1}), and Y_{Rainfed} is the yield under rainfed conditions (kg ha^{-1}).

An economic analysis was also incorporated to estimate the projected net profit for each crop. This analysis was based on yields simulated by AquaCrop, production costs, and projected market prices. Current production costs were sourced from technical-economic reports published by the Office of Agrarian Studies and Policies (ODEPA, 2023), and were annually adjusted using the Consumer Price Index (CPI) based on Quezada et al. (2025). To project future costs, a geometric growth rate (GGR) was applied, based on the CPI trend over the past 25 years, equivalent to 4.0% per year. It was assumed that real costs will evolve in line with this growth rate. The GGR was estimated using the following formula:

$$GGR = \left(\prod_{i=1}^{n} (1 + r_i) \right)^{\frac{1}{n}} - 1 \quad (3.4)$$

where r_i is the annual rate of change in year i, and n is the number of years in the period.

To estimate future market prices of the crops, the GGR of actual observed sales prices in previous years was used (COTRISA, 2025). Based on this rate, three price scenarios were defined: a baseline scenario applying the GGR, an optimistic scenario with a growth rate 0.5% above the GGR, and a pessimistic scenario where prices grow at the same rate as costs (i.e., at the CPI rate). The projected growth rates for each crop and economic scenario are presented in Table 19.

Table 19: Projected growth rates for the analyzed crops under three economic scenarios: baseline, optimistic, and pessimistic.

Crop	Baseline Scenario (%)	Optimistic Scenario (%)	Pessimistic Scenario (%)
Maize	4.99	5.49	4.00
Sugar beet	6.48	6.98	4.00
Wheat	4.95	5.45	4.00

Finally, additional simulations were defined to evaluate adaptation measures to climate change. These included modifications in sowing dates to analyze their effect on yield, water demand, and projected economic returns under future scenarios. The overall methodological framework, including input variables, processing stages, and output indicators, is summarized in Figure 27.

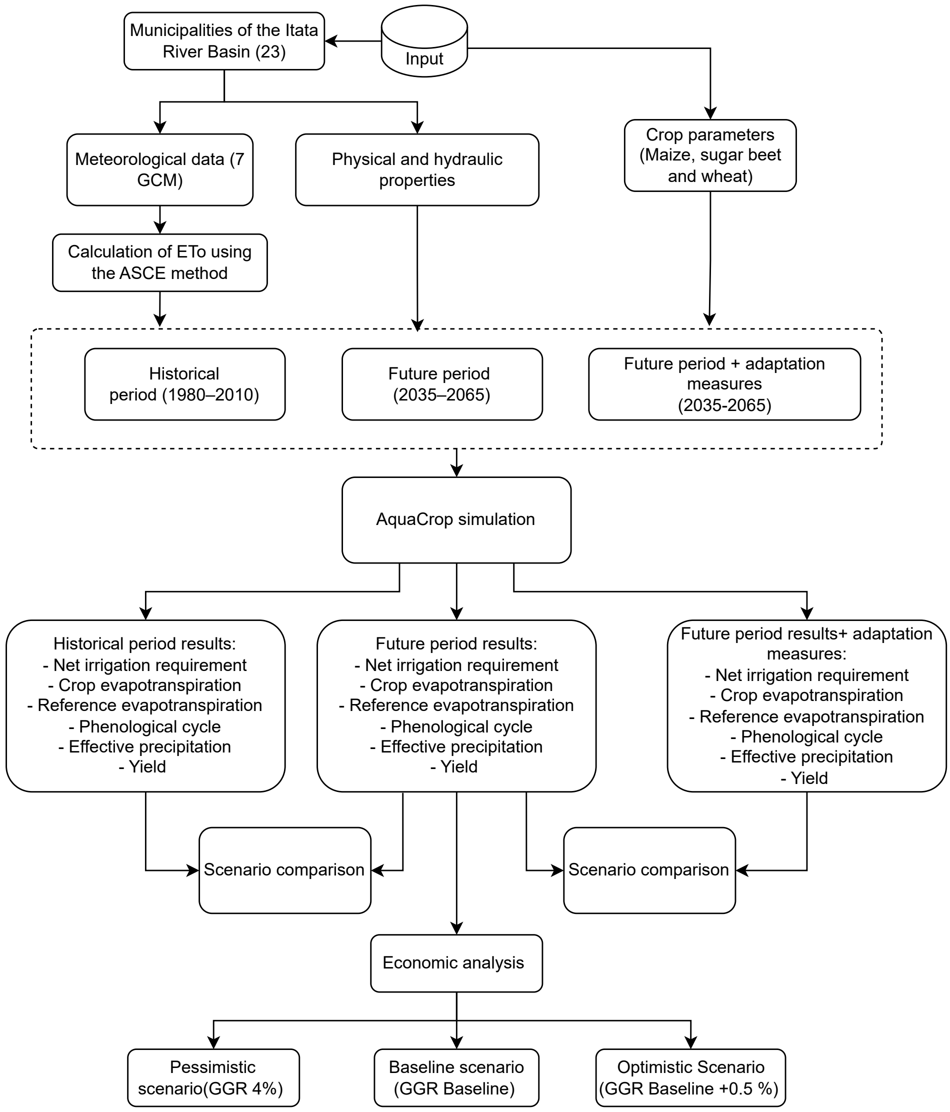

Figure 27: Flow diagram of the methodological framework applied in this study.

3.3 Results and Discussion

3.3.1 Net Irrigation Requirement

Figure 28 shows the spatial distribution of the projected average NIR for the period 2035–2065 under the RCP8.5 climate scenario for maize, sugar beet, and wheat crops in the Itata River basin. The results reveal a marked spatial variability in the NIR for each crop, reflecting differences among the basin's municipalities. This heterogeneity arises from the interaction of agroclimatic and edaphic factors characteristic of each area. In general, summer crops such as maize and sugar beet exhibit higher water requirements due to their growth coinciding with the period of peak evapotranspiration and low rainfall, whereas wheat, which develops during winter and is harvested in early summer, shows lower water demands.

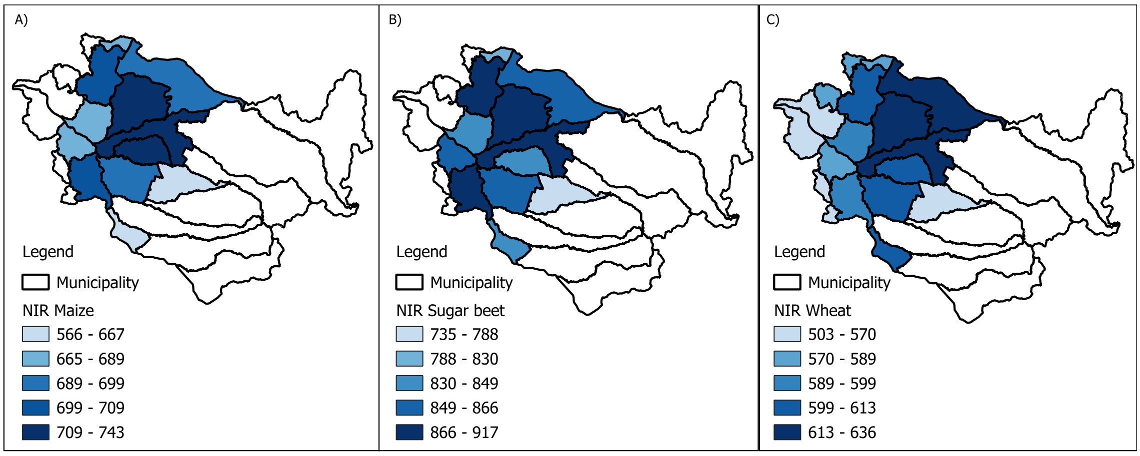

Figure 28: Projected Net Irrigation Requirement (NIR, mm) for the period 2035–2065 under the RCP8.5 scenario for maize (A), sugar beet (B), and wheat (C) in the Itata River basin. Values represent municipal averages derived from simulations with seven GCMs.

For maize projected average NIR values ranged from 566 to 733 mm (Figure 28A). The highest demands were observed in the central municipalities, particularly Chillán, Chillán Viejo, and San Nicolás, associated with mean ETa values of 828, 830, and 841 mm, respectively. In contrast, the municipalities of Cabrero and San Ignacio showed the lowest NIR values, attributed to lower crop demand, with an ETa of 658 mm in Cabrero and more favorable local conditions in San Ignacio.

Sugar beet exhibited the highest NIR values among the analyzed crops, ranging from 735 to 917 mm (Figure 28B). The elevated water demand is attributed to its long growing cycle, which spans the months of maximum evapotranspiration. The municipalities of Chillán, San Nicolás, Quillón, and Ninhue recorded the highest NIR values due to high ETa and below-average precipitation. The lowest NIR values were recorded in San Ignacio and Cauquenes, the latter due to lower water demand in the region.

Wheat showed the lowest NIR values among the evaluated crops, ranging from 503 to 636 mm (Figure 28C). Municipalities with the highest irrigation requirements were Chillán, San Carlos, and San Nicolás, where ETa reached 757, 768, and 772 mm, respectively. The lowest NIR values were observed in coastal municipalities such as Coelemu and Treguaco, associated with lower temperatures and reduced ETa values (659 and 667 mm, respectively).

The municipality of San Ignacio consistently recorded the lowest NIR values for all three crops analyzed: 591 mm for maize, 736 mm for sugar beet, and 512 mm for wheat. This condition is mainly explained by two factors: first, the soils in San Ignacio possess high water retention capacity, facilitating effective use of precipitation; second, climate models project higher precipitation levels for this area compared to other municipalities in the central valley.

Finally, it is important to note that municipalities located in the upper part of the basin were excluded from the analysis due to the significant influence of elevation on projected climatic variables. At higher altitudes, mean temperatures decrease and precipitation increases substantially, generating conditions that are not representative when averaged at the municipal scale. These conditions artificially extend phenological cycles in simulations and produce a non-representative reduction in NIR, thereby compromising the validity of the study results.

3.3.2 Comparison between historical and future scenarios

Figure 29 presents a comparison between the historical climate scenario (1980–2010) and the future scenario (2035–2065, RCP8.5) for agroclimatic and productive variables estimated using the AquaCrop model, applied to maize, sugar beet, and wheat crops in the Itata River basin. The analyzed variables include NIR, in-season precipitation (Rain), reference evapotranspiration (ETo), actual evapotranspiration (ETa), phenological cycle duration (Cycle), and dry matter yield (Yield dry). Table 20 summarizes the average relative changes between both scenarios for each variable and crop, expressed as percentage or absolute variations, as appropriate.

Table 20: Relative changes between the historical and future climate scenarios for the analyzed variables. Values correspond to municipal averages for each crop.

Crop	NIR (%)	Rain (%)	ETo (%)	E (%)	Tr (%)	ETa (%)	Cycle (Days)	Yield (%)
Maize	4.18	–114.21	–3.34	–3.97	–0.01	–1.75	–28.75	–0.77
Sugar beet	0.23	–40.17	–1.18	–10.55	–3.16	–4.51	–21.73	16.19
Wheat	–0.18	–31.55	–0.10	–3.36	–4.08	–3.99	–6.32	19.46

NIR showed a crop-specific response (Figure 29A). For maize, an average increase of 4.18% was projected, while sugar beet and wheat exhibited smaller variations of 0.23% and –0.18%, respectively (Table 20). Although the medians are similar between scenarios, a reduction in the dispersion of future data is notable, suggesting lower spatial and interannual variability in NIR, possibly associated with phenological synchronization induced by the shortened growth cycle and less variable atmospheric conditions during crop development.

Projected precipitation decreased significantly across all crops (Figure 29B), with reductions of 114.21% for maize, 0.17% for sugar beet, and 31.55% for wheat (Table 20). Both medians and means show a marked decline for all crops in the future scenario, confirming the trend toward reduced rainfall contributions under climate change conditions. A contraction in value dispersion is also observed, indicating lower spatial and interannual variability. The highest dispersion occurs in sugar beet due to its longer cycle spanning winter through summer, exposing it to more contrasting climatic conditions.

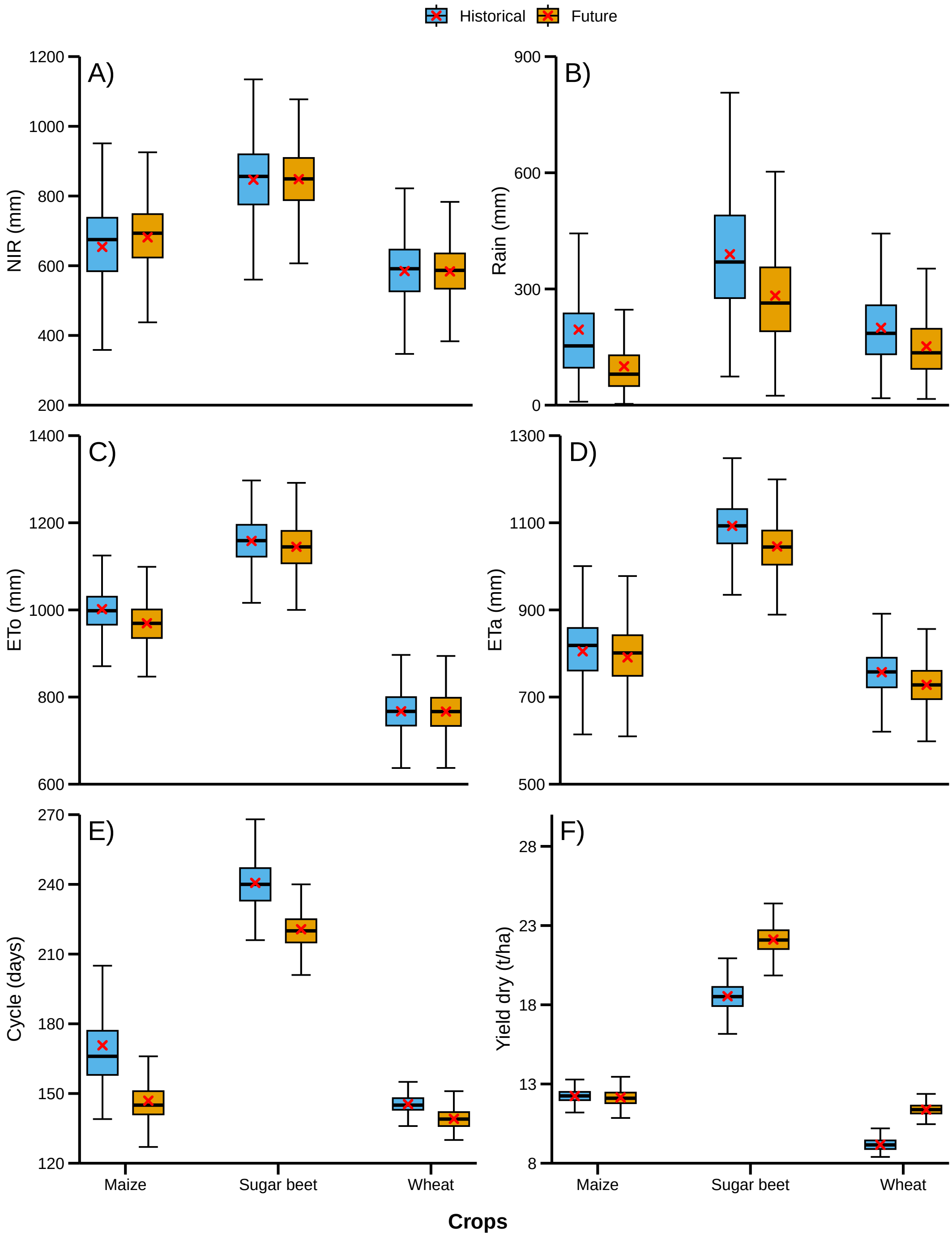

Figure 29: Comparative boxplots for the historical (1980–2010) and future (2035–2065, RCP8.5) scenarios for maize, sugar beet, and wheat in the Itata River basin. Variables include: (A) NIR, (B) precipitation, (C) ETo, (D) ETa, (E) phenological cycle duration, and (F) dry matter yield.

Regarding ETo, a moderate decrease was observed for maize, a slight reduction for sugar beet, and virtually no change for wheat (Figure 29C), with average variations of

3.34%, 1.18%, and 0.10%, respectively (Table 20). These trends are consistent with the reductions recorded in ETa (Figure 29D), with decreases of 1.75% for maize, –4.51% for sugar beet, and 3.99% for wheat (Table 20). These reductions are not due to lower daily atmospheric demand but rather to the shortening of the productive cycle, which reduces the period available for ETo and ETa accumulation. Although future projected temperatures are higher, the shorter phenological cycles limit total evapotranspiration during crop development. Reductions in soil evaporation (E) and transpiration (Tr) followed the same decreasing pattern across all three crops, with sugar beet showing the largest declines (10.55% in E and 3.16% in Tr).

All crops showed a reduction in phenological cycle duration under future conditions (Figure 29E), with average decreases of 28.75 days for maize, 21.73 days for sugar beet, and 6.32 days for wheat (Table 20). A lower dispersion in cycle duration is also observed, with means closer to medians in the future scenario, indicating greater spatial and interannual phenological uniformity. This phenological contraction reflects the impact of thermal increases on growing degree day accumulation, accelerating development stages.

Finally, dry matter yields showed different responses depending on the crop (Figure 29F). Sugar beet and wheat recorded increases of 16.2% and 19.5%, respectively, while maize showed a decrease of 0.77% (Table 20). This differentiated response aligns with the physiological differences between C3 and C4 crops (Allen et al., 2004). In our simulations, the average atmospheric CO_2 concentration was 362.3 ppm in the historical scenario and 545.3 ppm in the future scenario. C3 crops, such as wheat and sugar beet, exhibit a more pronounced positive response to elevated atmospheric CO_2 concentrations, as CO_2 is a limiting substrate for photosynthesis in this metabolism type (Saha et al., 2020). This effect enhances carbon assimilation and consequently biomass accumulation, especially under non-limiting water and nutrient conditions (Opoku et al., 2024; Srinivasarao et al., 2016). In contrast, maize (a C4 crop) does not benefit similarly and the cycle shortening may limit the grain filling period, explaining the observed stability or slight decline (Kellner et al., 2019; Rezaei et al., 2023).

These findings are consistent with previous studies projecting that rising temperatures under climate change scenarios accelerate phenological development, reducing cycle duration and, consequently, total evapotranspiration (Bouras et al., 2019; Ishaque et al., 2023). Notably, simulations conducted with AquaCrop and other models have reported yield increases in wheat and sugar beet under elevated CO_2 conditions, provided there are no severe limitations in water or nutrients (Sánchez-Sastre et al., 2020; Vanuytrecht et al., 2016). However, for maize, yield reductions under future RCP8.5 conditions have also been reported, linked to shorter cycles and more restrictive growing conditions (He et al., 2020; Raes et al., 2021). Furthermore, the projected reduction in effective precipitation observed in this study aligns with trends identified in various agricultural regions of central Chile and other Mediterranean areas (Araya-Osses et al., 2020; Bozkurt et al., 2018), reinforcing the need for adaptation strategies that ensure production stability under future, more arid, and variable climate conditions.

3.3.3 Water productivity

Figure 30 shows the spatial distribution of projected Irrigation Water Productivity (IWP) for the period 2035–2065 under the RCP8.5 climate scenario for maize, sugar beet, and wheat crops in the Itata River basin. The spatial assessment of IWP allows identification of areas where irrigation generates the greatest productive benefits, which is particularly relevant for efficient water planning under climate change scenarios.

For maize, projected IWP ranged from 1.60 to 2.18 kg m^{-3} (Figure 30A). The lowest values (<1.72 kg m^{-3}) were concentrated in central municipalities of the basin, such as Chillán, Chillán Viejo, San Nicolás, and Ninhue, indicating lower marginal irrigation efficiency in those areas. This pattern corresponds to zones with the highest NIR, whose values ranged from 7,087 to 7,430 m^3 ha^{-1} (Figure 28), and where rainfall during the crop cycle was below 100 mm, leading to low rainfed yields. However, Cabrero registered the highest IWP value (2.18 kg m^{-3}), explained by its lower water requirement (NIR of 5,663 m^3 ha^{-1}) associated with reduced atmospheric demand.

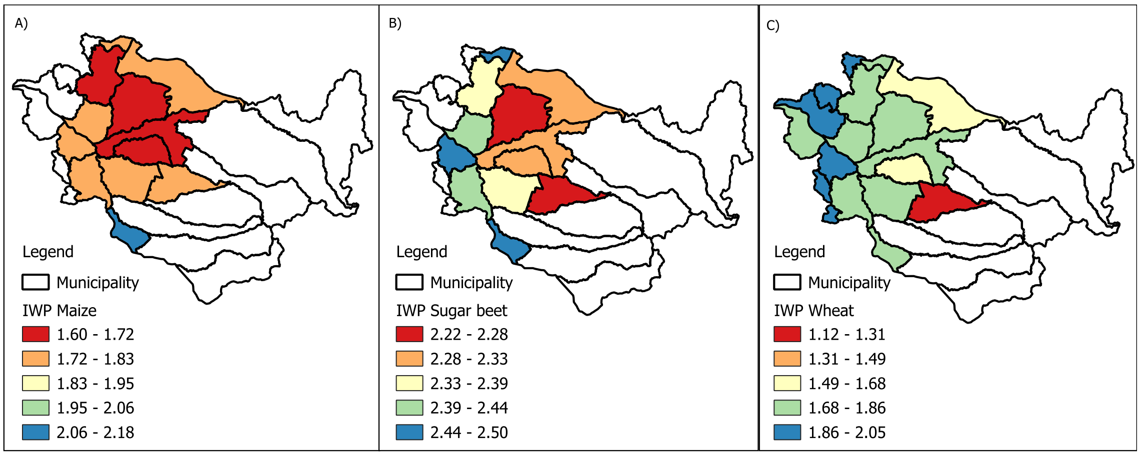

Figure 30: Spatial distribution of irrigation water productivity (IWP) projected for the period 2035–2065 under the RCP8.5 scenario for maize (A), sugar beet (B), and wheat (C) in the Itata River basin. Values represent municipal averages derived from simulations using seven GCMs.

For sugar beet, IWP values ranged from 2.22 to 2.50 kg m^{-3} (Figure 30B), making it the crop with the highest marginal irrigation efficiency among those analyzed. It also showed the smallest spatial range in IWP (0.28 kg m^{-3}), indicating more uniform irrigation response across municipalities. The highest values were recorded in Cabrero, Ránquil, and Cauquenes, which achieved the highest irrigated yields (22.1 to 22.4 t ha^{-1}). In contrast, the lowest IWP values were observed in San Nicolás, where yield was the lowest and NIR the highest, followed by San Ignacio, where low NIR is due to high soil moisture retention and higher projected rainfall, reducing the marginal benefit of irrigation.

For wheat, IWP ranged from 1.12 to 2.05 kg m^{-3} (Figure 30C). The spatial distribution was relatively homogeneous in the central part of the basin, with values between 1.64 and 1.86 kg m^{-3} and lower inter-municipal contrasts. The highest values were recorded in coastal municipalities, where a combination of high irrigated yields and low NIR (Figure 28) was present. A particular case is the municipality of Coelemu, where despite having the lowest NIR in the basin, soils with high water retention capacity enabled high rainfed yields, reducing the marginal impact of irrigation. A similar situation occurred in San Ignacio, where IWP reached its minimum (1.12 kg m^{-3}), due to a combination of high soil moisture retention and greater rainfall during the cycle, which diminished the yield gap between irrigated and rainfed conditions.

Table 21 summarizes average IWP values for each crop under historical and future scenarios, along with the projected percentage variation. An increase in water productivity was observed for sugar beet (18.5%) and wheat (26.6%), while maize showed a reduction of 4.8%. This behavior can also be interpreted through the lens of physiological water use efficiency under elevated CO_2 conditions. In C3 crops, such as wheat and sugar beet, increased CO_2 not only enhances the photosynthetic rate but also reduces stomatal opening, resulting in lower water loss through transpiration (Cao et al., 2022; Kimball, 2016). This dual effect substantially improves irrigation water productivity by increasing the biomass produced per unit of water applied (Guo et al., 2010). In contrast, C4 crops like maize already possess internal mechanisms to optimize CO_2 concentration at fixation sites, and thus their intrinsic water use efficiency shows limited responsiveness to increased atmospheric CO_2, constraining their potential to enhance marginal irrigation efficiency under future climatic conditions (Ye et al., 2024).

Table 21: Comparison of average IWP under historical (1980–2010) and future (2035–2065) scenarios for each crop, and projected percentage variation.

Crop	Historical IWP (kg m^{-3})	Future IWP (kg m^{-3})	Variation (%)
Maize	1.86	1.77	–4.8
Sugar beet	2.00	2.37	18.5
Wheat	1.39	1.76	26.6

3.3.4 Economic Analysis

Figure 31 shows the projected annual evolution of fresh yield and phenological cycle duration for maize (A), sugar beet (B), and wheat (C) in the Itata River basin during the 2035–2065 period under the RCP8.5 climate scenario. This figure allows for analysis of the relationship between productive performance and interannual phenological development for each crop.

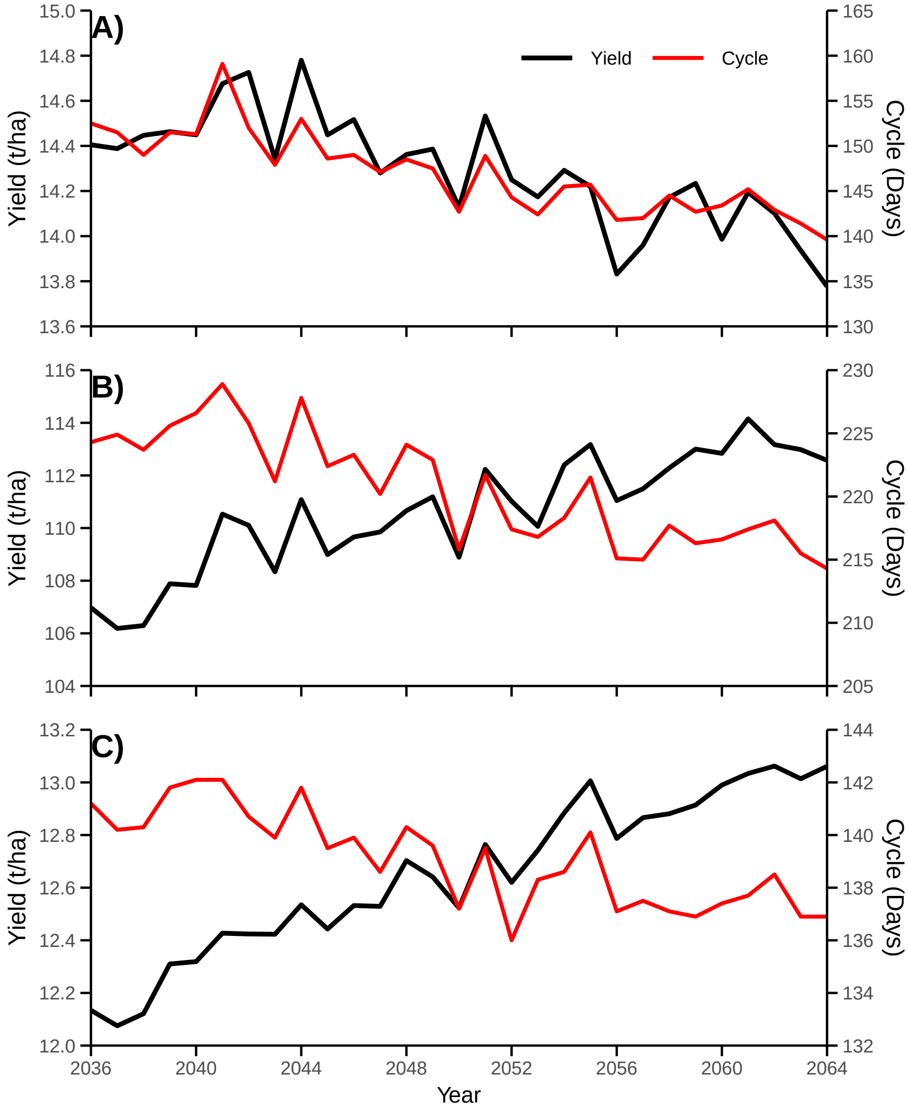

Figure 31: Interannual evolution of fresh yield (Yield) and phenological cycle duration (Cycle) for A) maize, B) sugar beet, and C) wheat during 2035–2065 under the RCP8.5 climate scenario. Values represent municipal averages simulated with AquaCrop.

All crops exhibit a decreasing trend in phenological cycle duration over the simulation period. This behavior is directly associated with the projected temperature increase in the study area, which accelerates growing degree day accumulation, thereby shortening phenological stages. This contraction of the growth cycle directly affects yield by reducing the time available for key processes such as vegetative growth. In general, years with abrupt variations in cycle duration coincide with sharp fluctuations in yields. This pattern is particularly evident in 2043, 2050, and 2051 for maize; 2043, 2044, and 2056 for sugar beet; and 2050, 2052, and 2055 for wheat. These oscillations reflect the high sensitivity of yield to cycle duration, especially when critical developmental stages are compressed, limiting productive potential.

Despite this general trend, the crops display differentiated behaviors. Maize shows a slight decrease in yield toward the end of the period, reflecting its greater sensitivity to cycle shortening. In contrast, sugar beet and wheat exhibit upward trends, with net increases in average yield, provided nitrogen requirements are met. This difference is related to the ability of C3 crops to maintain high rates of carbon assimilation and water use efficiency under elevated CO_2 conditions, which promotes more effective biomass accumulation even when development time is compressed (Aranjuelo et al., 2015; Wang et al., 2013). In these crops, elevated CO_2 enhances not only photosynthetic efficiency but also significantly increases nitrogen demand, as greater nutrient availability is needed to sustain the enhanced carbon assimilation (Asif et al., 2020; Kant et al., 2012). Thus, projected yields for wheat and sugar beet depend not only on CO_2-induced physiological responses but also on sufficient nitrogen nutrition to realize that potential (Dong et al., 2023; Han et al., 2015). In contrast, maize, with its shorter cycle and lower phenological plasticity under projected conditions, fails to fully offset the restrictive effects of thermal increases, resulting in stagnant productivity (Alvar-Beltrán et al., 2025; Khan et al., 2025; Markelz et al., 2011).

These results underscore the importance of considering the interaction between physiology, cycle duration, and nutrient management when projecting future productive performance. This dynamic is fundamental for anticipating the evolution of net agricultural profit, as yield is the primary determinant of projected profitability.

Figure 32 shows the projected temporal evolution of agricultural profit from 2036 to 2064 under three economic scenarios—optimistic, baseline, and pessimistic—for maize (A), sugar beet (B), and wheat (C). Each line represents the annual mean value, while the shaded bands indicate the variability range (10th to 90th percentile), derived from the seven GCMs and municipal variability estimated by the model in the study area. These results were obtained by integrating simulated yields with projected prices and inflation-adjusted costs, following the methodology described in Section 3.2.4

It is important to note that for sugar beet, an initial GGR of 6.48% was calculated. However, since the value of this crop is indexed to the U.S. dollar—whose GGR for the same period was 4.89%—its price is heavily influenced by external factors. To avoid overestimating profits in the most optimistic scenarios, which projected returns close to 88 million CLP, a more conservative GGR of 4.5% was applied in the economic analysis. Figure 32 was constructed using this adjusted rate for the baseline scenario.

All three crops show a progressive increase in net profits in the baseline and optimistic scenarios, with a steeper slope toward the end of the period. This pattern reflects not only the projected price increase but also the compounding effect of using a geometric growth rate, which produces an exponential trajectory in the projections. As time progresses, this dynamic amplifies differences between scenarios, especially in the later simulation years. However, it is crucial to consider that these projections are based on assumptions of continuous price growth, which introduces increasing uncertainty. This uncertainty is compounded by external factors not modeled, such as international market volatility or changes in agricultural policy. Additionally, since costs were adjusted for inflation, profits are presented in nominal terms, meaning part of the projected growth also reflects accumulated inflation.

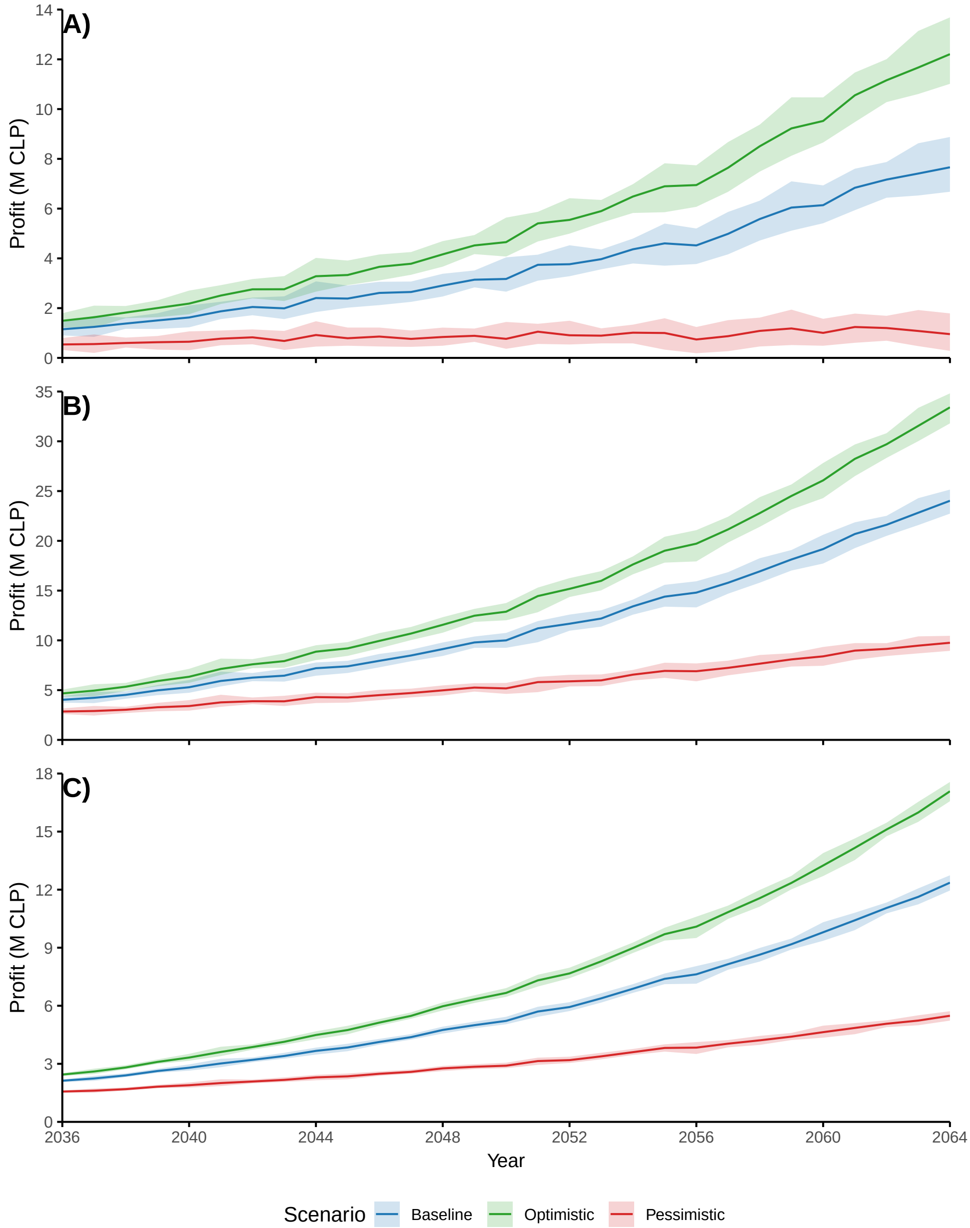

Figure 32: Projected annual net profit for maize (A), sugar beet (B), and wheat (C) under optimistic (green), baseline (red), and pessimistic (blue) price scenarios. Bands indicate variability associated with municipalities and climate models.

For maize, a modest increase in profit is observed in the baseline and optimistic scenarios, while in the pessimistic scenario it remains nearly constant. This stagnation implies a progressive loss of purchasing power, reflecting a declining real profit over time. This condition is directly related to the projected yield decline (Figure 31A), which fails to offset cost increases driven by inflation. Therefore, maize profitability will critically depend on its ability to adapt to more restrictive production conditions. In contrast, wheat and sugar beet display increasing trajectories across all scenarios, including the pessimistic one, driven mainly by the sustained increase in simulated yields (Figures 31B and 31C). To achieve these yields, annual nitrogen requirements for each crop were estimated and incorporated into the total projected cost.

3.3.5 Adaptation Measure

Figure 33 compares the future scenario without adaptation and the adaptation scenario (earlier sowing date) for agroclimatic, phenological, and productive variables simulated for maize, sugar beet, and wheat crops. Table 22 summarizes the average relative changes between both scenarios for each variable and crop, expressed as percentages or absolute values, as appropriate.

NIR showed crop-specific responses (Figure 33A). Wheat recorded a considerable reduction of 20.4%; maize saw a 3.6% decrease, though accompanied by increased spatial and interannual variability; and sugar beet showed a slight increase of 0.3% (Table 22). These responses are mainly related to the increase in precipitation during the growing cycle (Figure 33B), which reached 34.8% for maize, 29.0% for sugar beet, and 44.9% for wheat (Table 22). Advancing the sowing date allowed crops to coincide with greater water availability during winter and spring months, thus reducing the need for supplemental irrigation.

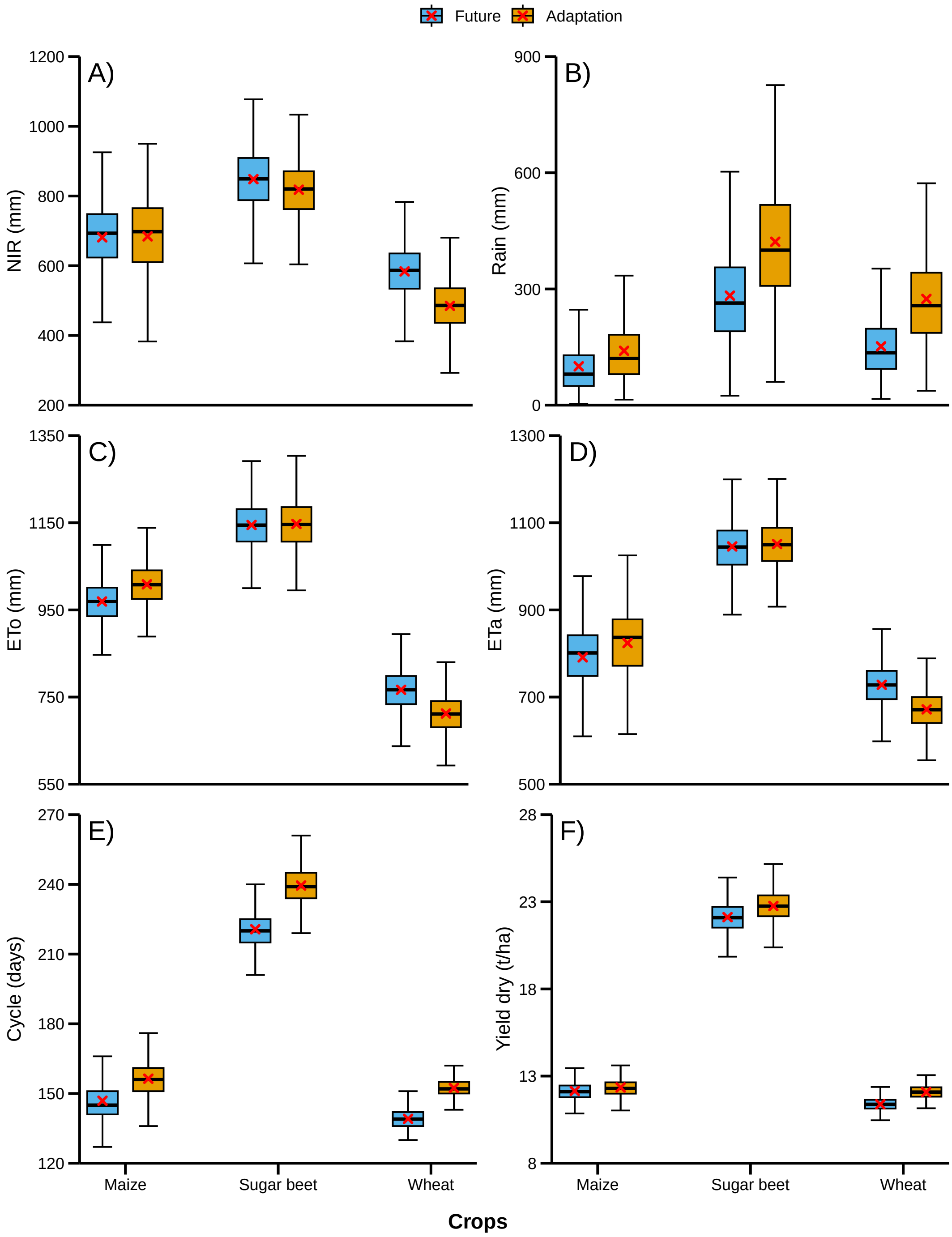

Figure 33: Comparative boxplots between future and adaptation scenarios (2035–2065, RCP8.5) scenarios for maize, sugar beet, and wheat in the Itata River basin. Variables include: (A) NIR, (B) precipitation, (C) ETo, (D) ETa, (E) phenological cycle duration, and (F) dry matter yield.

Regarding ETo (Figure 33C), a 0.2% increase was observed for maize, 3.9% for sugar beet, and a 7.6% decrease for wheat (Table 22). These changes are partly explained by the alteration in cycle duration: longer cycles in maize and sugar beet resulted in higher cumulative atmospheric demand; for wheat, earlier sowing shifted much of its development to months with lower demand. A similar pattern was observed for ETa (Figure 33D), with increases of 0.5% for maize and 4.0% for sugar beet, while wheat saw an 8.4% decrease. This dynamic reaffirms the influence of seasonal ETo distribution: early sowing allows wheat to develop during periods of lower evaporative rates, reducing effective transpiration; whereas the maize and sugar beet cycles extend into summer months with higher atmospheric demand.

Cycle duration (Figure 33E) increased in all three crops under the adaptation scenario, reflecting the direct effect of earlier sowing and exposure to more moderate temperatures that slow development. Increases were 18.9 days for maize, 9.4 days for sugar beet, and 13.3 days for wheat (Table 22). This cycle extension directly impacted yields (Figure 33F), which increased across all crops: 2.8% for maize, 1.6% for sugar beet, and 5.8% for wheat. This effect results from longer vegetative and reproductive phases, which promote greater biomass accumulation. In C3 crops such as wheat and sugar beet, this benefit is further enhanced by improved photosynthetic efficiency under CO_2 enrichment, as previously discussed.

Table 22: Relative changes between the future climate and adaptation scenarios for the analyzed variables. Values correspond to municipal averages for each crop.

Crop	NIR (%)	Rain (%)	ETo (%)	E (%)	Tr (%)	ETa (%)	Cycle (Days)	Yield (%)
Maize	–3.6	34.8	0.2	–2.7	1.3	0.5	18.9	2.8
Sugar beet	0.3	29.0	3.9	2.4	5.1	4.0	9.4	1.6
Wheat	–20.4	44.9	–7.6	–10.1	–8.2	–8.4	13.3	5.8

It is important to note that the results of the adaptation scenario assume that climatic conditions will permit sowing operations during the winter months, which constitutes a relevant operational premise. Based on these results, it becomes evident that, under projected climate change conditions for the RCP8.5 scenario, altering sowing dates and selecting appropriate varieties becomes a critical component of agronomic adaptation

(Alvar-Beltrán et al., 2025; Chekole & Mohammed Ahmed, 2023; Islam et al., 2022; Mo et al., 2016). Specifically, for maize, the yield reduction associated with a shortened cycle suggests that using longer-cycle varieties may be necessary to mitigate productive losses (Koimbori et al., 2022; Martins et al., 2019). This measure would help extend key phenological stages, such as grain filling, which are compromised under future scenarios (He et al., 2018; Holzkämper, 2020). On the other hand, in C3 crops like wheat and sugar beet, extending the cycle is even more beneficial, as it allows for a prolonged utilization of CO2-enhanced photosynthesis, potentially leading to further yield increases (Alvar-Beltrán et al., 2021; Wen et al., 2023). In this context, selecting cultivars with longer phenological cycles stands out as a fundamental agronomic adaptation measure to cope with climate change.

3.4 Conclusions

This study evaluated the projected agroclimatic, productive, hydrological, and economic impacts for maize, sugar beet, and wheat crops in the Itata River basin under the RCP8.5 climate scenario (2035–2065), incorporating simulations using seven global climate models with the AquaCrop model. The results reveal marked spatial heterogeneity in Net Irrigation Requirement (NIR), explained by the interaction of soil and climatic factors specific to each municipality. Sugar beet showed the highest water demands (735–917 mm), followed by maize (566–733 mm), and lastly wheat (503–636 mm), reflecting differences in developmental seasonality and phenological duration.

The comparison between historical (1980–2010) and future (2035-2064) climate scenarios revealed a generalized reduction in precipitation and crop cycle duration for all three crops, attributed to increased temperatures and accelerated accumulation of growing degree days. This cycle contraction reduced accumulated ETo and ETa values, partially mitigating projected increases in water requirements. However, yield impacts were variable: sugar beet and wheat showed increases of 16.2% and 19.5%, respectively, while maize exhibited a slight decline of 0.77%. This behavior was mirrored in

IWP, with increases of 26.6% in wheat and 18.5% in sugar beet, and a 4.8% decrease in maize. These differences reflect the greater physiological sensitivity of C3 crops to increased atmospheric CO_2 concentrations, which enhances their photosynthetic efficiency and reduces stomatal transpiration, promoting greater biomass accumulation per unit of applied water, unlike C4 crops.

From the economic results obtained under the assumptions considered in this study, wheat and sugar beet showed sustained growth in agricultural profit, driven by progressively increasing yields over the period, while maize exhibited a stagnating trend, particularly under the pessimistic scenario. This trend reflects a progressive loss in purchasing power, attributed to the yield decline linked to shortened phenological cycles, combined with inflation-driven cost increases, which compromise future profitability.

Finally, the evaluation of the adaptation scenario based on earlier sowing dates revealed relevant agronomic benefits by extending the phenological cycle and increasing yields in all three crops, along with a reduction in NIR for wheat and maize. These results highlight the need to incorporate adaptive agronomic strategies, such as timely adjustments to sowing dates, the selection of longer-cycle varieties, and efficient nutrient management, as a robust response to sustain agricultural productivity and profitability under the impacts of climate change in the study area.

Chapter 4

Conclusiones

El desarrollo del modelo de optimización propuesto en el capítulo 1 permitió abordar la complejidad de la planificación agrícola en huertos frutales desde una perspectiva integral, incorporando variables físicas, económicas, operativas y de riesgo. La inclusión explícita del riesgo, especialmente asociado a la volatilidad de precios, resaltó la importancia de la diversificación productiva y de la implementación de estrategias adaptativas para gestionar las incertidumbres inherentes al mercado agrícola. Asimismo, los análisis de sensibilidad sobre la disponibilidad de mano de obra y agua evidenciaron que las variaciones en estos recursos afectan significativamente la configuración y la sostenibilidad del sistema productivo. El patrón óptimo propuesto mantuvo la viabilidad económica con reducciones de utilidades del 5,7 % ante un déficit hídrico del 30 % y utilizando un 24 % de la mano de obra disponible. Estos resultados ponen de manifiesto la necesidad de adoptar enfoques proactivos basados en la diversificación y en una asignación equilibrada de recursos críticos. Si bien el modelo presenta limitaciones propias de su naturaleza teórica, ofrece una base metodo lógica robusta que permite explorar soluciones óptimas de asignación predial, contribuyendo como herramienta complementaria a la toma de decisiones estratégicas orientadas a una fruticultura más resiliente, eficiente y sostenible.

La aplicación práctica del modelo de optimización a una empresa agrícola, presentada en el capítulo 2, permitió constatar que la eficiencia en la gestión del agua es un factor determinante que influye directamente en la rentabilidad y en la reducción de la vulnerabilidad frente a escenarios de déficit hídrico. Con una eficiencia de distribución total (EDT) del 90 %, las utilidades se redujeron entre un 1,0 y un 2,2 %, mientras que, en escenarios con una EDT del 70 %, la disminución de utilidades osciló entre un 4,7 y un 8,5 %. La comparación entre patrones históricos y un escenario optimizado evidenció mejoras económicas del 32,7 % respecto del patrón base, alcanzadas mediante una asignación estratégica y eficiente de los recursos. El análisis de sensibilidad mostró que variables como la disponibilidad hídrica y las condiciones de mercado pueden modificar sustancialmente la rentabilidad predial, lo que refuerza la necesidad de evaluar los patrones de establecimiento bajo múltiples escenarios. Además, se identificó que las decisiones operativas no dependen exclusivamente de factores técnicos o económicos, sino también de elementos subjetivos como las preferencias del productor y las prioridades de la dirección. Esto resalta la importancia de articular enfoques científicos con las dinámicas prácticas del predio, promoviendo una integración que maximice tanto la rentabilidad como la sostenibilidad en contextos agrícolas específicos.

Por otra parte, la aplicación del modelo de simulación AquaCrop presentado en el capítulo 3, permitió evaluar los impactos proyectados del cambio climático (escenario RCP8.5) sobre la demanda hídrica y el rendimiento de cultivos anuales como maíz, remolacha azucarera y trigo en la cuenca del río Itata, para el período 2035–2065. Los resultados revelaron una notable heterogeneidad espacial en los requerimientos netos de riego, explicada por la variabilidad edáfica y climática entre comunas. A nivel fisiológico, se observó una reducción generalizada en la duración de los ciclos fenológicos, con disminuciones promedio de 28,75 días en maíz, 21,73 días en remolacha y 6,32 días en trigo, producto del incremento térmico y la acumulación acelerada de grados-día. Esta contracción del ciclo redujo los valores acumulados de evapotranspiración potencial y real, limitando el tiempo disponible para la acumulación de biomasa. Como consecuencia, se observaron respuestas diferenciadas en la productividad: mientras trigo y remolacha mostraron incrementos medios del 19,5 % y 16,2 %, respectivamente, el maíz presentó una leve disminución del 0,77 %. Estas diferencias reflejan la mayor capacidad de respuesta fisiológica de los cultivos C3 frente al incremento de CO_2, en comparación con los cultivos C4. En conjunto, los hallazgos subrayan la necesidad de incorporar estrategias agronómicas adaptativas, como el ajuste del calendario de siembra o la selección de variedades de ciclo más largo, para sostener la productividad y rentabilidad agrícola frente a los efectos del cambio climático.

4.1 Limitaciones del estudio

El modelo de optimización para asignar agua y superficie a huertos frutales a lo largo de un período de 20 años presenta limitaciones derivadas de su naturaleza determinista, lo que impide captar plenamente la complejidad de la realidad agrícola. No considera factores relevantes de manejo, como plagas, podas, aplicación de fertilizantes, entre otros. Una de las variables más importantes empleadas por el modelo son las funciones de producción, obtenidas a partir de condiciones específicas de manejo y de la zona en la que se recopiló la información, asumiendo que su comportamiento se mantiene constante durante todo el período de análisis. Además, aunque la información sobre este tipo de funciones en frutales es escasa, no existen estudios que determinen cómo varían con la edad de los frutales, por lo que el modelo no posee una validación empírica. Si bien constituye una herramienta útil para la toma de decisiones, algunos parámetros son difíciles de predecir, como el precio de venta de la fruta, lo que obliga a basar las proyecciones en supuestos definidos al momento de realizar el análisis. Finalmente, aunque el modelo optimiza la asignación de recursos a escala predial, no considera los posibles impactos aguas abajo, tales como alteraciones en la disponibilidad de agua para otros usuarios o ecosistemas.

Una limitación de este estudio es el uso de proyecciones climáticas basadas en escenarios RCP (CMIP5), en particular el RCP8.5, debido a que al momento de la investigación no se disponía de datos bajo el marco CMIP6. A diferencia de los RCP, definidos únicamente por un forzamiento radiativo objetivo, los escenarios SSP incorporan proyecciones cuantitativas de variables socioeconómicas y tecnológicas que condicionan las trayectorias de emisiones, además de estar asociados a modelos climáticos actualizados con mejoras en la física de nubes, océanos y los procesos de retroalimentación, lo que se traduce en proyecciones más consistentes y coherentes con las evaluaciones más recientes del IPCC AR6.

4.2 Futuras investigaciones

Futuras investigaciones podrían avanzar hacia la evaluación de patrones óptimos de cultivo a escala de cuenca, integrando tanto especies anuales como perennes en una planificación conjunta que consideren períodos de planificación a largo plazo. Este enfoque permitiría una gestión más estratégica y sostenible de los recursos agrícolas, en particular bajo escenarios de déficit hídrico, donde se recomienda priorizar el uso del agua en cultivos frutales debido a su carácter perenne y a la inversión de largo plazo que implican, mientras que los cultivos anuales, por su flexibilidad, pueden actuar como zonas de amortiguación para ajustar la planificación según la disponibilidad de recursos. Asimismo, es necesario desarrollar modelos de optimización integrados que articulen la eficiencia productiva a nivel predial con la sostenibilidad hídrica a escala de cuenca, considerando los posibles efectos indirectos sobre usuarios ubicados aguas abajo.

En relación con los escenarios de cambio climático, futuras investigaciones deberían actualizar las proyecciones climáticas empleadas incorporando los escenarios SSP del marco CMIP6, que integran de manera explícita factores socioeconómicos, energéticos y de uso del suelo. Esto permitiría analizar tendencias y diseñar estrategias de adaptación agrícola mejor contextualizadas, alineadas con las proyecciones más recientes del IPCC AR6. Se recomienda incluir trayectorias de emisiones contrastantes, como SSP1–2.6 y SSP2–4.5 (más conservadoras), así como SSP5–8.5 (altas emisiones), con el fin de capturar una mayor diversidad de respuestas climáticas y socioeconómicas. Finalmente, se propone comparar estos impactos en distintas zonas agrícolas del norte, centro y sur de Chile, considerando la sensibilidad agroclimática particular de cada cultivo en su contexto regional, para diseñar estrategias de adaptación diferenciadas que fortalezcan la resiliencia del sector agrícola frente a la variabilidad y el cambio climático.

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