PONTIFICIA UNIVERSIDAD CATÓLICA DE CHILE
ESCUELA DE INGENIERÍA

# ANALYZING THE IMPACT OF ERRORS IN THE BELIEFS IN PLANNING OF WINE GRAPE HARVESTING OPERATIONS USING A MULTI-STAGE STOCHASTIC MODEL APPROACH

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Thesis submitted to the Office of Research and Graduate Studies
in partial fulfillment of the requirements for the degree of
Master of Engineering Sciences

Supervisor:
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Santiago de Chile, January, 2022

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Santiago de Chile, January, 2022

*Gratefully to my family*

## ACKNOWLEDGEMENTS

I want to express my deep thanks to my family for their constant support, to my father Omar and my brother Matías for supporting me at all the time, becoming my fundamental mainstay that allowed me to develop myself academically and as a person.

I would like to thank professors Alejandro Cataldo and Gustavo Angulo from the Operations Research department, who gave me excellent tools and knowledge to successfully carry out this research.

Finally, I would greatly appreciate the constant support of my supervising professor Alejandro Mac Cawley, who constantly guided me and maintained a constant disposition and closeness for any need I had.

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## ABSTRACT

Forecasts and future beliefs play a critical role in the planning to hire harvest labor, especially when fixing previously made decisions implies incurring high costs. In this article, we study the effect that a bad forecast/belief has on the wine-grape harvest planning process. To achieve this, we induce errors in the prediction of yields and the estimation of transition probabilities through the yield-stock states. Using a multistage stochastic programming model, we analyze the impact that forecast-accuracy errors have on the profits and efficiency of the harvesting process. We also study how flexibility, in the form of second-stage decisions, affects the ability to fix the planning decisions and generate value. First, we develop a multistage stochastic model that considers grape growth uncertainty, given a belief in future events. The model decision variables are hiring, firing, and maintaining harvest labor through designated periods and the harvested quantities in each period and block. Once the model defines the plan for the coming season, the mistake in the forecast appears, and the decision-maker can adjust future decisions and beliefs. Results indicate that the effect of the errors in yield determination is not symmetrical; underestimations of the yields have a more significant negative effect on the objective function, while overestimation does not. Flexibility to revise hiring decisions does not make a significant difference if the yields are overestimated. Since they correspond to a significant proportion of the income, lower levels of losses of the better-quality grapes account for the largest portion of income loss. Last, grapes that have an early improvement of their quality give the decision-maker an extra level of flexibility to adjust the harvesting plan.

As this kind of grape reaches its optimal quality earlier and stays in that condition longer, the planner can start the harvest earlier, if necessary.

## RESUMEN

Los pronósticos y las creencias futuras juegan un papel fundamental en la planificación de la contratación de mano de obra de cosecha, especialmente cuando la corrección de decisiones tomadas anteriormente implican incurrir en altos costos. En este artículo estudiamos el efecto que tiene un mal pronóstico en el proceso de planificación de la cosecha. Para lograr esto, inducimos errores en la predicción de las productividades y en la estimación de las probabilidades de transición entre los estados de productividad. Utilizando un modelo de optimización estocástico de múltiples etapas, analizamos el impacto que los errores en la precisión del pronóstico tienen sobre las ganancias y la eficiencia del proceso de recolección. También estudiamos cómo la flexibilidad, en forma de decisiones de segunda etapa, afecta la capacidad de fijar las decisiones de planificación y generar valor. En un primer paso, desarrollamos un modelo estocástico de múltiples etapas que considera la incertidumbre del crecimiento de la uva dada la creencia en eventos futuros. Las variables de decisión del modelo son: contratación, despido y mantenimiento de la mano de obra de cosecha a lo largo de los períodos, y también las cantidades cosechadas en cada período y bloque. Una vez que el modelo define el plan para la época venidera se revela el error en el pronóstico y el tomador de decisiones puede ajustar sus decisiones y creencias futuras. Los resultados indican que el efecto de los errores en la determinación del rendimiento no es simétrico; las subestimaciones de los rendimientos tienen un efecto negativo más significativo en la función objetivo, mientras que la sobreestimación no. La flexibilidad para ajustar las decisiones de contratación no supone una diferencia significativa si se sobrestiman los rendimientos. Un menor nivel de pérdidas de las uvas de mejor calidad, al corresponder a una proporción significativa de los ingresos, explican la mayor parte de la pérdida de ingresos. Y por último, las uvas que tienen una mejora temprana de su calidad le dan al tomador de decisiones un nivel adicional de flexibilidad para ajustar el plan de cosecha. Como este tipo de uva alcanza su calidad óptima antes y permanece en

esa condición por más períodos, el planificador puede comenzar su vendimia si es necesario.

# 1. INTRODUCTION

## 1.1. Agriculture

Highly uncertain environments (HUEs), such as agriculture, forestry, mining, or any natural-resource-based productive system, must deal with several biological, environmental, and market factors that are inherently uncertain and add variability into the productive process. These uncertainties derive first from the fact that the environmental, climatic, and soil conditions that prevail at production directly affect a natural-resource-based production system. In these HUEs, the decision-maker must ponder all information and sources of uncertainty (biological, environmental, and market) in the decision-making (DM) process, before taking a course of action that will affect the economic future of the system.

Weather factors, such as rain and temperature, are also an important source of uncertainty in agriculture productive systems. As Ahumada  Villalobos, 2009 point out in their review, what differentiates agricultural supply chains from other supply chains is the importance of such factors as food quality and safety, as well as weather-related variability. Moreover, weather conditions directly affect harvesting operations. Scarcity, concern for the environmental effects of production, and the need for efficient production processes are other common problems that HUEs share. These usually differ in the nature of the resources and their handling, the options for time horizons, the planning and operational processes, and the environmental impacts.

## 1.2. Uncertainty

In the real world, many forms of uncertainty may affect production. According to Ho, 1989, categorizing uncertainties can produce two groups: environmental uncertainty and system uncertainty. Environmental uncertainty includes uncertainties beyond the production process, such as demand uncertainty and supply uncertainty. System uncertainty relates to uncertainty within the production process, such as operation yields and production lead times. As both types of uncertainty degrade the performance of the wine supply chain, researchers work to find ways to diminish their effects.

Bohle et al., 2010 address system uncertainty at the grape production stage, proposing a mixed-integer linear programming (MILP) model that handles harvesting productivity uncertainty by using the robust optimization approach of Bertsimas  Sim, 2004. Varas Valdés et al., 2016 address environmental uncertainty at the packaging stage by developing an MILP model that handles demand uncertainty through a rolling-horizon framework. Cheng  Tang, 2018 develop a robust optimization approach for handling demand uncertainty in multistage production systems. Dolgui et al., 2018 analyze a type of uncertainty called ”ripple effect.”

## 1.3. Operation Planning in Agriculture

Operations planning is an important step in any activity; it aligns resources to achieve the optimal economic value of production. This is particularly critical in agriculture operations, where uncertainty is always present. In fact, agricultural planners must deal with a number of inherently uncertain factors, such as biological, environmental, and market factors, which can generate significant variability and add complexity to the production planning process. They must ponder these different sources of uncertainty and the scarce available information in the production planning process, to make decisions that will determine the economic future of their production.

Looking into production planning amid uncertainty in agricultural systems receives increasing attention from researchers and practitioners in recent years (Borodin et al., 2016). Such studies use different approaches, including stochastic optimization, chance constraint, and robust or dynamic optimization. Moghaddam DePuy, 2011 use a stochastic optimization model with chance-constrained optimization to determine the optimal number of acres of hay a farm should harvest for its own horses' consumption, as well as how much hay to purchase and sell to maximize the farm's total profit.

Borodin et al., 2014 present a stochastic optimization model for an annual harvest scheduling problem with a farmers' entire cereal crop production at optimum maturity, using the meteorological conditions as the deciding factor that affects the harvest scheduling and progress. Kennedy, 1988 has published a complete book, in which he looks at applying dynamic and stochastic dynamic programming to agriculture and natural resources. Finally, a more recent work by Dowson et al., 2019 presents a stochastic optimization model for a dairy farm.

Other applications in HUEs include those in the work of Kazemi Zanjani et al., 2010, who look at a sawmill production planning problem with uncertainty in the quality of raw materials and demand; Ahumada et al., 2012, who develop a two-stage stochastic program to plan the production and distribution of fresh agricultural products amid uncertainty; Lobos Vera, 2016, who determine the benefits of using a stochastic modeling approach in a sawmill production environment; Veliz et al., 2015, who present a harvesting and road-construction decisions problem in the forestry sector in the presence of uncertainty, modeled as a multistage problem; and X. Chen et al., 2018 pursuing the problem of a seed-producing company.

### 1.4. Scenario Generation

In many of these cases, we do not have complete information about the distribution of future events, and we can only rely on historical data to infer such distributions. Determining how we use and process the historical information to generate the future scenarios is relevant, and different approaches include forecasting methods, clustering methods, and heuristics. Dowson et al., 2020 present a framework where a policy graph provides a natural means for deconstructing the multistage stochastic program into a collection of subproblems, with arcs that link them representing the flow of information through time. This allows naturally accounting for the information update as the states of nature reveal themselves. It also allows solving a partially observable problem with continuous state and control variables, using a stochastic dual dynamic programming (SDDP) approach.

Another way of considering uncertainty is using a multistage stochastic model (MSSP) (Birge & Louveaux, 2011; Pflug & Pichler, 2016) which involves making the decision for each node of a tree of events by considering its history as well as possible futures. The MSSP approach is more complex to obtain computationally, but it prescribes a tree of decisions, according to the evolution of the uncertainty over time. Just a few very recent examples of applications of stochastic optimization characterize agriculture. Dowson et al., 2019 formulate a stochastic optimization model of a dairy farm, Flores Villalobos, 2020 develop a framework to plan planting and harvesting schedules, and Nadal-Roig et al., 2020 develop a two-stage stochastic model for zone delineation and crop planning under uncertainty. Ahumada et al., 2012 develop a two-stage stochastic model, in which the first-stage decisions are planting constraints and costs associated with the planting decisions, such as labor cost and availability.

Several techniques using a MSSP approach can benchmark generated value. K. Huang Ahmed, 2009 propose a simple way of measuring the input of the decision process as the difference between the values of the objective functions. They present the case for capacity planning, comparing the values that a multistage stochastic model with a two-stage model produce. Escudero et al., 2007 propose comparing the expected result of using the deterministic mode (EEV) solution; the wait-and-see solution value (WS) corresponding to the expected value of using the optimal solution for each scenario; and, finally, the here-and-now solution corresponding to the optimal solution value in the recursion problem (RP), or MSSO. Thus, we can determine the EVPI = WS – RP, denoting the expected value of perfect information and comparing here-and-now and wait-and-see, and VSS = RP  EEV, denoting the value of the stochastic solution and comparing the here-and-now and expected-values approaches.

Ahumada  Villalobos, 2009 conclude that planning models in agriculture very often fail to incorporate realistic stochastic issues in the agriculture. They go further and indicate that perhaps the reason for this lack of more realistic scenarios is the added complexity of finding solutions for the resulting models. Despite their expressive ability in modeling various real-life problems, multistage stochastic models are notoriously difficult to solve and, thus, not widely used in practice.

### 1.5. Forecast Errors

The literature includes studies of the impact that forecast errors have on the overall quality of the plan and the value of the objective function, which analyze optimal learning levels. He  Powell, 2018 analyzes the value of information by maximizing an objective function, represented by a nonlinear parametric belief model, while simultaneously learning the unknown parameters by guiding a sequential experimentation process, which is expensive. Y. Huang et al., 2019 determines that an accurate evaluation of the expected operational cost associated with an allocation decision can be very expensive. They propose a learning policy that adaptively selects the fleet allocation to learn the underlying expected operational cost function by incorporating the value of information. Related to production planning, Altendorfer et al., 2016 study the effect of long-term forecast error on the optimal planned utilization factor for a production system facing stochastic demand. The researcher can transmit forecast errors to the farmer by recommendations (Kolajo et al., 1988). Thus, the choice of model and the assumptions incorporated in it may constitute a source of errors. In a warehouse environment study, Sanders Graman, 2009 find that forecast biases have a considerably greater impact on organizational cost than forecast standard deviation.

Using historical data for the generation of future scenarios is not new in the agricultural sector. C.-C. Chen et al., 2004 study how climate change influences on the distribution of future crop yields, specifically analyzing the effect that the variance has on production. Murynin et al., 2013 uses image sequences over 10 years to build and compare four yield-prediction models, developed through gradual addition of complexity. The initial model is based on linear regression using vegetation indices; the final model is non-linear.

As noted, to reduce the effect that variability has on production planning, managers seek information and forecasting methods that can reduce the uncertainty of future events. However, these models can generate errors that must be handled as the state of nature reveals itself. Thus, another way to handle uncertainty is through the possibility or flexibility of reassigning after the uncertainty reveals itself, creating a performance advantage (Avanzini et al., 2021).

### 1.6. Flexibility

Flexibility relates to the ability to reallocate or redistribute resources most effectively, after any uncertainty has appeared (X. Chen et al., 2018). Its nature links to uncertainty management because it makes possible adjusting resources, depending on the state of the system. However, resources are not the only way of implementing flexibility; the decision process could also offer flexibility, i.e., the number of stages or instants of decision-making, or anticipating or postponing decisions (Mandelbaum & Buzacott, 1990). Flexibility is not only a desirable characteristic; it is quickly becoming a requirement for the survival of production-oriented companies (Shi & Daniels, 2003; Patel, 2011; Arafa & El-Maraghy, 2012; Patel et al., 2012; Barad, 2013; Chryssolouris et al., 2013). It has appeared in various disciplines as a strategy for managing different types of uncertainty Esmaeilikia et al., 2016. The many definitions of flexibility vary from one discipline or context to another. In the case of manufacturing, flexibility refers to the ability of a manufacturing system to react by shifting between various states of the system with little penalty in time, cost, and performance (Swafford et al., 2006).

In multistage stochastic optimization models, the sources of flexibility and its value has not received much attention, especially in the agricultural context. Soto-Silva et al., 2016 indicates that flexible decision support and models play an important role in helping managers through the entire food supply chain, which is in continuous change because of various uncertainties. Borodin et al., 2016 goes further, indicating that to overcome the new challenges facing the agricultural sector, crop production supply chains should be very reactive and flexible, with a high yield at low cost. Lobos Vera, 2016 study the benefits of using a stochastic modeling approach versus a rolling horizon for the case of a sawmill operation.

Measuring flexibility is not simple; many authors focus their attention on measuring the effect that each or several dimensions of flexibility have on the organization's performance, such as volume, variety, process, and material handling. A body of research relates to the empirical measurement of flexibility, which includes research on developing an instrument for measuring and analyzing flexibility (Gupta & Somers, 1996; Koste et al., 2004).

Even so, there is still not enough significant research on quantitative or analytical measures of flexibility, especially in the agricultural sector. One important point in analyzing the convenience of models is the value that they report to the decision-maker. K. Huang Ahmed, 2009 propose a very simple way of comparing decision processes, namely, the difference between the values of the objective functions. They present the case for a capacity-planning problem, comparing the values that a multistage stochastic optimization model with a two-stage model produce. Buzacott Mandelbaum, 2008 indicates that if we want to measure the value of added versatility in the system, we can do it by determining the expected value with and without the possibility of altering decisions, then take the difference to determine the value of the added flexibility.

## 1.7. Quality

Quality plays an important role in the agricultural supply chain. Since the product is biological in nature, the prevailing environmental conditions (e.g., rain, drought, excessive temperature) affect its quality, and it also evolves from the moment of harvesting (Van Der Vorst et al., 2009). The literature continuously tries effort to model and capture the quality degradation of agricultural products. Rong et al., 2011 model the quality degradation of products by time and temperature as they pass through the supply chain in different facilities and transportation modes. Ahumada et al., 2012 model the harvesting, packing, and distribution of crops with the objective of maximizing revenues. The model accounts for labor availability, price dynamics, and the variable effects in product quality of the weather and plant biology through different functions and approximations.

## 1.8. Wine Production Planning

The Chilean wine industry has developed greatly in the last few decades. It currently exports over 1,500 million US dollars annually and plays an important role in the Chilean economy (Mora, 2019). Although the Chilean wine industry only contributes about 0.5% of the Chilean gross domestic product, it represents about 5.7% of the total non-copper exports. It has a significant role in positioning Chile as a brand around the world (Egan

& Bell, 2002). In fact, in the last decades, Chilean wineries have turned from local-consumption-focused companies to export-focused companies, entering more extensive and competitive markets (Overton & Murray, 2011). Thus, local wineries must improve their efficiency and productivity along the whole wine supply chain to remain competitive in the global market. Between 1997 and 2013, the annual output of Chilean wines increased from 4.3 to 12.8 million hectoliters, and the market share of Chilean wine shows continuing growth (Figure 1.1).

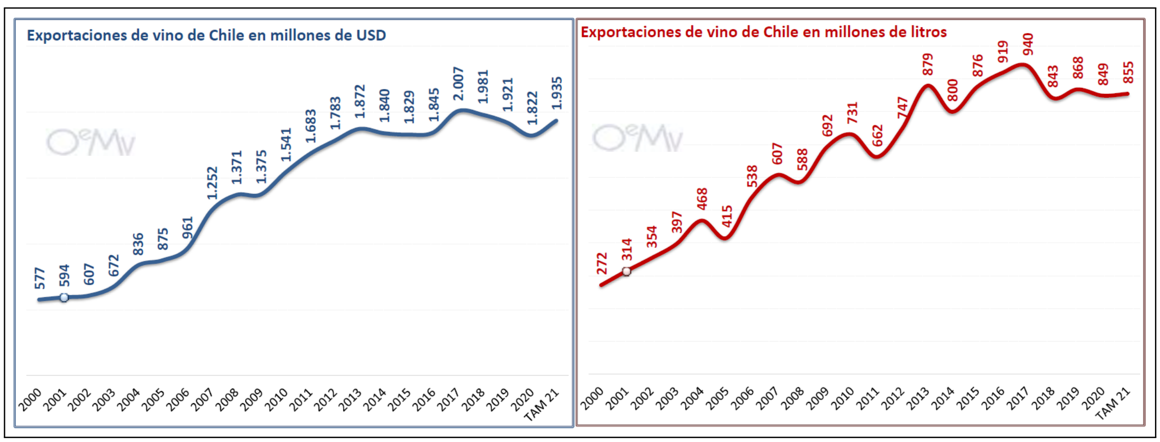


FIGURE 1.1. Chilean wine annual exports in USD and million liters. Source: Observatorio Español del Mercado del Vino, 2021

Supporting wine production operations in an increasingly global market has grown ever more challenging. Forecasts tend not to be accurate enough, and wineries must be able to quickly react to changes. Many studies have explored how to make wine supply chains lean and otherwise improve operations through operations research models (Moccia, 2013). In the case of wine-grape production planning, Ferrer et al., 2008 present a mixed-integer linear programming (MILP) model to support harvest scheduling, labor allocation, and routing decisions. They incorporate a loss function to represent quality reductions due to premature or delaying harvests. At the wine-manufacturing stage, Cakici et al., 2006 present a MILP model that analyses the cellar tank piping network at E. J. Gallo Winery, to minimize wine damage while optimizing the resources used.

A more recent work by Avanzini et al., 2021 presents a MSSOM model to plan the harvest operations of wine grapes where uncertainty in weather conditions can affect the quality of grapes. They consider decisions on labor allocation and harvesting schedules, bearing in mind the uncertainty of future rain. They model weather uncertainty following a Markov Chain approach, in which rain affects the quality of grapes and labor productivity. Climatic factors deteriorate grape quality over time and if they are not harvested during the optimal ripeness period. Finally, they also consider the effect on labor flexibility as the differences in ability between workers, which impact how they will cope with the effects of rain.

Ferrer et al., 2008 show how planning decisions can affect grape quality. For example, in the case of harvesting, the grapes can have an optimal harvest date, and any deviation from that date implies a reduction in the quality or value. Bohle et al., 2010 uses a robust optimization approach to the wine-grape harvest scheduling optimization problem, subject to several uncertainties. Other great contributions in wine-grape planning are the works by Jones et al., 2005; Van Leeuwen  Darriet, 2016; Lorenzo et al., 2013, which study the impacts of weather factors and climate change in viticulture: intensity and length of the grape, and wine quality. Finally, the work by Varas et al., 2018 looks at the problem of a wine-export-focused company facing its bottling planning problem of demand uncertainty.

### 1.9. Lack of Research in Wine-Grape Production Planning

As mentioned, Ferrer et al., 2008 present a grape-harvesting optimization model that accounts for the quality degradation if the grapes are not harvested on their optimal date. However, they do not account for variability in the grape growth nor stock uncertainty. A more recent work by Arnaout  Maatouk, 2010 presents a multifarm, multiperiod model that considers demand, maturation, harvest, and yield risk, and solves an expected value problem. They find that considering the uncertainties performs better than not doing so. However, in this case the authors do not account for the possibility of the planner revising its decisions as the state of nature reveals itself.

In addition to this, no one has analyzed the relation between the quality of the scenario generation and the flexibility of the system, and how that relation affects the value of using an MSSO approach. Powell, 2019 points out in his research challenges that almost no attention goes to analyzing the quality of a stochastic look-ahead model. Going further, he indicates the need for more research, to understand the impact of the different types of errors that the approximations introduce.

### 1.10. This Work's Contributions

We consider the planning of harvesting operations for grapes destined for wine production, where uncertainty results from different rates of grape yields and their transition probabilities, affecting the future grape stocks and revenue. In this setting, the decision-maker must decide the number of workers to hire, their allocation and harvesting schedule, to account for an uncertain future grape stock. We consider here a quantitative analysis of forecast accuracy's impacts on the economic value of production planning, depending also on the grape's quality behavior and the level of flexibility to fix decisions, based on a multistage stochastic optimization model.

Our model also considers the improvement and deterioration of grape quality over time; if it is not harvested in the optimal ripeness period, the grape losses economic value (Ferrer et al., 2008). We present a multistage stochastic optimization model that accounts for the variability in the grape yields over time, future stock beliefs, the grape quality behavior, and the decision-maker's level of flexibility to adjust the plan decision after uncertainty reveals itself. We extend the previous model by Ferrer et al., 2008 adding uncertainty into it by considering two main sources: variability in the possible grape's yields and allocating to them transition probabilities between periods but setting the grapes qualities values known over time.

The contribution of this work is threefold: first, to model the effect that errors in the planners' beliefs have on the quality of the harvesting plan; second, to identify conditions under which these mistakes strongly impact the plan; and, finally, how resource flexibility affects it. To achieve this contribution, we compare the results of different schedules depending on the accuracy of the future belief and the level of flexibility to fix decisions after uncertainty appears, using our MSSP model, and determine a quantitative value for flexibility and accuracy's impact on the economic value of production planning. Thus, this research makes additional contributions. First, we present an MSSP approach for the case of grape harvesting, where the grape's possible yields and transition probabilities between them are the uncertainty. Second, we compare the value of the MSSP approach with perfect information, with the differing values according to the belief accuracy and the level of flexibility to fix decisions.

These comparisons occur separately, for two types of grape quality behavior over time: having grapes with different ripening rates until optimal quality and having grape blocks with different maximum reachable quality. We also determine how much the flexibility to update information and fix decisions in the harvest planning generates value. Also, we will analyze how the quality characteristics of the grape affects the production value under these scenarios.

### 1.11. Objectives and Main Hypothesis of this Thesis

The main objective of this work is to develop a multistage stochastic model, for the problem of hiring labor for the wine grape harvest, that considers uncertainty in the grape yields, their variability between periods, and grape quality improvement and deterioration. Then, we use the model to analyze the impacts on the harvest planning value and production utilities of grape yields and transition probabilities beliefs that differ from reality, for different levels of flexibility to adjust decisions. Finally, from the analysis of the results, we obtain conclusions that add value such as identifying what type of errors are the most expensive and where they are generated, and the type of grapes with which it it is advisable to work. Among the specific objectives are: 1) To develop a consistent and representative multistage stochastic model of the reality of grape harvest planning that encompasses uncertainty in grape growth; 2) To implement a method to compare the effects of the decisions the model makes, according to the estimated values, with those based on the real values.

The main hypothesis of this work is that through the development of a multistage stochastic model that considers uncertainty in the grape growth rate and its variability over the time horizon, it is possible to determine the effects of belief errors on the wine grape harvesting planning value.

### 1.12. Thesis Outline

The document is organized as follows. In Section 2.2, we present a literature review on how uncertainty has been incorporated in production planning and how quality has been explored. In Section 2.3, we present the original optimization model, then its modifications to add uncertainty and the two grape's quality behaviors considered in the analysis. Then, in Section 2.4, we explain how this work determines the belief errors. In Section 2.5, we present the analysis methodology to obtain our main results. Finally, Section 2.6 shows the main results, for discussion and conclusion in Section 2.7.

# 2. ANALYZING THE IMPACT OF BELIEFS ERRORS IN THE PLANNING OF WINE GRAPE HARVESTING OPERATIONS USING A MULTI-STAGE STOCHASTIC MODEL APPROACH

## 2.1. Introduction

Operations planning is an important step in any activity; it aligns resources to achieve the optimal economic value of production. This is particularly critical in agriculture operations, where uncertainty is always present. In fact, agricultural planners must deal with several uncertain factors, such as biological and environmental, which can generate significant variability and add complexity to the production planning process.

To reduce the effect that variability has on the production planning, managers seek information and forecasting methods that aim to reduce the uncertainty of future events. However, these models generate errors that must be handled as the state of nature appears. Another way to handle uncertainty is the possibility or flexibility to reassign after the uncertainty reveals itself, creating a performance advantage (Avanzini et al., 2021). Flexibility relates to the ability to reallocate or redistribute resources most effectively, after any uncertainty has materialized (X. Chen et al., 2018). However, resources are not the only way of implementing flexibility; the decision process also could offer flexibility, i.e. the number of stages or instants of decision-making or by anticipating or postponing decisions (Mandelbaum & Buzacott, 1990). Flexibility is not only a desirable characteristic; it is quickly becoming a requirement for survival of production-oriented companies (Shi

& Daniels, 2003; Patel, 2011; Arafa & ElMaraghy, 2012; Patel et al., 2012; Barad, 2013; Chryssolouris et al., 2013)

Ferrer et al., 2008 and Arnaout  Maatouk, 2010 present a grape-harvesting optimization model that accounts for the quality degradation if the grapes are not harvested on their optimal date. They do not account for variability in the grape growth nor stock uncertainty. More recently, Avanzini et al., 2021 present a multifarm, multiperiod model that considers demand, maturation, harvest, and yield risk, and solves an expected value problem. They find that considering the uncertainties produces more value than not doing it. However, in this case, the authors did not account for the possibility of the planner revising its decisions as the state of nature reveals itself. Another way of considering the uncertainty is using a multistage stochastic model (MSSP) (Birge & Louveaux, 2011; Pflug & Pichler, 2016) where the decision for each node of a tree of events considers its history as well as its possible futures. The MSSP approach is more complex to obtain computationally, but it prescribes a tree of decisions according to the evolution of the uncertainty over time. The work by Ahumada et al., 2012 develops a two-stage stochastic model, in which the decisions in the first stage are planting constraints and the costs associated with the planting decisions, such as labor cost and availability.

In this research, we consider the planning of harvesting operations for grapes destined for wine production, where uncertainty accompanies different grape yields and their transition probabilities, affecting the future grape stock and revenue. In this setting, the decision-maker must decide the number of workers to hire, their allocation and harvesting schedule, accounting for an uncertain future grape stock. We study the effect that forecast accuracy or decision-maker beliefs have on the economic value of production planning, depending on the grape's quality behavior and the level of flexibility to fix decisions in place, using a multistage stochastic optimization model. We model the uncertainty by considering two main sources: different possible grape yields and the allocation of transition probabilities between them over certain periods. The model will also consider the grapes' quality over time, so if it is not harvested in the optimal ripeness period, the grape loses economic value (Ferrer et al., 2008). We present a multistage stochastic optimization model that accounts for the variability in the grape yields over time, future stock beliefs, the grape quality behavior, and the decision-maker's level of flexibility to adjust the decision plan after uncertainty reveals itself.

The contribution of this work is threefold: first, to model the effect that errors in the planners' beliefs have on the quality of the harvesting plan; second, to identify conditions under which these mistakes strongly impact the plan; third, how resource flexibility affects it. We compare the results of different schedules depending on the accuracy of the future belief and the level of flexibility to fix decisions after uncertainty appears, using our MSSP model, and determine a quantitative value for flexibility and accuracy and their impact on the economic value of production planning. Finally, we analyze how the quality characteristics of the grape affects the production value under these scenarios.

The document proceeds as follows. In Section 2, we present a literature review on the incorporation of uncertainty in production planning and exploration of the quality.

In Section 3, we present the original optimization model, then its modifications to add uncertainty and the two grape's quality behaviors the analysis considers. Then, in Section 4, we explain how this work determines the belief errors. In Section 5, we present the analytical methodology for obtaining our main results. Finally, Section 6 shows the main results, discussed and concluded in Section 7.

### 2.2. Literature Review

Production planning involving uncertainty in agricultural systems is getting increasing attention from researchers and practitioners (Borodin et al., 2016). Previous studies use different approaches, including stochastic optimization, chance constraint, robust or dynamic optimization. Bohle et al., 2010 uses a robust optimization approach to the scheduling optimization problem, subject to uncertainties that accompany wine-grape harvesting. Moghaddam  DePuy, 2011 uses a stochastic optimization model with chance constrained optimization to determine the optimal number of acres of hay a farm should harvest for their own horses' consumption, as well as how much hay to purchase and sell to maximize the total profit of the farm. Borodin et al., 2014 presents a stochastic optimization model for the annual harvest scheduling problem of the farmers' entire cereal crop production at optimum maturity, using the meteorological conditions as the deciding factor that affects the harvest scheduling and progress. Kennedy, 1988 looks at the applications of dynamic and stochastic dynamic programming to agriculture and natural resources. Finally, a more recent work by Dowson et al., 2019 presents a stochastic optimization model for a dairy farm. However the agricultural sector still does not offer many applications of MSSOM.

In wine production planning, a more recent work by Avanzini et al., 2021 presents a MSSOM model to plan the harvest operations of wine grapes where uncertainty in weather conditions can affect their quality. They consider decisions on labor allocation and harvesting schedules, bearing in mind the uncertainty of future rain. Modeling weather uncertainty follows a Markov Chain approach, in which rain affects the quality of grapes and labor productivity. Climatic factors deteriorate grape quality over if they are not harvested in the optimal ripeness period. Finally, they also consider the effect on labor flexibility—i.e., differences in ability between workers—which impact how they will cope with the effects of rain. Ahumada Villalobos, 2009 conclude that planning models in agriculture very often fail to incorporate realistic stochastic issues in agriculture. They also indicate that perhaps the reason for this lack of more realistic scenarios is the added complexity of finding solutions for the resulting models. Despite their expressive ability in modeling various real-life problems, multistage stochastic modeling is somewhat impractical and rarely used, due to the well-known difficulty of solving them. Only a few very recent examples illustrate applications of stochastic optimization in agriculture. Dowson et al., 2019 formulate a stochastic optimization model of a dairy farm, Flores Villalobos, 2020 develop a framework to plan planting and harvesting, and Avanzini et al., 2021 plan wine-grape harvesting.

An important aspect of building a multistage stochastic model is developing an approximate representation of the underlying uncertainty. A common representation can take the form of a scenario tree (Heitsch & Römisch, 2009). The process of obtaining such reduced scenarios may vary, but generally it uses variance reduction techniques (Higle, 1998; Shapiro, 2003). Löhndorf, 2016 summarizes the state of the art of scenario generation of multivariate random variables for sample average approximation in quasi-Monte Carlo methods, based on probability metrics, and moment matching. Still, these techniques build on the premise that we know the underlying distribution of the events, so the objective is to define a reduced representation to make the problem tractable.

In many cases, we do not have complete information about the distribution of future events and can only rely on historical data to infer it. In these cases, determining how we use and process the historical information to generate the future scenarios is relevant. Different approaches exist, including forecasting methods, clustering methods, and heuristics. Dowson et al., 2020 present a framework where a policy graph provides a natural means for subdividing the multistage stochastic program into a set of subproblems, with arcs linking them to represent the flow of information through time. This enables naturally accounting for updating information as the states of nature reveal themselves. It also enables solving a partially observable problem with continuous state and control variables, using a stochastic dual dynamic programming (SDDP) approach.

Using historical data for the generation of future scenarios is not new in the agricultural sector. C.-C. Chen et al., 2004 study the influence of climate change on the distribution of future crop yields. Specifically, they analyze the effect of the variance on production. Murynin et al., 2013 use image sequences over 10 years to build and compare four yield-prediction models developed by gradual addition of complexity. The initial model is based on linear regression using vegetation indices; the final model is non-linear.

The literature includes studies of the impact that forecast errors have on the overall quality of the plan and value of the objective function, through analyses of the optimal learning levels. He Powell, 2018 analyze the value of information by maximizing an objective function that a nonlinear parametric belief model represents, while simultaneously learning the unknown parameters by guiding an (expensive) sequential experimentation process. Similarly, Y. Huang et al., 2019 determine that an accurate evaluation of the expected operational cost of an allocation decision can be very expensive. They propose a learning policy that adaptively selects the fleet allocation, to learn the underlying expected operational cost function by incorporating the value of information. Regarding production planning, Altendorfer et al., 2016 study the effect of long-term-forecast errors on the optimal planned utilization factor, for a production system facing stochastic demand. The researcher can transmit forecast errors to the farmer through recommendations (Kolajo et al., 1988). Thus, the choice of model and the assumptions it includes may constitute a source of errors. In a warehouse environment study, Sanders Graman, 2009 find that forecast biases impact organizational cost considerably more than forecast standard deviation.

Several techniques can benchmark the value that using an MSSO approach generates. K. Huang  Ahmed, 2009 propose a simple way of measuring the input of the decision process, namely, obtaining the difference between the values of the objective functions. Their work presents the case for capacity planning, comparing the values a multistage stochastic model produces with those from a two-stage model. Escudero et al., 2007 propose comparing the expected result of using the solution of the deterministic mode (EEV); the wait-and-see solution value (WS) that corresponds to the expected value of using the optimal solution for each scenario; and the here-and-now solution corresponding to the optimal solution value to the recursion problem (RP) or MSSO. These results enable determining the EVPI = WS – RP, denoting the expected value of perfect information and comparing here-and-now and wait-and-see; and VSS = RP – EEV, denoting the value of the stochastic solution and comparing the here-and-now and expected-values approaches.

None of these techniques analyze the relation between the quality of scenario generation and the flexibility of the system, and how that relation affects the value of using an MSSO approach. Powell, 2019 points out that hardly any attention goes to analyzing the quality of a stochastic look-ahead model and indicates a need for more research, to understand the impact of different types of errors that the approximations introduce.

### 2.3. Problem Formulation

In this section, we present first a stylized version of the Ferrer et al., 2008 deterministic model. Second, we discuss how we add uncertainty to the model, in the form of grape-yield variability and its behavior over time. Then, we present the reformulated model as a multistage stochastic model that considers uncertainty. Finally we present the analytical method, to estimate the forecast accuracy's impact on the economic value of harvest planning.

### 2.3.1. Deterministic Grape-Harvesting Problem

We propose a wine-grape harvesting model based on the work by Ferrer et al., 2008. There, the authors present a deterministic optimization model that minimizes the labor and machine cost as well as the quality degradation of the grapes. They introduce a quality loss function that generates extra costs when harvesting deviates from the ideal date. The model determines the amount of labor and number of machines, their assignment to each lot and day, and the kilograms of grape to be harvested and sent to the cellar.

For our model, we assume that a farmer owns $J$ blocks that contain wine grapes, with an initial stock $s_{j,0}$, expressed in $kilograms$. The goal of the farmer or farm manager is to maximize the final profit of the wine grapes. To do that, the farmer faces a decision window of $T$ periods, and in each period, he/she must decide regarding the amount of work entered and dismissed, $x_t$ and $y_t$, respectively, and the quantity of labor to allocate $z_{j,t}$, implying a capacity of harvesting in that period and in that block. The net labor available in period $t$ is denoted by $m_t$, and $\beta$ is the productivity of the resource ($kilograms/period$). Grapes harvested go to a winery during the same period, where $K$ is the single-period reception capacity of the winery.

The costs mainly relate to the labor force and include costs of hiring $C_e$, termination $C_f$, and keeping labor between periods $C_k$. Additionally, the harvesting cost $C_h$ ($\$/kilograms$) is a productivity payment.

Selling the harvested grapes at a market price, which we denote by $b_j$ for the grapes of block $j$, generates income. However, the final quality of grapes, which depends on the specific harvest time, affects the actual price. We represent this by a quality factor, $q_{j,t}$, equal to 1 when $t$ is the optimal period for harvesting (which depends on grape ripeness) and decreases when $t$ differs from that optimal period. This is a similar representation to the one that Ferrer et al., 2008 use; later, we explain the specifics of this coefficient. Thus, the total net income at any time is $\sum_{j \in J} b_j q_{j,t} h_{j,t}$, where $h_{j,t}$ is the harvested amount from block $j$ in period $t$.

The basic deterministic model is the following:

$$\min \quad \sum_{j=1}^{J}\left\{\sum_{t=1}^{T}\{(C_h - b_j q_{j,t})h_{j,t} + C_e x_t + C_f y_t + C_k m_t\}\right\}$$

$s.t.$

$$
\begin{array}{lll}
m_t = m_{t-1} + x_t - y_t & t = 1, ..., T & (d1) \\
\sum_{j=1}^{J} z_{j,t} \leq m_t & t = 1, ..., T & (d2) \\
\sum_{j=1}^{J} h_{j,t} \leq \beta m_t & t = 1, ..., T & (d3) \\
h_{j,t} = \beta z_{j,t} & t = 1, ..., T & (d4) \\
\sum_{j=1}^{J} h_{j,t} \leq K & t = 1, ..., T & (d5) \\
h_{j,t} \leq S_{j,0} - \sum_{l=1}^{t-1} h_{j,l} & t = 1, ..., T, j = 1, ..., J & (d6) \\
h_{j,t} \geq 0 & t = 1, ..., T, j = 1, ..., J & (d7) \\
x_t, y_t, m_t, z_t \geq 0, \in \mathbb{Z}_+ & t = 1, ..., T & (d8)
\end{array}
$$

The objective function computes net income (with negative sign to be solved as a minimization problem). Expression (d1) is the manpower balance, while relation (d2) limits the number of allocated resources. Relation (d3) bounds the total harvest in terms of labor capability, and relation (d4) indicates that every assigned worker produces in accordance with his/her productivity level. Relation (d5) bounds the total harvest in terms of single-period reception capacity, as we assume that all grapes harvested in a given period must be processed during the period. On the other hand, relation (d6) establishes that the remaining volume available in the block bounds the harvest. Finally, relations (d7) and (d8) establish the nature of the variables.

### 2.3.2. Uncertainty Sources

#### 2.3.2.1. Grape Yields

The grape yield depends directly on weather, pests, and land conditions during the productive period, and these conditions account for the main sources of uncertainty that add complexity to the harvest planning process. To account for these uncertainties, we model the effect of the aforementioned factors on the grape yield within a single period.

In this light, for each possible stage $\omega$, we model the pre-harvest grape stock or yield, given by $S^{\omega}_{j,t}$ for a certain block $j$ in a certain period $t$. If the harvest performed each period is given by $h^{\omega}_{j,t-1}$, we use a factor $\alpha^{\omega}_{t}$ that can take values in three different scenarios of 1.1, 1.5, or 2 and account for the uncertainty, given by the level of increase in the remaining grape stock. Then, the remaining available grape for harvest is given by:

$$S^{\omega}_{j,t} = \alpha^{\omega}_{t}(S^{\omega}_{j,t-1} - h^{\omega}_{j,t-1})$$

#### 2.3.2.2. Transition Probabilities

Transition probabilities account for the variability of weather conditions over the time horizon and represent the errors in the forecast. These probabilities directly relate to the possible grape-yield changes in each time period, and they finally determine the occurrence of a given growth ratio in the available grape stock.

Previously, we considered three possible grape-yield growth scenarios (1.1, 1.5, or 2). Each scenario has his own associated transition probability, which gives a total of nine possible states and probabilities (Table 2.1). This modeling allows us to generate a scenario tree, in which each node corresponds to a possible future stage of a certain scenario (path) to consider for the harvest decisions planning. Accordingly, the resulting solution corresponds to not only a harvest plan but also a decision policy that allows the decision-maker to adjust the previous decision plan after uncertainty is revealed, when flexibility allows.

TABLE 2.1. Matrix of transition probabilities.

| $\alpha_i$ | $\alpha_1$ | $\alpha_2$ | $\alpha_3$ |
|---|---|---|---|
| $\alpha_1$ | $p_{11}$ | $p_{12}$ | $p_{13}$ |
| $\alpha_2$ | $p_{21}$ | $p_{22}$ | $p_{23}$ |
| $\alpha_3$ | $p_{31}$ | $p_{32}$ | $p_{33}$ |

Based on the table above, we estimate the probability $p_t^\omega$ of a specific stage $\omega$ in a certain period $t$, by calculating the pitatory of the transition probabilities that shape the path from the initial node to the respective one. In Graph 2.1, we can observe the corresponding representation.

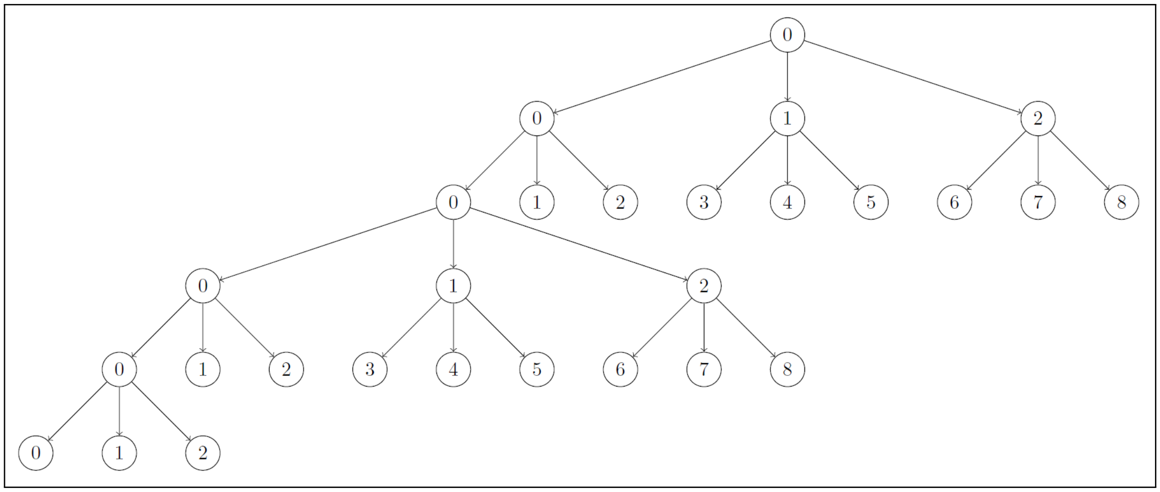


FIGURE 2.1. Grape yield scenario tree

The occurrence probability $p_t^\omega$ of a certain stage $\omega$ (node) is calculated as the pitatory of the transition probabilities associated with its path from the initial stage. Defining $\mathbb{S}$ as the set of arcs $\{ij\}$ that describe the path to node n, we have:

$$p_t^\omega = \prod_{\{ij\} \in \mathbb{S}} p_{ij}$$

### 2.3.3. Grape quality parameters

We have divided grape quality into two aspects. The first is the maximum reachable quality that acknowledges the existence of different grape types (premium, reserve, and varietal). The second quality aspect relates to the rate at which the grapes ripen or attain maximum quality level. Higher quality grapes tend to have faster ripening rates than those of lower quality.

Ferrer et al., 2008 were the first to propose a maximum reachable quality level. For our case, we model this as a weight to the grape price, whose value varies between zero and one. The closer to one it is, the better is the grape quality. We use three different types of grapes—premium, reserve, and varietal—which can reach a maximum price or quality of 100%, 60%, or 30%, respectively. Graph 2.2 shows a representation of these three types of grapes.

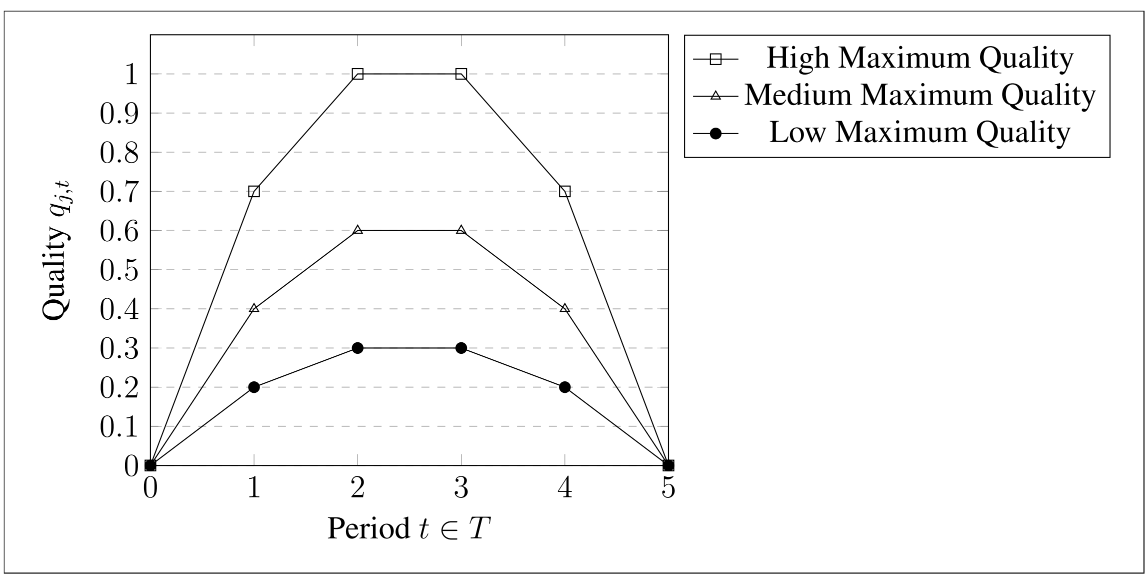


FIGURE 2.2. Grape quality behavior: Different maximum reachable qualities by block

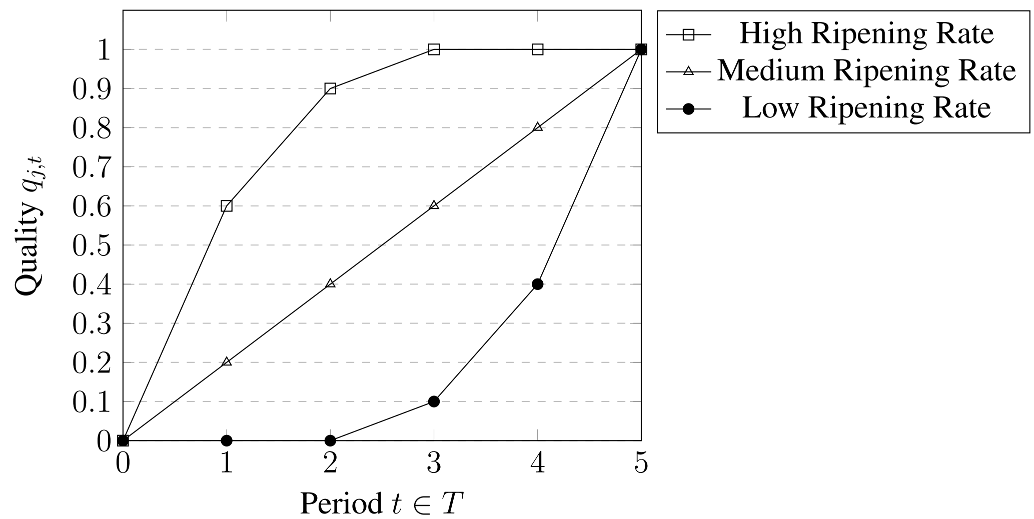


FIGURE 2.3. Grape quality behavior: Different ripening rates by block

To account for the different ripening rates of quality, we considered grape blocks whose qualities all start from zero and finish at one. Hence, there is no difference in the maximum reachable quality. The ripening rates directly affect the moment in which maximum quality is achieved. In the case of a high ripening rate, the maximum quality is achieved in the $3^{rd}$ period; one with a low ripening rate starts its ripening in the $2^{nd}$ period and achieves full quality at the $6^{th}$ period. The medium type has a lineal ripening rate. Graph 2.3 shows a representation of these rates.

### 2.3.4. Multi-Stage Stochastic Optimization Model

We now present a multistage stochastic model that accounts for uncertainty, using the previously presented grape yield and transition probabilities.

- **Sets**

- $T$: set of periods in the time horizon.
- $J$: set of grape blocks of the vineyard.
- $\Omega$: set of future possible stages.

- **Parameters**
  - $b_j$: price of the grape in lot $j \in J$ ($/kilograms).
  - $C_{e,t}$: cost of hiring in period $t \in T$ ($/worker).
  - $C_f$: cost to lay-off a worker ($/worker).
  - $C_k$: cost of keeping idle labor between periods ($/worker per period).
  - $C_h$: harvest cost ($/kilograms).
  - $S_{j,0}$: initial grape stock in block $j$ (kilograms). $j \in J$
  - $q_{j,t}$: grape quality of block $j \in J$, in the period $t \in T$.
  - $q_j^{max}$: maximum reachable grape quality of block $j \in J$.
  - $K$: maximum available reception capacity by the winery (kilograms/period).
  - $\beta$: worker maximum harvest productivity (kilograms/period).
  - $\alpha_t^{\omega}$: grape yield before harvest, at time $t \in T$ in stage $\omega \in \Omega$ (positive real number).
  - $p_t^{\omega}$: probability of occurrence of the stage $\omega \in \Omega$ at time $t \in T$. (positive real number $\in \{0, 1\}$).

- **Variables**
  - $x_t^{\omega}$: number of workers hired at time $t \in T$ in stage $\omega \in \Omega$ (workers).

- $y_t^\omega$: number of workers laid off at time $t \in T$ in stage $\omega \in \Omega$ (workers).
- $m_t^\omega$: available manpower or labor force at time $t \in T$ in stage $\omega \in \Omega$ (workers).
- $h_{j,t}^\omega$: harvested grape quantity at $j \in J$ block in period $t \in T$ in stage $\omega \in \Omega$ (kilograms/period).
- $S_{j,t}^\omega$: available grape stock in block $j \in J$ at period $t \in T$ in stage $\omega \in \Omega$. (kilograms).

- **Objective Function and constraints**

$$\min \sum_{\omega=1}^{\Omega} \left\{ \sum_{t=1}^{T} p_t^\omega \Big( C_{e,t} x_t^\omega + C_f y_t^\omega + C_k m_t^\omega + \sum_{j=1}^{J} (C_h - b_j q_{j,t}) h_{j,t}^\omega \Big) + \sum_{j=1}^{J} p_T^\omega \Big( b_j q_j^{max} (S_{j,T}^\omega - h_{j,T}^\omega) \Big) \right\}$$

$s.t.$

$$m_t^\omega = m_{t-1}^\omega + x_t^\omega - y_t^\omega \qquad \forall t \in T, \forall \omega \in \Omega \qquad (d1)$$

$$m_t^\omega = m_t^\tau, x_t^\omega = x_t^\tau, y_t^\omega = y_t^\tau \qquad \forall t \in T, \forall \omega, \tau : \Omega_{[t]}^\omega = \Omega_{[t]}^\tau \qquad (d2)$$

$$y_T^\omega = m_T^\omega \qquad \forall \omega \in \Omega \qquad (d3)$$

$$\sum_{j=1}^{J} h_{j,t}^\omega \leq \beta m_t^\omega \qquad \forall t \in T, \forall \omega \in \Omega \qquad (d4)$$

$$h_{j,t}^\omega \leq S_{j,t}^\omega \qquad \forall j \in J, \forall t \in T, \forall \omega \in \Omega \qquad (d5)$$

$$\sum_{j=1}^{J} h_{j,t}^\omega \leq K \qquad \forall t \in T, \forall \omega \in \Omega \qquad (d6)$$

$$S_{j,t}^\omega = \alpha_t^\omega (S_{j,t-1}^\omega - h_{j,t-1}^\omega) \qquad \forall j \in J, \forall t \in T, \forall \omega \in \Omega \qquad (d7)$$

$$h_{j,t}^\omega \geq 0 \qquad \forall j \in J, \forall t \in T \qquad (d8)$$

$$x_t^\omega, y_t^\omega, m_t^\omega \geq 0, \in \mathbb{Z}_+ \qquad \forall t \in T, \forall \omega \in \Omega \qquad (d9)$$

The objective function computes the expected net income amid uncertainty. The income is minimized because costs are set as positive and income as negative. The net income is given first by the fixed labor costs, given by the hiring, lay-off and idle; second, the harvest cost minus the quality-adjusted price of the grape times the amount of grapes harvested and, finally, the non-harvested grape left in the vineyard. Expression (d1) is the manpower balance for each possible stage $\omega$, while (d2) corresponds to nonanticipativity constraints. Expession (d3) guarantees firing the remaining harvest labor at the end of the planning. Expression (d4) bounds the total harvest in terms of labor capability and relation, while expression (d5) establishes that the harvest is bounded by the volume available in the block. Relation (d6) bounds the total harvest in terms of single-period reception capacity, as we assume that all grapes harvested in a given period must be processed during the period. Expression (d7) updates the grape stock of the block from the previous period stock and harvested amount values and the yield of the respective stage. Finally, relations (d8) and (d9) establish the nature of the variables.

This allows to build not only a decision-making plan but a harvest decision policy that indicates the best decisions, subject to the actual stage conditions and possible future stages.

### 2.4. Defining belief errors

The main focus of this research is to study the effect of errors in decision-maker beliefs on the decisions and the value of the plan. Specifically, we study the effect of errors in grape-yield forecasts and the transition probabilities beliefs.

To achieve this, we suppose that the decision-maker must make decisions having available just partial information, presented in such forms as historical data, tendencies, forecasts, and sensorization. All of this information then figures in determining the yield forecast. As the decision-maker does not have perfect information, the believed values that he uses to make the harvest plan differ from the real values. We represent this type of error as believed grape-yield values, distinct from the real ones.

In the case of transition probabilities, the same phenomenon occurs when the decision-maker does not have perfect information. The believed probabilities of the scenarios can differ from the real ones. The decision-maker represents these errors using a transition probability matrix that shows differences from the one defined as the real transition probabilities matrix.

These two types of errors are finally represented as an over- or under-estimation of the real available quantities of grapes. We suppose that the decision-maker does not update or recalculate its beliefs as new information is available, since we focus on determining the effect of errors in beliefs and not on an optimal decision-maker learning process. Once the state of nature reveals itself, and considering the level of flexibility, the decision-maker must adjust its original plan to account for these errors.

### 2.5. Benchmarking Methodology

To determine and quantify the consequence that differences or errors in the beliefs have for the value of using an MSSP approach, we study the effect that they have on the production decisions, performance, and economic value. We also analyze the impact that grape quality, grape-ripening rate, and the level of flexibility have on the aforementioned indicators.

To achieve this, we divide the analysis into four separate analyses. The first two focus on the impacts of errors in beliefs in grape yields, and the last two analyze the impacts of errors in beliefs in transition probabilities. Each pair of analyses considers separately two kinds of behaviors of grape quality over time, by analyzing different ripening rates and maximum reachable qualities. Finally, for each analysis, we look at the impact of different flexibility levels.

To quantify the effect that errors in the yields and transition-matrix beliefs have, we must compare the productive plan value generated and actions the decision-maker takes under two scenarios. First, with perfect information and no mistakes, the plan is the "perfect information scenario," ($\mathcal{PI}$) and we compare it to the plan containing mistakes in beliefs, the "believed scenario" ($\mathcal{BS}$). Finally, to determine the effective value of the plan with errors in beliefs, now under the effective yields, we determine the value of the plan with the real yields but, using the decisions in the context of the believed scenario, we define this as the "real scenario" ($\mathcal{RS}$). With these three values, we can determine the effect that errors in the grape yields have on the decisions and value of using an MSSP approach.

To study the effect of flexibility on the decisions and value with errors in the beliefs, we add the possibility of the decision-maker modifying the harvest plan after a certain number of periods as uncertainty reveals itself. The number of periods that pass before changing the schedule is possible aims to represent the level of the decision-maker's flexibility. As fewer periods pass before it can modify its decisions, the level of flexibility rises. As indicated, we suppose that the decision-maker does not update or recalculate its beliefs as new information is available, since we focus on determining the effect of errors in the beliefs and not an optimal learning process for the decision-maker.

To quantify the effect that the errors have and determine where the value is lost or gained, we look into five components of the objective function and use them as evaluation metrics: first, the absolute objective function value for each level of error ($\mathbb{OF}$); second, the relative difference between the objective of the PI scenario and the real scenario ($\mathbb{OFD}$); third, the income deficit of the real scenario compared to the PI scenario ($\mathbb{ID}$) and the percentage reduction in incomes that it represents ($\mathbb{RI}$); fourth, the percentage impact of unharvested grapes ($\mathbb{UG}$) and, fifth, the average quality of harvested grapes on total incomes ($\mathbb{AQ}$). These indicators allow us to determine the effect of errors in beliefs on plan value, decisions, and the quality effect.

Determining each of these factors appears in the following pseudo-code and equations:

**Input:** real values of yields and transition probabilities ($\alpha_1^{PI}, \alpha_2^{PI}, \alpha_3^{PI}, \mathbb{P}^{PI}$);

**Run** the MSSOM;

$\mathcal{D}^{PI} \leftarrow (x_1, ..., x_T, y_1, ..., y_T, h_1, ..., h_T)$ ;

$\mathbb{OF}^{PI} \leftarrow$ objective function value ;

$\mathbb{I}^{PI} \leftarrow$ net incomes ;

**Input:** believed values of yields or transition probabilities (according to the analysis) ;

**Run** the MSSOM;

$\mathcal{D}^{BS} \leftarrow (x_1, ..., x_T, y_1, ..., y_T, h_1, ..., h_T)$ ;

$\mathbb{OF}^{BS} \leftarrow$ objective function value ;

$\mathbb{I}^{BS} \leftarrow$ net incomes ;

**Input:** ($\alpha_1^{PI}, \alpha_2^{PI}, \alpha_3^{PI}, \mathbb{P}^{PI}$), $\mathcal{D}^{BS}$, number of periods passed $f$ before re-optimize the decision plan;

**While** $t <= f$ **do**;

$x_t \leftarrow x_t^{BS}, y_t \leftarrow y_t^{BS}, h_t \leftarrow h_t^{BS}$ ;

**Run** the MSSOM for $t > f$;

$\mathcal{D}^{RS} \leftarrow$

$(x_1^{BS}, ..., x_f^{BS}, x_{f+1}, ..., x_T, y_1^{BS}, ..., y_f^{BS}, y_{f+1}, ..., y_T, h_1^{BS}, ..., h_f^{BS}, h_{f+1}, ..., h_T)$ ;

$\mathbb{OF}^{RS} \leftarrow$ objective function value ;

$\mathbb{I}^{RS} \leftarrow$ net incomes ;

**Calculate:** $\mathbb{OFD}, \mathbb{ID}, \mathbb{RI}, \mathbb{UG}, \mathbb{AQ}$

**Algorithm 1**: Pseudo code for optimization methodology

$$\mathbb{OF} = \sum_{\omega=1}^{\Omega} \Bigg\{ \sum_{t=1}^{T} p_t^\omega \Big( C_{e,t} x_t^\omega + C_f y_t^\omega + C_k m_t^\omega + \sum_{j=1}^{J} (C_h - b_j q_{j,t}) h_{j,t}^\omega \Big) + \sum_{j=1}^{J} p_T^\omega \Big( b_j q_j^{max} (S_{j,T}^\omega - h_{j,T}^\omega) \Big) \Bigg\} \tag{2.1}$$

$$\mathbb{OFD} = \mathbb{OF}^{PI} - \mathbb{OF}^{RS} \tag{2.2}$$

$$\mathbb{I} = \sum_{\omega=1}^{\Omega} \sum_{t=1}^{T} p_t^\omega \Big( \sum_{j=1}^{J} (-b_j q_{j,t}) h_{j,t}^\omega \Big) \tag{2.3}$$

$$\mathbb{ID} = \mathbb{I}^{PI} - \mathbb{I}^{RS} \tag{2.4}$$

$$\mathbb{RI} = \mathbb{ID}/\mathbb{I}^{PI} \tag{2.5}$$

$$\mathbb{H} = \sum_{\omega=1}^{\Omega} \sum_{t=1}^{T} p_t^\omega \sum_{j=1}^{J} h_{j,t}^\omega \tag{2.6}$$

$$\mathbb{UG} = \mathbb{H}^{PI} - \mathbb{H}^{RS} \tag{2.7}$$

$$\mathbb{AQ} = \mathbb{I}^{RS} - \mathbb{I}^{PI} (\mathbb{H}^{RS}/\mathbb{H}^{PI}) \tag{2.8}$$

### 2.6. Model Parameters

We based our model parameters on the previous work by Ferrer et al., 2008 and Avanzini et al., 2021. Table 2.2 presents the vineyard characteristics.

TABLE 2.2. Model base parameters

| Model Parameter | Notation | Value | Units |
|---|---|---|---|
| Grape price | $b_j$ | 215 | \$/kilograms |
| Initial harvest stock | $S_{j,0}$ | 7,000 | kilograms |
| Worker productivity | $\beta$ | 1,600 | kilograms/period |
| Vineyard blocks | $n(J)$ | 6 | blocks |
| Planning time horizon | $n(T)$ | 6 | periods |

#### 2.6.1. Costs

To account for scarcity of labor as the harvesting season advances, we represent it by using an exponential cost function. The cost of hiring labor at each period $t$ is represented by:

$$C_{e,t} = C_e(t) = 100,000 \cdot 1.7^t \quad \forall t \in T \quad (\$/worker)$$

The other labor costs appear in Table 2.3

TABLE 2.3. Model costs parameters

| Model Parameter | Notation | Value | Units |
|---|---|---|---|
| Cost of firing | $C_f$ | 4,000 | \$/worker |
| Cost of keeping labor | $C_k$ | 3,500 | \$/worker |
| Cost of harvesting | $C_h$ | 21 | \$/kilograms |

### 2.6.2. Grape Yields

Since the decision-maker does not have perfect information about the future, the believed grape yields differ from the real values. As indicated, we use a factor $\alpha_t^\omega$ that can take values in three different scenarios of 1.1, 1.5, or 2 and account for the uncertainty in the level of increase in the remaining grape stock.

Using these values of alpha at the end of the planning period, we find that the scenarios of under- or over-estimation of the yields are: $\{3, 2, 1.5, 1.1, 1, 0.9, 0.7, 0.5\}$. This means that if the level of overestimation was 0.5, the decision-maker overestimated the harvest by 50% (expecting a level of 1 and obtaining a level of 0.5). On the other side, if the level is 1.5, the decision-maker underestimated the yields by 50% (expecting a level of 1, obtaining a level of 1.5), and so forth.

### 2.6.3. Transition Probability scenarios

Transition probabilities determine how the grape growth rate will vary over periods, since they determine whether yields will rise or fall in the next period and by which factor ($\alpha_i$). The producer forecasts these probabilities as the grape yields, and they can also differ from what he had believed them to be.

For our base case, we suppose that each growth rate has equal probability of occurrence (Scenario 4) and reflect the producer's current beliefs. From this base scenario, the real transition probabilities can differ, ranging from the pessimist scenario (Scenario 1) where, initially, the probabilities were thought to be equi-probable and, finally, the growth factor is absorbed to a value of 2. At the other extreme, the optimist scenario (scenario 8) was again thought to be equi-probable, but, finally, the growth factor is absorbed to a value of 1.1. Between these extremes is a continuum of scenarios of transition probabilities representing different levels of pessimist scenarios.

Scenario 1 (Optimist)

| $\alpha_i$ | 1.1 | 1.5 | 2 |
|---|---|---|---|
| 1.1 | 1 | 0 | 0 |
| 1.5 | 1 | 0 | 0 |
| 2 | 1 | 0 | 0 |

Scenario 2

| $\alpha_i$ | 1.1 | 1.5 | 2 |
|---|---|---|---|
| 1.1 | 0.5 | 0.5 | 0 |
| 1.5 | 0.5 | 0.5 | 0 |
| 2 | 0.5 | 0.5 | 0 |

Scenario 3

| $\alpha_i$ | 1.1 | 1.5 | 2 |
|---|---|---|---|
| 1.1 | 0.6 | 0.3 | 0.1 |
| 1.5 | 0.4 | 0.3 | 0.3 |
| 2 | 0.5 | 0.3 | 0.2 |

Scenario 4

| $\alpha_i$ | 1.1 | 1.5 | 2 |
|---|---|---|---|
| 1.1 | 0.3 | 0.6 | 0.1 |
| 1.5 | 0.3 | 0.4 | 0.3 |
| 2 | 0.3 | 0.5 | 0.2 |

Scenario 5 Base case

| $\alpha_i$ | 1.1 | 1.5 | 2 |
|---|---|---|---|
| 1.1 | $0.\overline{3}$ | $0.\overline{3}$ | $0.\overline{3}$ |
| 1.5 | $0.\overline{3}$ | $0.\overline{3}$ | $0.\overline{3}$ |
| 2 | $0.\overline{3}$ | $0.\overline{3}$ | $0.\overline{3}$ |

Scenario 6

| $\alpha_i$ | 1.1 | 1.5 | 2 |
|---|---|---|---|
| 1.1 | 0.1 | 0.3 | 0.6 |
| 1.5 | 0.3 | 0.3 | 0.4 |
| 2 | 0.2 | 0.3 | 0.5 |

| Scenario 7 | | | |
| --- | --- | --- | --- |
| $\alpha_i$ | 1.1 | 1.5 | 2 |
| 1.1 | 0 | 0.5 | 0.5 |
| 1.5 | 0 | 0.5 | 0.5 |
| 2 | 0 | 0.5 | 0.5 |

| Scenario 8 (Pessimist) | | | |
| --- | --- | --- | --- |
| $\alpha_i$ | 1.1 | 1.5 | 2 |
| 1.1 | 0 | 0 | 1 |
| 1.5 | 0 | 0 | 1 |
| 2 | 0 | 0 | 1 |

### 2.7. Results

In this section, we present the main results, starting with the effect of errors in grape-yield estimation on the different evaluation metrics, then proceeding with the effect of errors on forecasting transition probabilities.

For both sources of errors (yields and transition matrix), we present the results obtained for lots having different maximum reachable quality levels and those having the same maximum quality but different ripening rates. Finally, for all cases, we compare the effect that different flexibility levels have on the metrics.

These results enable us to compare, analyze, and identify the economic and production performance impacts of the harvest plans as the results of forecast accuracy.

### 2.7.1. Effects of errors in grape yields beliefs

We study different scenarios of under- or over-estimation of yields. The proposed scenarios are levels of under- or over-estimation of $\{3, 2, 1.5, 1.1, 1, 0.9, 0.7, 0.5\}$ times the believed yield level.

#### 2.7.1.1. Different Maximum Reachable Quality Case

Figure 2.4 presents the absolute change in the objective function value under different grape-yield errors, for three levels of flexibility. It is important to indicate that we are minimizing the objective value, so the more negative the value is, the better it is. We observe that the effect of the errors in yield determination are asymmetrical; underestimations of the yields (Yield factor $> 1$) have a significant positive effect on the objective value, due to the larger availability of grapes, while overestimation (Yield factor $< 1$) does not show such a significant effect on the absolute value. Flexibility can significantly affect the objective value as it increases (Flex 1), which means the decision-maker can fix its decisions in an earlier period—the objective function change is larger to the negative side, enabling capture of more value. Hence, if yields are underestimated, flexibility plays an important role; as the flexibility increases, workers can harvest more, and reduced flexibility ameliorates this effect.

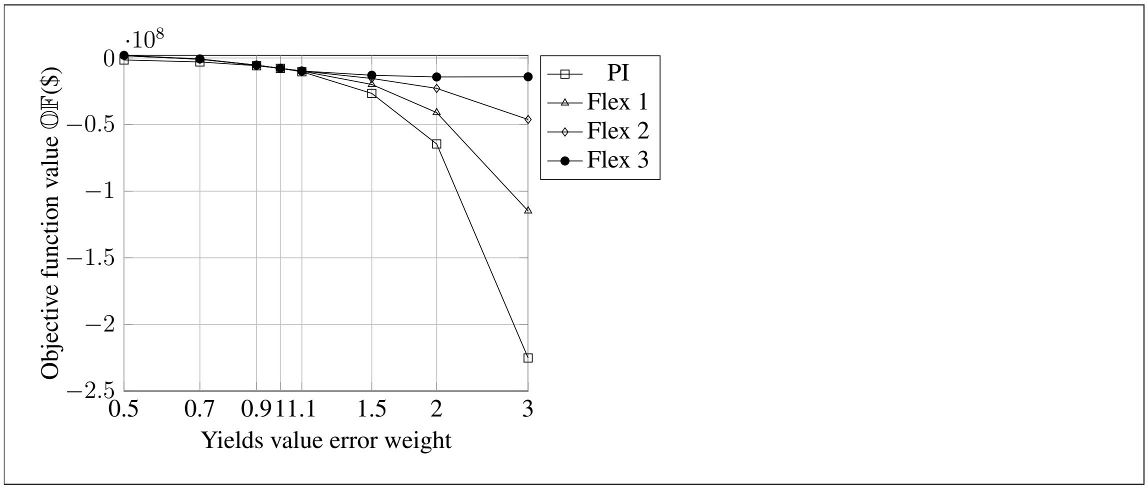


FIGURE 2.4. Objective function differences in value for grape yields errors and flexibility levels

Figure 2.5 shows the relative reduction of value of the real plan (the value of the plan with the real yields but using the decisions in the believed scenario) with respect to the prefect-information plan (𝕆𝔽𝔻). When yields are overestimated, the reduction in the objective function for the real plan, as a percentage of the prefect-information plan, is much larger, with up to a 200% loss in value against the prefect-information plan, when the yields are 50% of what was expected. In the case of underestimated yields, when the underestimated level is 100%, the loss in objective value can range from 36% to 77.9%. Figure 2.6 shows the income deficit of the real scenario compared to the PI scenario (𝕀𝔻). When the yields are overestimated, they decrease, and when they are underestimated, they increase, compared to the original plan. However, neither reduction nor increase in income is proportional to the percentage reduction or increment. When yields decrease by 50%

the incomes only decrease by 17%. Underestimating yields by 100% increases income between 18% and 83%.

Defined as the ability to revise hiring decisions, flexibility does not significantly affect either the objective function or profits if the yields are overestimated. However, when the yields are underestimated, flexibility plays an important role in reducing the effect on the objective value and the income. Underestimating the yields by 100% and having the ability to immediately re-plan in the second period can reduce the objective function and income by 36% and 25%, respectively. If flexibility is reduced by allowing re-planning only in the fourth period, the objective function and income are now reduced by 77.9% and 83.68%, respectively.

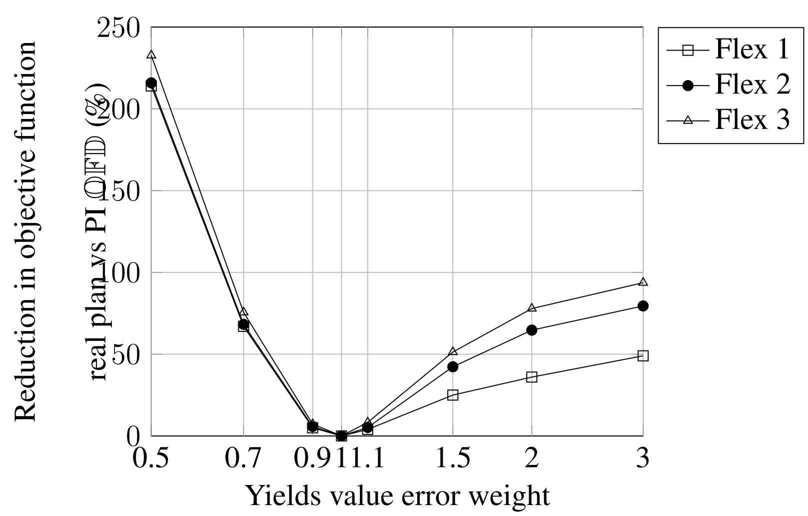


FIGURE 2.5. Percentage reduction in objective function from original plan (No error in the beliefs) by flexibility level.

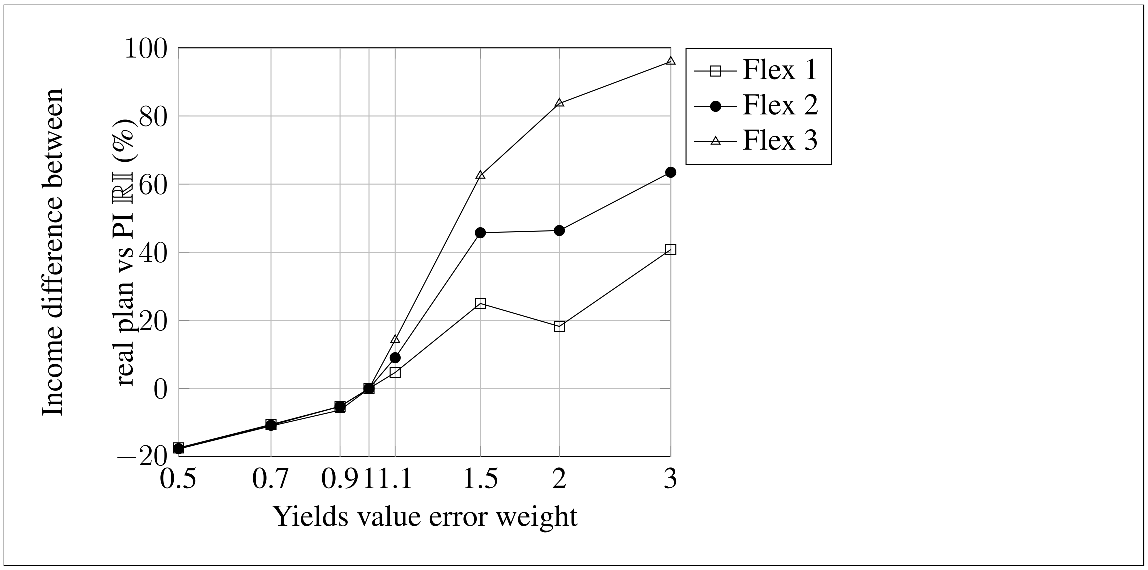


FIGURE 2.6. Percentage reduction in income from original plan (No error in the beliefs) by flexibility level.

In Figure 2.7, we can observe the distribution of the income increment/loss between unharvested and suboptimally harvested grapes, for different levels of errors in the beliefs, compared to the case in which there was no error in beliefs. We observe that in the case of underestimating yields, the main source of income losses comes from the increasing levels of unharvested grape. On the other hand, overestimating these rates implies an increment in harvested grape as well as a higher average quality and, thus, more profits per unit. This compensates for part of the loss due to over-hiring labor.

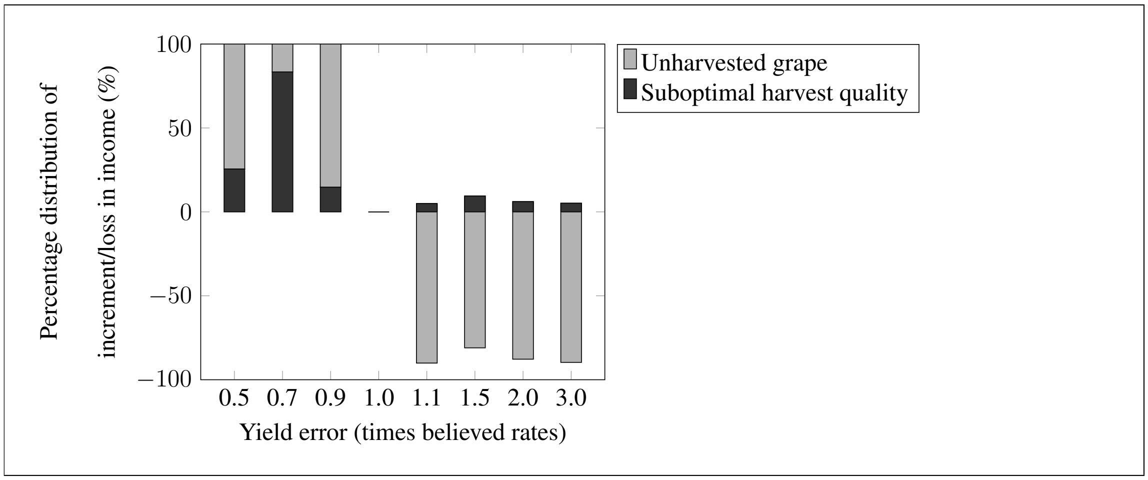


FIGURE 2.7. Distribution of income increment/loss between unharvested and suboptimally harvested grapes.

Figures 2.8 and 2.9 present the results for three distinct blocks with different maximum reachable quality of grapes for flexibility level 2 We observe that in the case of an underestimation scenario, the model privileges the most premium grape (high maximum quality), trying to leave unharvested the least amount possible, while the worst grape suffers the higher percentage of losses in the face of variability. Looking at the effect on income, we notice that despite a lower level of losses of the better-quality grapes, they correspond to a significant proportion of income and, thus, account for the largest portion of income loss. Hence the decision-maker must prioritize the premium blocks, allocating as much labor to these blocks as the firm can.

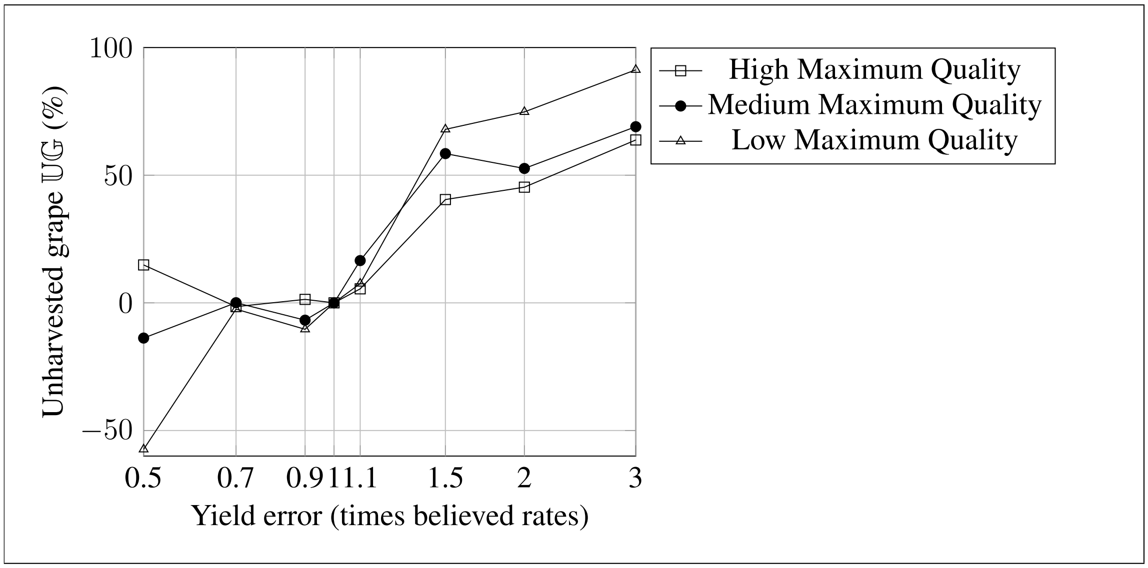


FIGURE 2.8. Percentage unharvested grape by maximum reachable quality.

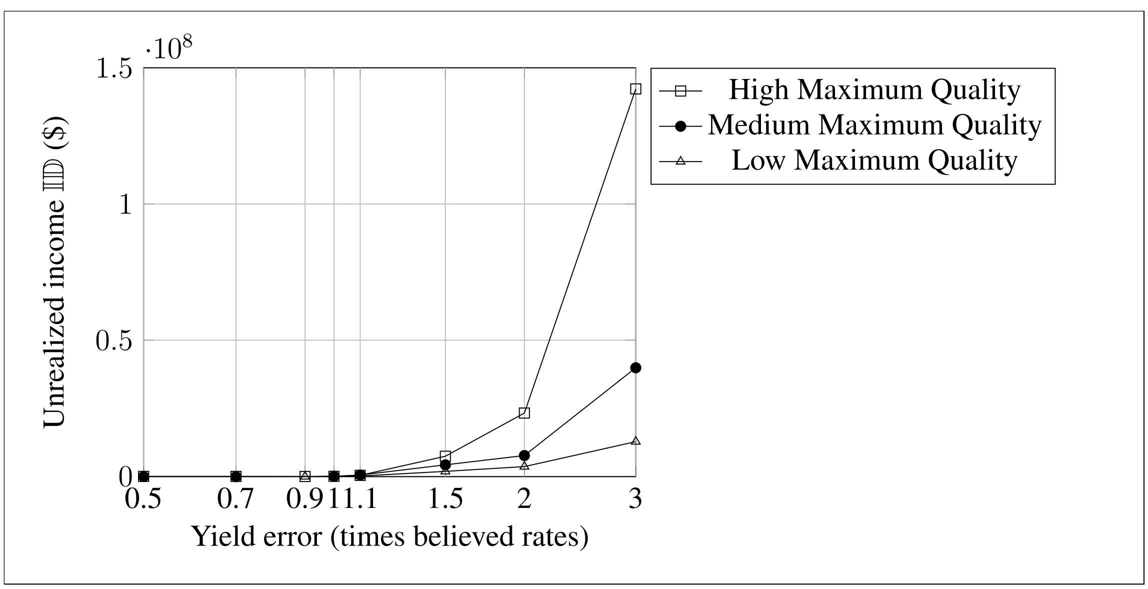


FIGURE 2.9. Unrealized income by maximum reachable quality.

### 2.7.1.2. Different Ripening Rates of Quality Case

Figure 2.10 presents the aggregate performance of harvest plans, dealing with grapes with different ripening rates in the context of the three different levels of flexibility. Here, we observe that the flexibility to fix the harvest labor plan similarly impacts the objective function. Having the possibility to fix the decisions immediately afterward, in the second period, manages to reduce the losses about 40%.

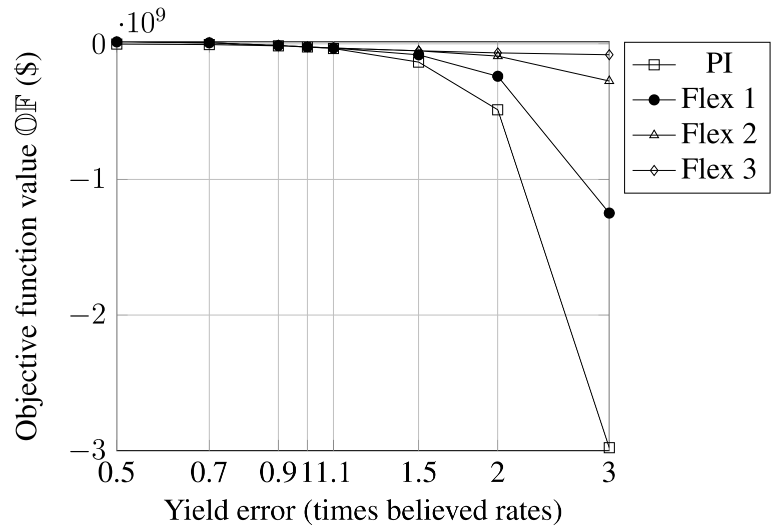


FIGURE 2.10. Objective function differences in value for grape yields errors and flexibility levels.

We observe in Figure 2.11 similar impacts on net incomes, the effect of under- and over-estimating grape yields with different grape ripening rates. About 60% of net income losses are avoidable by investing in improving flexibility. In the next figure, we notice that additional unharvested grape is the main source of income losses; when overestimating rates, both factors more equally generate extra income sources.

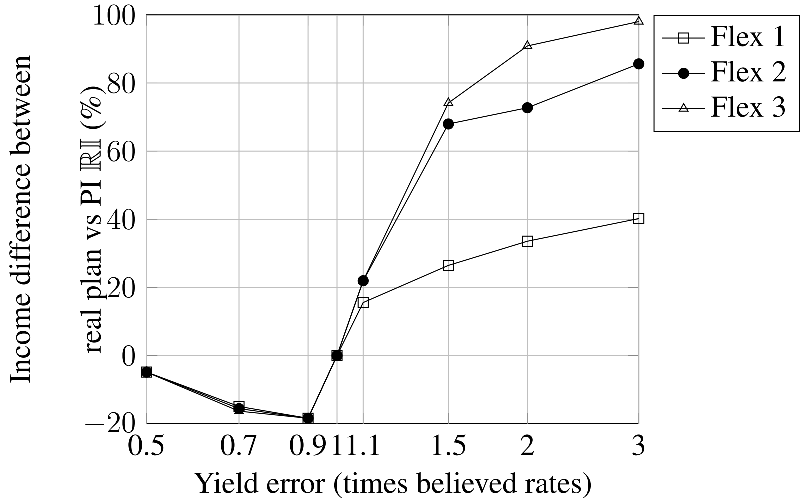


FIGURE 2.11. Percentage reduction in income from original plan (No error in beliefs) for different flexibility levels.

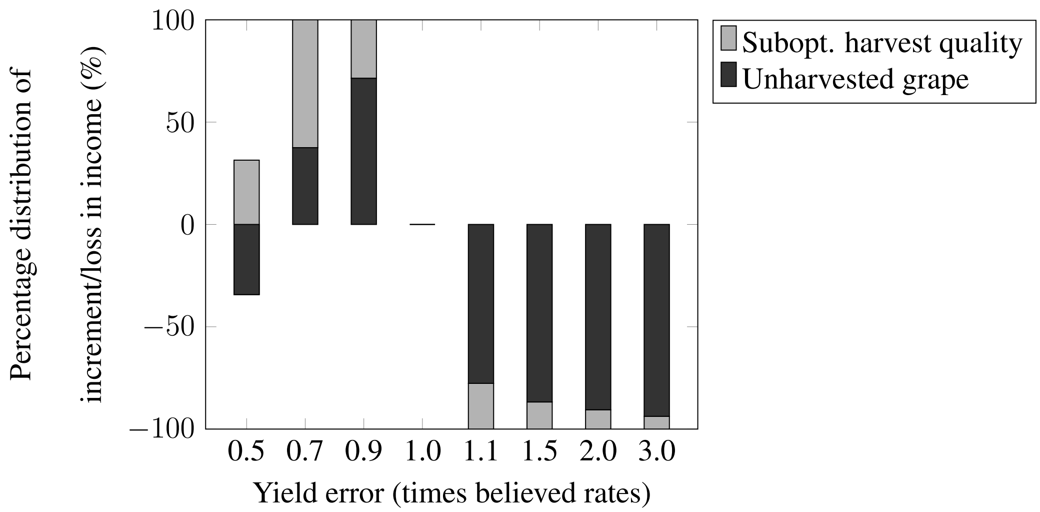


FIGURE 2.12. Distribution of income increment/loss between unharvested and suboptimally harvested grapes.

In the following graphs, we observe a very important facet of each quality behavior. The results show that grapes that improve their quality early give the decision-maker an extra level of flexibility to adjust the harvesting plan. As this kind of grape reaches its optimal quality early and stays in that condition for more periods, the planner can start its harvest earlier, if necessary. This appears in the lower amount of unharvested grape as the error increases. On the other hand, we see that the grapes with late quality improvement limit the decision-maker's flexibility to extend the harvest period, due to the quality rendering it unprofitable. These results are almost the same for the other two levels of flexibility, so we present just those corresponding to flexibility level 2.

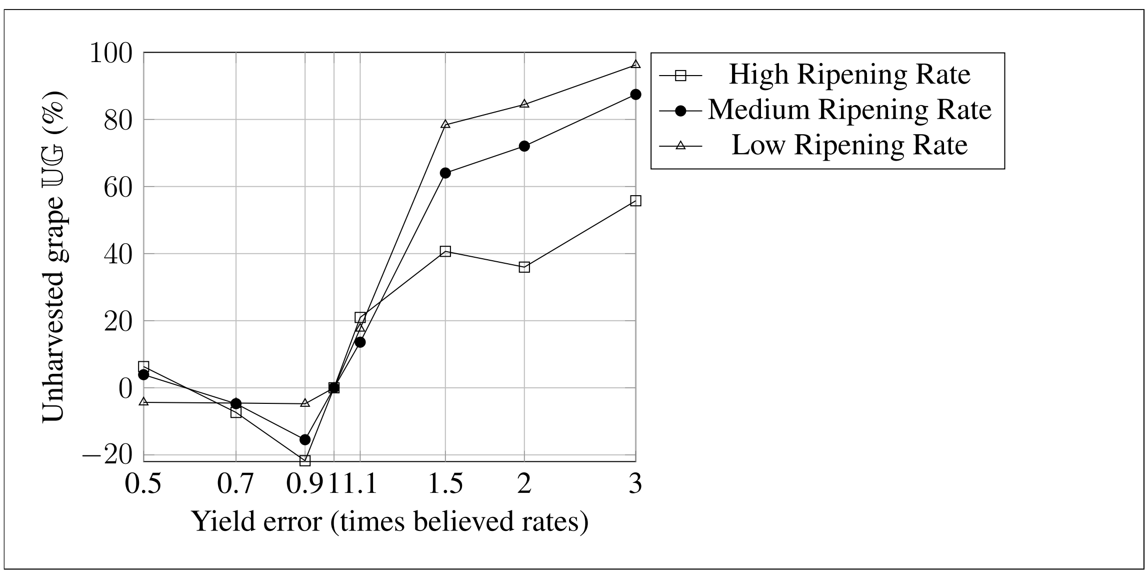


FIGURE 2.13. Percentage unharvested grape for different ripening rates of grapes.

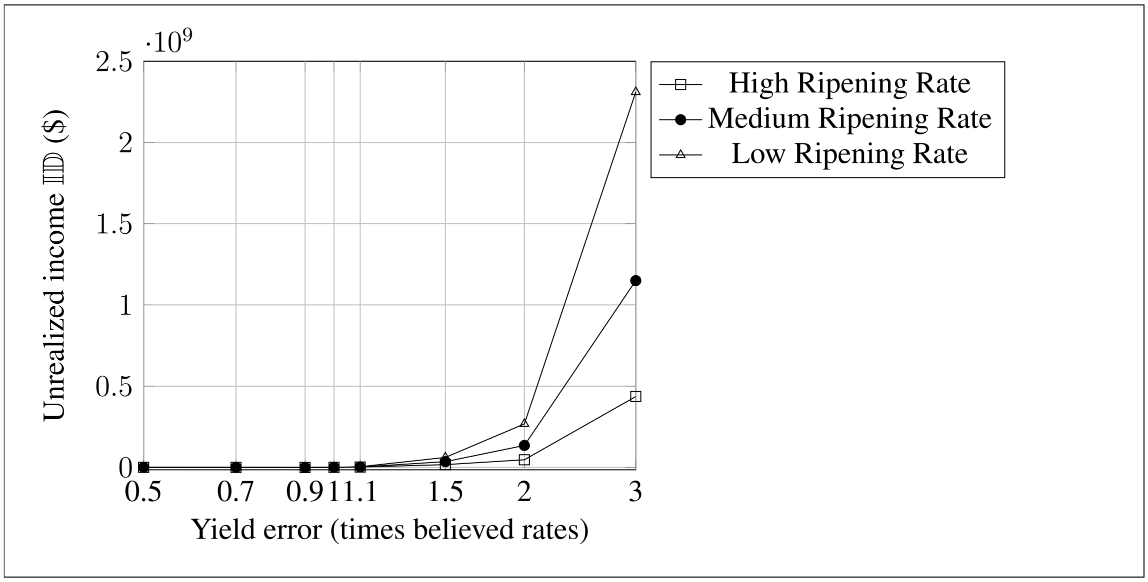


FIGURE 2.14. Unrealized income for different ripening rates of grapes.

### 2.7.2. Transition Probabilities Analysis

#### 2.7.2.1. Different Maximum Reachable Quality Case

In this analysis we can observe a more linear behavior in comparison with the grape-yield analysis. Despite this, the following graphs still show an asymmetric performance between overestimating and underestimating the probabilities of good scenarios. Under-estimating them can cost five times what overestimating them would cost.

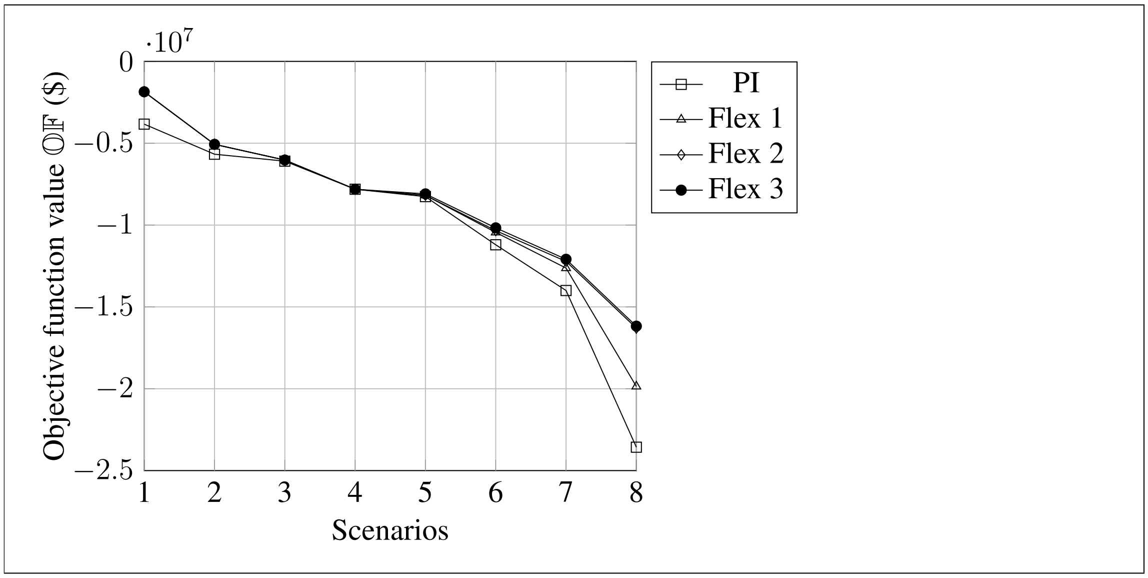


FIGURE 2.15. Objective function value for different scenarios and flexibility levels.

In the graphs 2.16 and 2.19, we notice that flexibility has less impact on global results than in the previous analysis. The reduction of a deficit could reach just about 15%. In addition, we observe that the less flexibility there is, the less impact the improvement of flexibility has on the ability to fix the schedule one period before. A very important result that we see here is the fact that flexibility makes no difference when bad-scenario probabilities are underestimated (left side of the graphs).

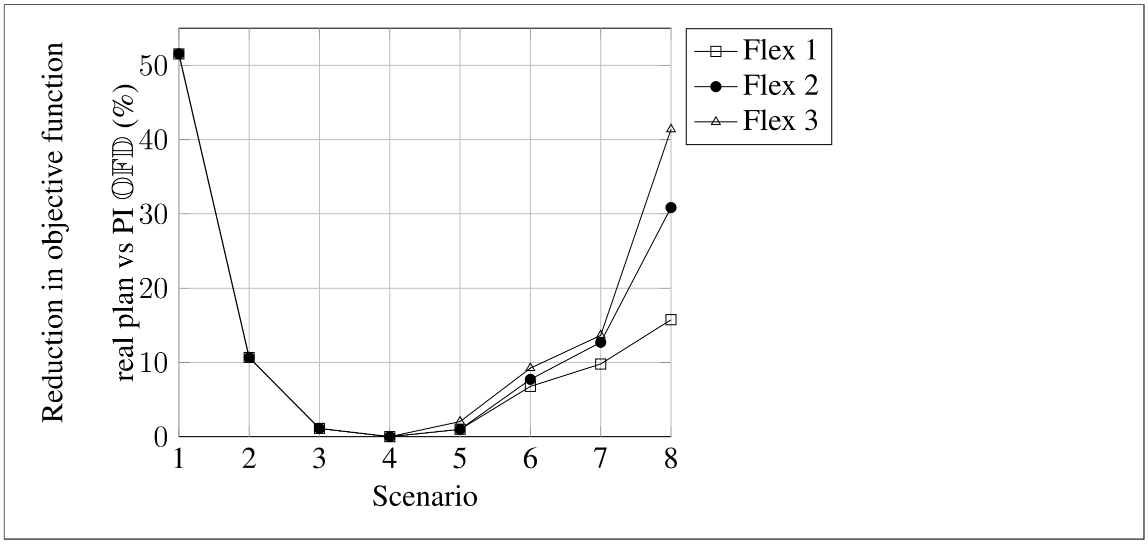


FIGURE 2.16. Percentage reduction in objective function from original plan (No error in beliefs) for different scenarios and flexibility levels.

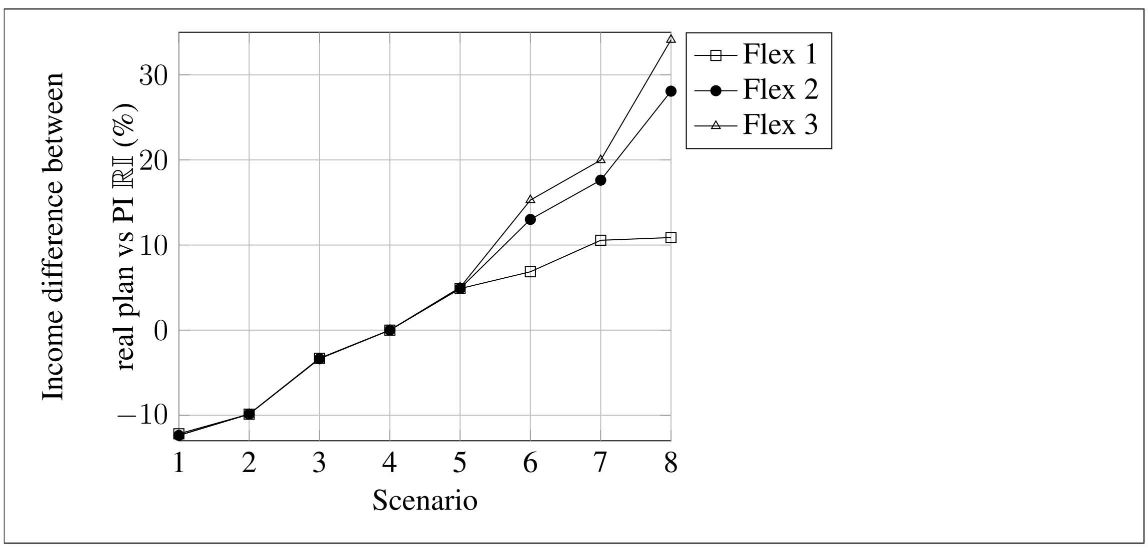


FIGURE 2.17. Percentage reduction in income from original plan (No error in beliefs) for different scenarios and flexibility levels.

As in the previous analysis, the next histogram shows the percentage implication for total incomes by two different factors. The extra or less unharvested grape, compared to the perfect-information scenario, means a variation in total incomes and a penalty for leaving this amount unharvested and the average quality of harvested grape that impacts on revenue. We observe similar results when yields are underestimated; here, too, the main source of income losses is the increasing levels of unharvested grape. But overestimating these rates does not imply the same result as before; the main source of loss compensation is the increment of harvested grape. These results are almost the same for the other two levels of flexibility, so we present just those corresponding to flexibility level 2.

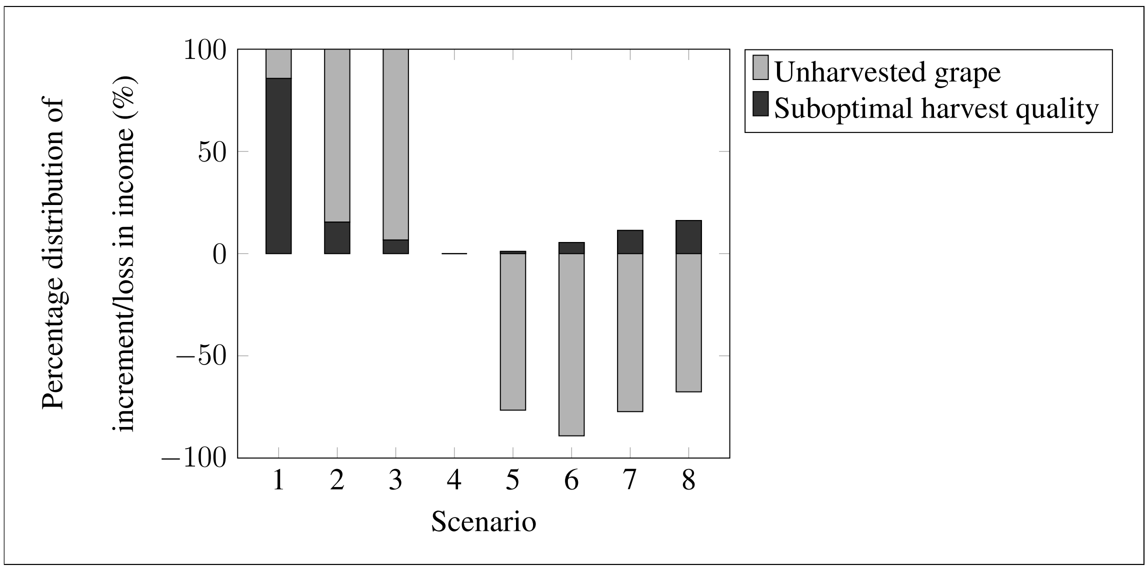


FIGURE 2.18. Distribution of income increment/loss between unharvested and suboptimally harvested grapes for different scenarios.

In the graphs 2.19 and 2.20, we present the main results separately by grapes with different maximum reachable quality for flexibility level 2, which the level of belief pessimism affects. Here, we observe similar outcomes. Unlike the lower quality grapes, he most premium grape is prioritized. Even so, it also happens that the extra unharvested premium-quality grape makes up the major part of income losses.

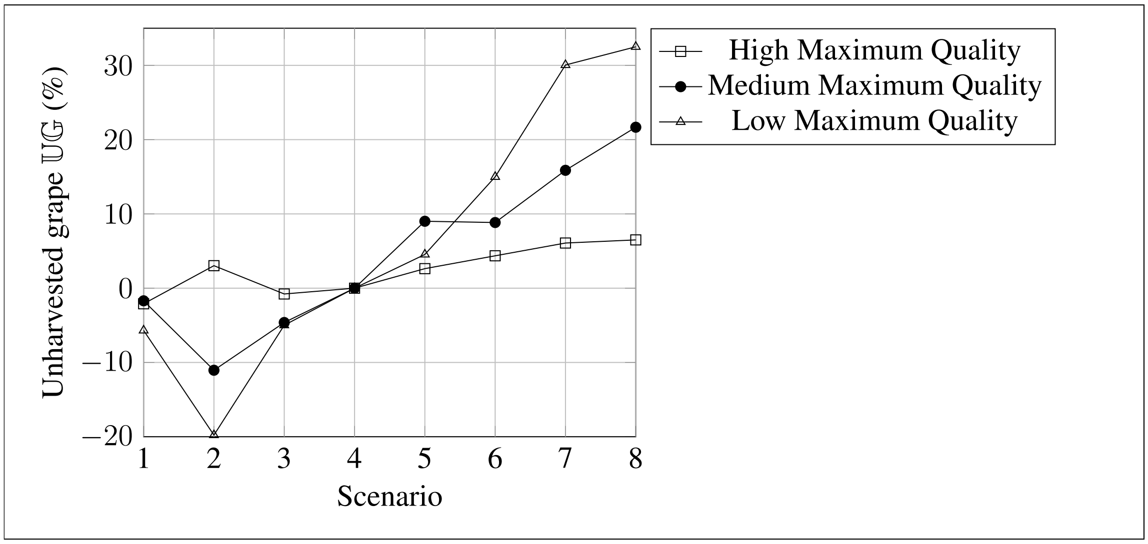


FIGURE 2.19. Percentage unharvested grape for different scenarios and maximum reachable quality.

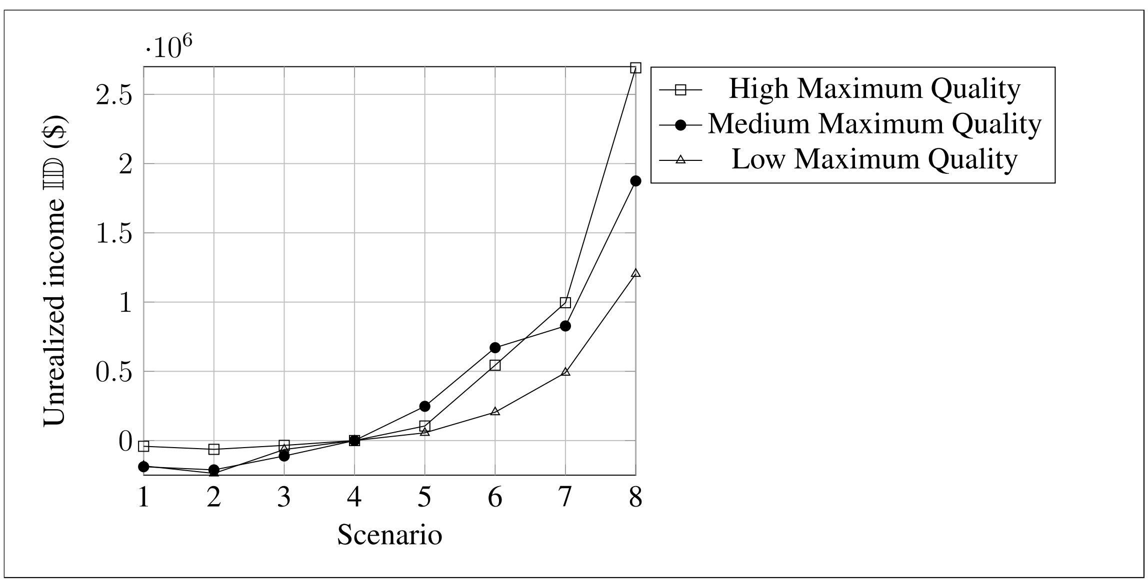


FIGURE 2.20. Unrealized income for different scenarios and maximum reachable quality.

### 2.7.2.2. Different ripening rates of grapes

In the following graphs (2.21 and 2.22) we observe that flexibility makes no difference when bad scenarios have greater probability of occurring than expected. On the other hand, flexibility again plays an important role when good-scenario probabilities are underestimated.

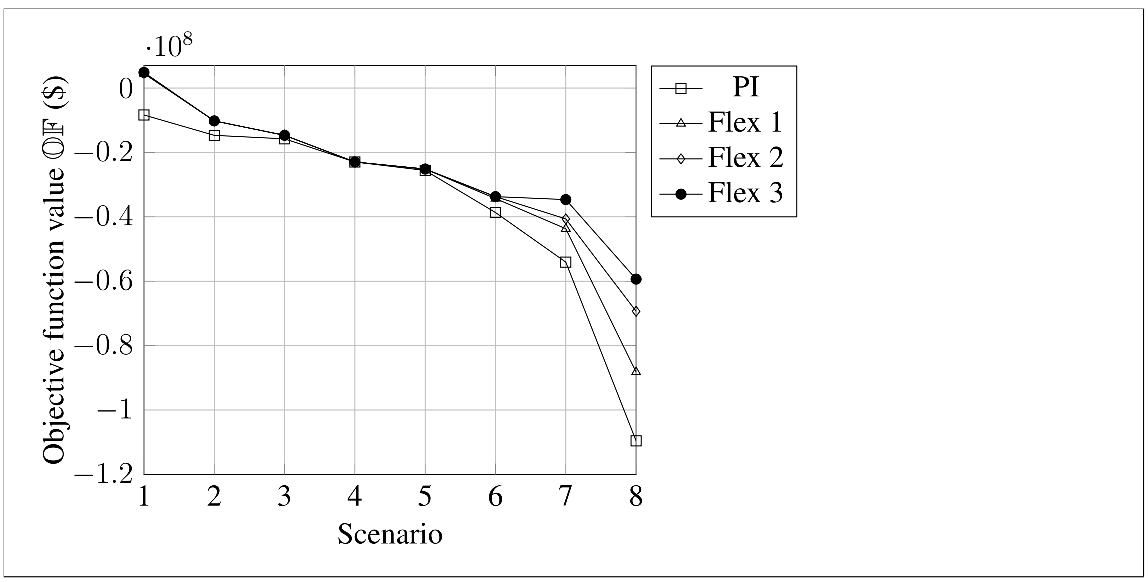


FIGURE 2.21. Objective function value for different scenarios and flexibility levels.

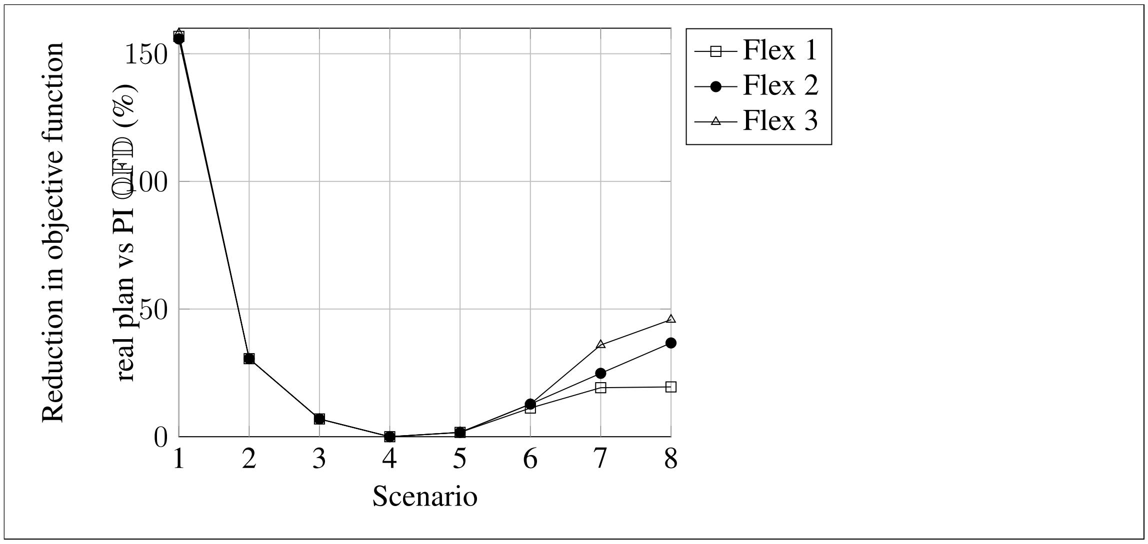


FIGURE 2.22. Percentage reduction in objective function from original plan (No error in beliefs) for different scenarios and flexibility levels.

We observe in figure 2.23 a similar behavior to that in the previous analysis. Underestimated good-scenario probabilities lead to the main source of income losses corresponding to the increment of unharvested grape. On the other hand, when good-rate scenarios are overestimated, the compensating extra income comprises more equally the increment of harvested grape and its better average quality. These results are almost the same for the other two levels of flexibility, so we present just those corresponding to flexibility level 2.

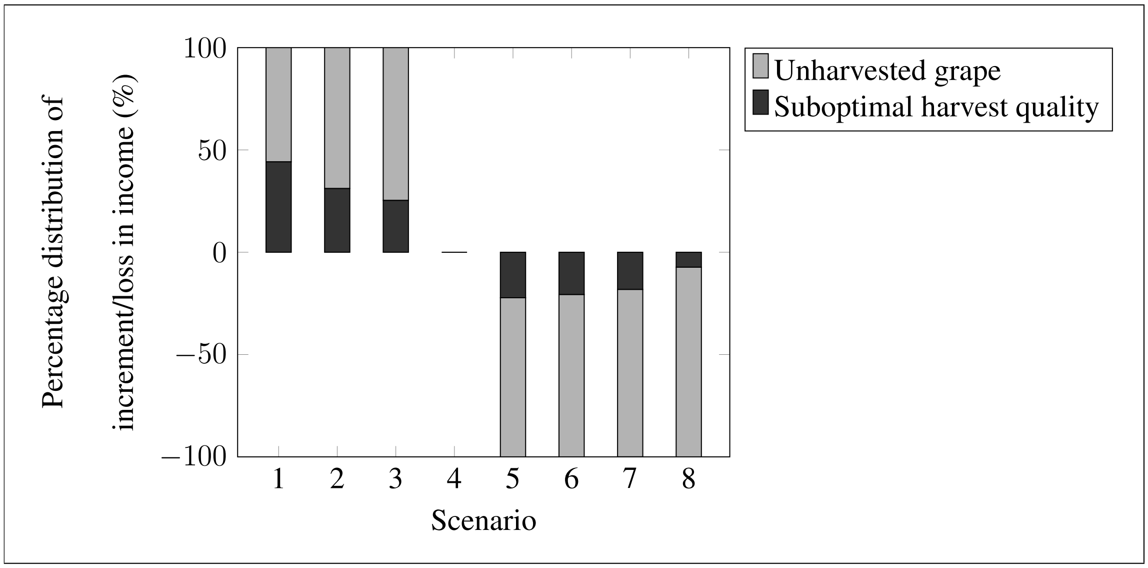


FIGURE 2.23. Distribution of income increment/loss between unharvested and sub-optimally harvested grapes for different scenarios.

The last two graphs show separately the results regarding grape performance by the ripening rates of grape for flexibility level 2. A high ripening rate corresponds to grapes whose quality improves earlier; then, a medium ripening rate improves linearly, and, last, low-ripening-rate grape quality improves later. Here, we observe again that grapes with late improvement reduce the decision-maker's ability to adjust the harvest schedule, according to its flexibility. We notice this in low-ripening-rate blocks, where the unharvested amount and the loss income are higher than the others.

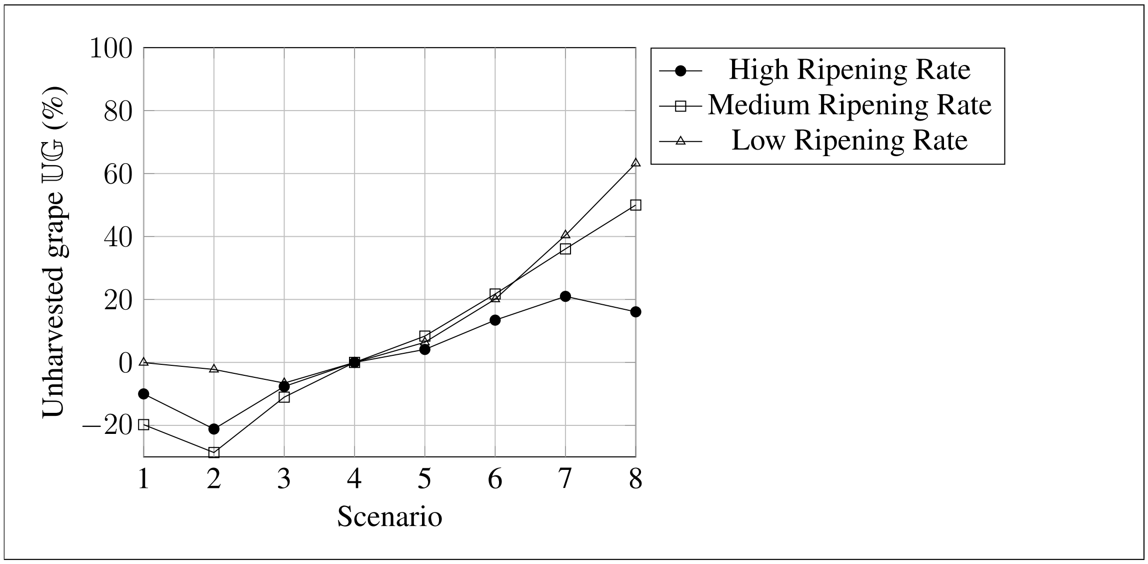


FIGURE 2.24. Percentage unharvested grape scenarios and ripening rates of grapes.

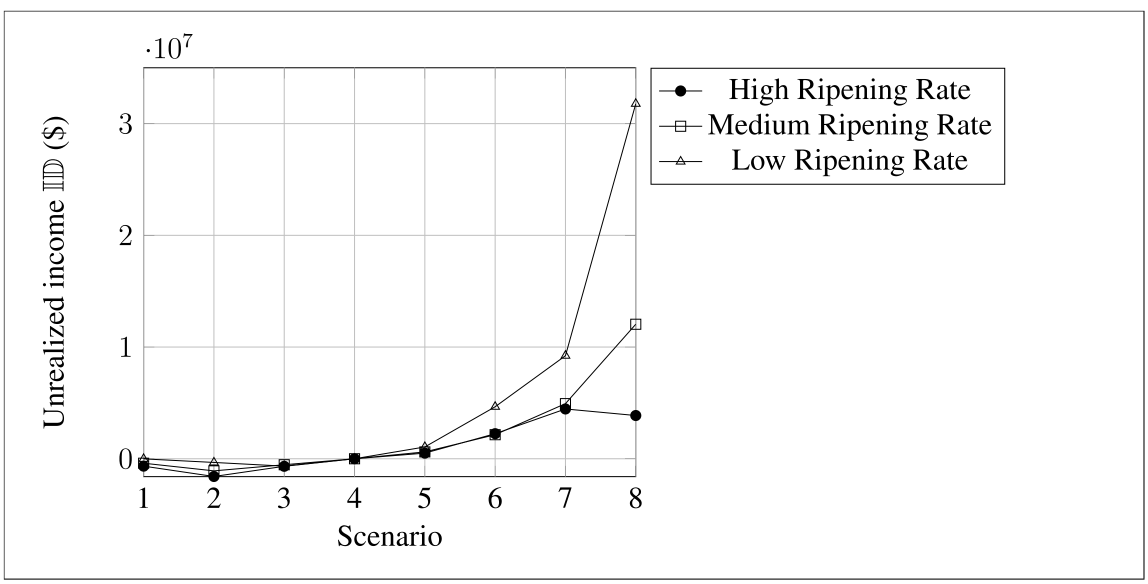


FIGURE 2.25. Unrealized income for different scenarios and ripening rates of grapes.

## 2.8. Discussion and Conclusions

In this research, we first develop a multistage optimization model, based on the one proposed by Ferrer et al., 2008 and differing from the one that Avanzini et al., 2021 present, since it considers the uncertainty in the yields and the transition probabilities. Using this model, we study the effect that errors in beliefs have on the value of using a Multistage Stochastic Optimization approach. Finally, we also analyze the effect that the quality and flexibility the resources have when errors in beliefs occur. From these findings, we can determine conditions under which acting to reduce the errors in future events will pay off, and conditions under which there is not much value to gain.

Results show that errors in grape-yield estimation have a significant impact on value, evidencing that it is not symmetrical when yields are over- or under-estimated. Reductions in value can be up to 77.9% and 232% when the yields are over- or under-estimated by 100%, respectively. They also show that an important part of these value losses comes from the reduction in net incomes, which can go up to 98% of the potential amount.

When yields are underestimated, flexibility or the ability to modify the decisions once the state of the nature reveals itself—for example, the process of adjusting the labor assignment—plays an important role. A high level of flexibility enables reducing the loss in value from the 77.9% to just 36%.

This effect is mainly attributable to the reduction of net income losses, which can decrease from 98% to 40% as flexibility increases. This occurs because the loss in value is lightly compensated with an increment in the income, due to the available grapes. However, since there it is not enough labor to harvest the grapes, a significant amount is left unharvested. If we look at how the model reacts in light of quality, it generally favors the harvest of high-quality grapes over low quality, but the unrealized income is greater for the high-quality grapes, due to their greater value.

On the other hand, when yields are overestimated, results show that flexibility does not play a significant role in ameliorating the value loss. This is because the adjustment of labor cannot compensate for the reduction in the amount of available grapes to harvest. However, the harvest of grapes that would been unharvested under normal conditions, as well as the increment of high-quality grapes being harvested on their optimal dates due to labor availability, offset some of the value loss.

Looking at the different quality of grape in the contexts of under- and over-estimation of yields, the model tries to reduce comparatively the amount of unharvested high-quality grapes compared to those of low quality. Only when the yields decrease by 50% is the percentage of high-quality grapes larger. If we compare value or unrealized gains from underestimated yields, most of the value loss comes from the high-quality grapes (due to their higher kg value) rather than those of low quality. However, in absolute terms, overestimated yields do not result in significant value loss.

For the same flexibility level, we analyzed the effect that the ripening rate has on the amount of unharvested grapes and on the unrealized gains when mistakes occur in the determination of the yields. When the ripening rate is low, grapes mature very close to their optimal date, and the yields are underestimated. The amount of unharvested grapes—hence, the unrealized gains—are largest, with insufficient labor to process them all. This amount decreases when the ripening rate is high with is a more ample window of time for harvesting the ripe grapes. This same effect occurs for the three levels of flexibility, and it increases as flexibility decreases.

We analyze the effect that errors in determining the transition probabilities have on the value of the plan. When the decision-maker is optimistic (the transition probabilities absorb the low yields), the value decreases significantly, with loss in value in the range of 50% for the most optimistic scenario. When the decision-maker is pessimistic (the transition probabilities absorb the high yields), we see less reduction in value, compared to the optimistic scenario, which can go between 15% and 30% when we approach the extreme cases.

If we look at the effect of flexibility on the value under different scenarios of transition-probability errors, results show that decision-maker optimism has no effect on reducing value loss. In pessimistic scenarios, flexibility ameliorates value loss by 15%, due to workers' ability to adjust productivity and reduce the amount of unharvested grapes.

For the case of the optimistic scenario, the reduction in value due to the change in the transition probabilities is attributable to high labor cost for the level of grape yields. Although reducing the unharvested grapes and harvesting them on dates closer to their optimal date produces some value, the reduction in yields and labor costs overcomes this value increment. In the pessimistic scenario, the value loss and unrealized gain results from the amount of unharvested grapes due to the lack of labor.

The maximum reachable quality of the grape also makes an important difference when errors in transition probabilities occur. When the decision-maker's level of pessimism is high, the better average quality of the harvested grape lightly compensates for the value loss from the unharvested grape due to lack of labor. In these cases, the model prioritizes harvesting the high-quality grapes, leaving more low-quality grape unharvested. High-quality grapes still represent the greater part of harvest value.

If we analyze the effect that the ripening rates have on value when the scenario is optimistic, the excess available labor leaves less grape unharvested. When the decision-maker is too pessimistic, grapes with a low ripening rate are more difficult to harvest, with the smaller window available for harvesting on optimal dates preventing their harvest starting earlier.

# 3. GENERAL CONCLUSIONS AND FURTHER RESEARCH

This thesis centers fundamentally on the application of operations research models and methodologies in agricultural industry problems, especially focusing here on wine-grape harvesting planning. We first developed a multistage optimization model, based on the one proposed by Ferrer et al., 2008, adding uncertainty in the yields and the transition probabilities. Using this model, we studied the effect that errors in beliefs have on the value of using a Multistage Stochastic Optimization approach. We also analyzed the effect that the quality and flexibility of the resources have when errors in occur.

## 3.1. Remarkable Results and General Conclusions

In general, errors in the yield and transition probabilities beliefs reduce the value of the plans. We observe that these reductions are not symmetrical when the yields are either under- or over-estimated, having a larger absolute effect when they are underestimated, but a higher relative effect when they are overestimated.

Three factors can affect the level of reduction in value: flexibility, grape maximum reachable quality, and ripening rate. Flexibility, the possibility to adjust the decision once the state of nature reveals itself, helps to ameliorate the value reduction when yields are underestimated, allowing for increased labor, and in pessimist scenarios.

When the maximum quality of the grapes is high and yields are underestimated, the value loss increases due to the unharvested grapes, rather than when the grapes are of low quality. The same happens in the pessimist scenario. The high-quality grapes represent the greatest part of the harvest value, so in the presence of a lack of labor, the model favors harvesting the high-quality grapes, leaving greater quantities of low-quality grape unharvested.

When the ripening rates are low and the grapes mature close to their optimal date, the value loss is greater, due to the small window of time available for harvesting them on optimal dates. This amount decreases when the ripening rate is high, with a more ample time window for harvesting the ripe grapes.

This research has several limitations. For example, we only analyzed errors in yields and transition probabilities beliefs. Many other errors in beliefs can occur, such as in labor productivity levels, grape quality level, probability of adverse climatic events (e.g., rain). A second limitation is that our assumptions do not allow the decision-maker to update future beliefs having learned from mistakes or the process.

### 3.2. Other Applications

Although the presented model was built from the wine-grape harvest problem, its nature and scope share common objectives and problems with many other industries besides agriculture where uncertainty is present, including how to improve forecast accuracy, a planning process, labor hiring, and other decisions with limited information about the future and flexibility to adjust decisions after uncertainty appears. The model helps the decision-making process in any highly uncertain environment, providing insights into how uncertainty affects planning performance. Some examples are:

**Warehouses and supply chain industries** where, in general, future demand is uncertain. Here, a multistage stochastic optimization to make decisions works similarly, with different scenarios that can happen and their respective probability, all of which the decision-maker must consider during the planning process. Also, cases of perishable products can be modeled in the same way, as the changing quality that affects the value function result. Different threshold quality can function to determine the optimal value of a certain product in a determined specific period.

**Hospitals**, where hiring and shift planning to attend a stochastic demand is very important, to prevent a lack of staff and ensure timely patient treatment. A good forecast to estimate the demand is also crucial. Furthermore, the optimal time to attend a patient functions the same as the optimal crop harvest date, with the same risk of value loss.

**Restaurants** and any service industries, where the time to attend the client matters, and revenues reflect the level of service. This problem can be approached in the same way as the harvesting planning and quality degradation.

### 3.3. Managerial Insights

According to our results, a manager facing the possibility that his beliefs can be incorrect or inaccurate would likely hire labor in excess of what planning recommended. This would allow him to face a potential underestimation of yields without incurring high-cost hiring at the last minute, forcing the leaving of unharvested grape due to lack of labor. This same behavior appears in other industries (e.g., airlines, where adding robustness to the flight crew pairs solutions by also adding ground time between the incoming and outgoing flights) (Ehrgott & Ryan, 2002; Yen & Birge, 2006; Weide et al., 2010; Dunbar et al., 2012).

Errors regarding yield estimation seem to have a larger effect on value than making the same mistakes in transition probabilities. Thus, facing the decision of where to invest in producing more reliable information, the decision should aim toward accuracy in determining grape yields.

Flexibility adds significant value to the planning process, as Avanzini et al., 2021 indicate. So, if possible, the manager should try to induce flexibility into the plan, making possible the adjusting of the plan as the states of nature appear. This could occur by directly relating the payments of the workers to productivity and reducing hiring and layoff costs. Finally, achieving a higher level of flexibility can occur if the decision-maker has a buffer for harvesting capacity by hiring extra workers.

Regarding the maximum achievable quality of the grapes, the harvesting plan should prioritize higher-quality grapes since these determine most of the income and net utilities of production. Also, a situation with a lack of available labor calls for adapting the harvest plan to leave as little high-quality grape unharvested as possible. Small increments of unharvested premium grape can cause higher income losses than low-quality grape produces.

In the case of ripening rates, the preferred possibility is to plant varieties that have high ripening rates and wider optimal harvest windows. This increases the flexibility of the decision-maker to adjust the harvest plan by starting the harvesting earlier than expected when reduced labor is available. Likewise, avoiding varieties with low ripening rates maintains the decision-maker's flexibility to modify the harvest plan.

Finally, the results this work obtains show that the effects of errors in beliefs on the planning value behave asymmetrically. This indicates that using regular optimization techniques to solve the problem at hand is not the best method. A better mechanism to handle errors in beliefs could be the use of a robust optimization approach (Ben-Tal et al., 2009) or a conditional value at risk (Rockafellar & Uryasev, 2002), which minimizes losses under worst-case scenarios or average expected costs considering them all, a more accurate approach to results more robust against uncertainty.

### 3.4. Further Research

This research focuses on analyzing the errors regarding yields and transition probability matrix beliefs. The agricultural realm includes many other errors in beliefs, such as: labor productivity levels, quality level of grapes, probability of adverse climatic events (e.g., rain). Further research that studies the effects of these errors would be a great contribution to the winery industry and agriculture in general.

Transition probabilities and scenarios were considered as discrete events. This work could go even further if continuous distribution functions were associated with the yields.

Also, the same could apply to the change of quality through periods, or ripening rates behavior. This would enable implementing a distributionally robust optimization model approach, and a closer representation to the real distribution could offer more useful managerial insights.

Our results indicate that the use of a labor buffer to act as a reserve, in cases of underestimating the harvested stock, is a desirable feature. The use of a robust optimization approach or a conditional value at risk helps by defining optimal buffer levels.

Finally, studying the effects of using different types of machine-learning schemes in improving the precision and accuracy of updating would reduce the gap between the believed values and the real ones. Since the quality and amount of information directly relates to the quality of the forecasts, studying the use and value of sensor applications on agricultural industries to collect better and larger amounts of information to support decision-making would be desirable.

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