Managing Risk in Premium Fruit and Vegetable Supply Chains

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Abstract

Production planning in premium fresh produce supply chains is challenging due to the uncertainty of both supply and demand. A two-stage planning algorithm using mixed integer linear programming and Monte Carlo simulation is developed for production planning in the case of a premium branded tomato. Output from the optimization model is sequentially input into the simulation to provide management with information on expected profit and customer service levels at the grocery retail distribution center. The models are formulated to incorporate uncertainty in demand, yield, and harvest failure. The outcome of the algorithm is an annual production plan that meets minimum customer service requirements, while optimizing profit.

The resulting timing, location, and quantity of acres suggested by the algorithm are evaluated against the current industry heuristic of performing deterministic calculations, based on average yield and demand, and then planting double the required acreage. The suggested two-stage planning algorithm achieves 90 percent customer service with 20 percent less planted acres and almost three times as much profit than the industry heuristic of doubling the acreage.

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1 Introduction

Trends in consumer preferences and production innovations are changing the agriculture and food marketplace. There are an increasing number of differentiated food products that appeal to specific consumer values, such as environmental-friendliness or locally grown. Furthermore the success of specialty retailers, such as Trader Joe's ® and Whole Foods Market®[1], demonstrates that high-quality, high-margin agriculture can be sustainable and successful in mainstream grocery retail.

The growth of successful niche agriculture markets brings both opportunities and risks to agriculture and food supply chains. The opportunity to differentiate agriculture produce and earn price premiums provides a welcome alternative to producers who lack the scale to compete effectively in commodity markets. On the other hand, high product value and limited market demand creates greater incentives to avoid under or over-supply situations. These premium fresh produce supply chains must balance customer service requirements against costly agriculture production investment. Targeting a specific quantity of demand makes production planning particularly challenging, given the inherent biological and environmental uncertainties in agriculture. This research suggests a more sophisticated production planning approach that will help production managers make better decisions that increase profitability while recognizing demand and supply risks.

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[1] Trader Joe's® and Whole Foods Market ® are registered trade marks of the respective companies

1.1 Growth in premium food and agriculture supply chains

The market opportunity for premium food products is being driven from both ends of the food and agriculture supply chain (Figure 1). Agricultural input suppliers are developing and providing seeds with superior genetic traits to meet the needs of food processors and consumers. A current example is soybeans with an improved fatty acid profile that allows food producers to lower or eliminate trans-fatty acids when frying (using the soy oil). At the same time, consumers are increasingly aware of how their food is being produced and are willing to pay a premium for products produced in alignment with their individual values. These market trends are creating opportunities for smaller farmers who do not have the economies of scale to compete with large corporate commodity farms. Farmers who are able to implement unique processes in production and post-harvest handling of produce can brand their products and earn price premiums at the wholesale and retail levels. In the fresh produce market segment, organics are a successful example of product differentiation through unique production processes and branding. Other examples include differentiation by geography, such as being "local" or from a specific region, or specialization in less common species, varieties, or breeds, such as Indian River citrus or Kobe beef.

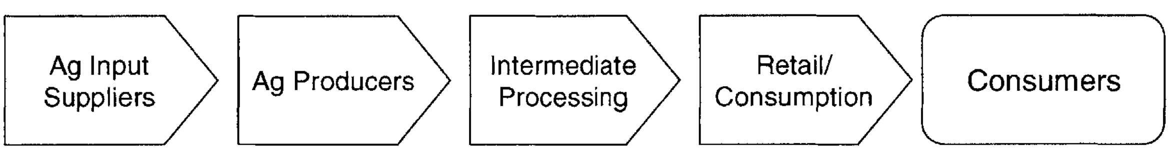


Figure 1: Simplified food and agriculture supply chain

1.2 Risks in premium food and agriculture supply chains

In traditional U.S. commodity agriculture, the primary goal is to maximize production at the minimal cost - assuming nearly unlimited demand. U.S. farmers are accustomed to a well functioning commodity market where they sell everything they produce at a price that usually covers their cost of production. De-commoditization of a market, through differentiated premium products, provides welcome opportunities for earning higher margins, but also brings increased risks.

One major risk of differentiated production is mismatching supply and demand. Differentiated products no longer have seemingly unlimited demand, due to their premium price, or unique characteristics that appeal only to select customer segments. These products often require higher investment in planting, producing, processing, and distribution, so overproduction is more costly than with a commodity product. Excess production will spoil, be sold at undesirable margins, or may appear in alternate unapproved channels. The last two of these three consequences can have far reaching negative impacts on the product brand image. Furthermore, when demand is not met, customer satisfaction will suffer more with a differentiated premium product than it would with a commodity product because of the inherent lack of substitutes. Economically, the opportunity cost of unsold items is also much greater with a premium product, simply because of the higher product margin.

Matching supply and demand is an important problem across all industries. The ability to correctly scale production and distribution of goods to meet market needs can define success or failure for a company. In agriculture and food supply chains, this problem is exacerbated by the biological nature of the production process. Production planning decisions are made months before actual demand is realized, with little to no flexibility to change the production system during the growing season. Few industrial products have such inflexible production schedules combined with long lead times. Additional production planning difficulties arise from unpredictable environmental conditions that influence the quantity actually produced, if production occurs at all. High winds, frost, hail, and even excessive amounts of rain, for example, can decimate a farmer's crop in a matter of hours. In addition, the increasing variability in fuel cost must be considered as many crops are transported significant distances to reach consumers.

1.3 Research question

This thesis seeks to improve the process of matching supply to demand in differentiated premium food and agriculture supply chains, by focusing on supply decisions. The supply decisions in agricultural production are:

- How many acres to plant
- Which crops to plant
- Where to plant
- What times to plant.

These decisions are under control of the production manager, whereas demand is typically determined by the market. Alternatively, demand management in food and agriculture supply chains is also a very effective lever for matching supply and demand and is an area that warrants further research. For the scope of this analysis, however, it is assumed that demand will not be proactively managed.

This research focuses on the reality of managing the risk from both demand and supply uncertainties in food and agriculture supply chains. For traditional commodity agriculture, demand is less of a concern because the market will adjust by finding a market-clearing price. Therefore, price variability is traditionally the primary marketing concern for commodity agriculture. The opposite problem exists for premium agriculture supply chains because niche products command a premium price, but demand may be highly unpredictable, particularly for new products. Furthermore, since there may be no direct substitutes for a premium product, producers must consider the impact of their decisions on customer service levels.

A specific case of managing risk in a real premium fresh fruit and vegetable supply chain is analyzed. A two-stage planning algorithm, involving mathematical modeling for decision-making, is presented that enables a supply chain integrator to make production decisions that maximize profit through better alignment of supply with demand. A unique aspect of this model is that it incorporates the various risks associated with food production and distribution. The model output is the optimal number and timing of acres to plant among different geographies to meet a minimum customer service level at the grocery retail distribution center.

1.4 Motivation

The primary motivation of this thesis research is to help fresh produce supply chains become more profitable. Improved profitability will be achieved by better matching supply to demand through improved recognition and management of risk. In addition, there are also indirect benefits from improving the profitability of premium food and agriculture supply chains. These include sustainable opportunities for farmers, particularly smaller family farms, and improved access, in terms of pricing and availability, to high quality fresh fruits and vegetables for consumers.

This research thesis is specifically focused on developing tools that help premium fresh produce supply chains make more money with less risk. This increased profitability is achieved through improved production planning that reduces waste throughout the system, ensures a consistent supply, and better quantifies risks from supply and demand uncertainties.

It should be emphasized that if oversupply occurs, produce will go to waste. Excess production will most likely be left in the field to rot or be tilled into the soil. If this happens, the objective becomes a minimization of cost associated with the unused perishable product. If it is possible to find a market for this produce, it will be sold at a discounted price. Not only is oversupply of product a financial loss, but there is also the chance that the premium product might enter uncontrolled alternative channels. This could hurt the premium brand image, as well as relationships with contracted growers.

If undersupply occurs, low customer service levels may damage important retail relationships and business. Grocery retailers demand a minimum customer service level, just for the right to do business with them. Any premium fresh produce firm must be able to achieve this minimum standard, while minimizing the oversupply risks as stated in the previous paragraph. Undersupply issues could also tarnish the supplier's image to expand their business further with existing and new grocery retail customers.

The ability to understand and quantify risk in a premium fresh produce supply chain, through the two-stage planning algorithm proposed in this thesis, is valuable in helping the production managers better allocate risk management resources. The working model not only helps them to better understand the risks in the system, but allows them to measure the relative impact of different uncertainties.

In summary, managing risk in premium fresh produce supply chains is a challenging issue that can limit future business growth. The proposed two-stage planning algorithm involves modeling the premium supply chain to determine a optimal and scalable solution that includes recognition of inherent risks in the system. The proposed solution allows the supply chain to increase profitability with less risk.

2 The case of a premium branded tomato

The research analysis for this thesis is performed on behalf of a firm operating in the fresh produce industry. The firm is introducing a new premium agriculture product and is seeking to improve their production planning ability. The proposed methodology and analysis, however, is applicable to other food and agriculture supply chains, or any supply chain where both production and demand uncertainty exist.

2.1 Description of the product and supply chain

The production planning approach suggested in this research is applied to a U.S. based premium-branded tomato production and marketing venture, forthwith referred to as "MaterCo." The tomatoes marketed by MaterCo are grown under strict controls and protocols, segmented through the supply chain, and only sold at select retail locations. The value offering from MaterCo to the grocery retailer is consistent high quality, including superior taste, full traceability, environmental stewardship, good agricultural practices employed on the farm, and retail-merchandising support. The premium-branded tomatoes from MaterCo will be referred to as "SuperT" throughout the remaining sections of this paper.

Whereas traditional commercial tomato varieties are chosen for their vigor and hardiness in the field, as well as the ability to withstand transport over significant distances, the SuperT tomatoes are carefully selected for desirable consumer traits. It is often the case in the fresh produce industry that desirable traits from a grower, repacker, and shipper standpoint may not necessarily make the tomato desirable for consumers. For example, a thick skinned meaty tomato, picked early, will travel much better than a thin skinned juicy ripe tomato. Less damage, or shrink, during shipment is obviously more profitable to both the grower and shipper. Consumers, on the other hand, typically prefer a thin skinned juicy ripe tomato, as opposed to the shipper-friendly variety. Furthermore, commercial tomatoes are increasingly grown in greenhouses to provide year round consistent quality. Consumers, however, are more likely to prefer the taste of traditional field-grown tomatoes

Consumer-minded decision making in agricultural production is a growing trend, and as stated above, the SuperT tomato is a proprietary variety carefully chosen for its consumer traits, instead of its growing and shipping traits. Growing and marketing these premium tomatoes requires more care and cost than traditional commercial production. It requires a grower who is willing to provide extra care to produce a premium variety economically. Many premium varieties are more sensitive to environmental factors, such as soil types, pests, and weather conditions than their commercial counterparts. It also takes an added incentive for agricultural producers to change their traditional farming practices and experiment with novel varieties. In the SuperT production system, growers are given the costly proprietary seed for free and receive top market prices for their produce.

The SuperT producers are also protected from low demand or high supply. If production exceeds demand for the SuperT tomato in any given week, MaterCo pays the contracted producers a portion of the average market price for those tomatoes that go to waste. This market protection is important due to the specialty nature of this tomato. With traditional commodity varieties there are alternative channels that can be used to move excess production. Since the SuperT is a branded product, MaterCo does not want this tomato to be sold through secondary channels, because of the potential harmful impact on brand image and price points. Furthermore, the SuperT is sold under contract to specific grocery retailers for semi-exclusive distribution.

Another alternative to leaving the excess fruit in the field would be to promote the sales through price discounts. This can be a very effective demand management tool, but will not work in every case of excess production. Too many promotions damage the ability of MaterCo to keep the high price point necessary to economically produce and market the SuperT.

The SuperT is also an indeterminate variety, meaning that it will produce fruit for multiple pickings. Pickings typically occur once or twice per week. Alternatively, the most common variety of tomatoes grown, called "Rounds," are picked only once. Multiple weeks of picking increase the difficulty of modeling the expected yields, because environmental conditions that affect yield and harvest can change from week to week. Furthermore, the harvest window, or potential weeks where picking is possible, may be dictated by external factors such as the labor availability of picking crews. The schedule of picking crews is driven by large commercial acreage, not specialty niche varieties. Once the large commercial acreage has been picked in a region, the picking crews are likely to move to another geographic region for picking, even if it is still possible to pick fruit from the SuperT plants. Since the SuperT is a premium tomato and an indeterminate variety, it doesn't require a large number of acres, and therefore doesn't have the economic power to dictate picking schedules.

Another characteristic of the SuperT tomato is that the production is solely in geographies east of the Mississippi river. It is not unusual to have tomatoes grown in Florida, but the finest quality SuperT tomatoes are produced as far north as Michigan. Other potential production geographies include Tennessee, Georgia, and North and South Carolina. Each of these geographies has different planting and harvesting windows (i.e. range of weeks) that must be considered when making production planning decisions. In addition, each of the geographies has different production economics in terms of local market prices, cost of production, and cost of transportation to the repacking facility.

Once the SuperT tomatoes are harvested from the field they are shipped in boxes, by truck, to a central repacking facility. The tomatoes undergo a quick quality inspection before they are picked from the vine, to determine appropriate size and maturity, and again when they are loaded on the trucks. At the repacking facility, the tomatoes are once again inspected for quality, and only those that meet the SuperT brand standards are carefully cleaned and placed into plastic clamshells with the appropriate retail labeling. Once the tomatoes are placed in the clamshells they are essentially ready for retail sales. The clamshells are then packed into cases for further transportation to the retailer distribution centers. Unless there is a full truckload of SuperT tomatoes, which is unlikely since they are a specialty item, the tomatoes will travel to the grocery retailer with other tomatoes and assorted produce. The consolidation of fresh produce into full truckloads is an important value-added service of the repacker that keeps transportation costs to a minimum. In other fresh produce supply chains, it is possible for the repacking function to be at the farm. In that case, the produce is shipped from the field directly to the grocery retailer.

The SuperT tomatoes are sold to grocery retailers by a marketing agent who represents the repacker. The repacker is responsible for the financial transactions with the SuperT growers and with the grocery retail customers, on behalf of MaterCo. Grower prices are determined based on a percentage markup of local market prices. Retail prices are negotiated with each weekly or bi-weekly shipment of produce. The prices are set at a level that ensures appropriate margins for both the retail customer and the MaterCo supply chain. The repacker's operating expenses (materials, labor, shipping, administration, and raw product costs) are reimbursed at cost from MaterCo's profit. The remaining net profit is shared between MaterCo and the repacking partner, at a previously agreed upon split.

2.2 Role of supply chain integrator

MaterCo's role in the SuperT supply chain is supply chain integrator. MaterCo owns and licenses the proprietary SuperT genetics (seeds) to select growers, with whom they maintain close relationships. MaterCo works with the repacker(s) to select and sell appropriate growers on the SuperT concept. MaterCo also jointly sells the SuperT tomatoes to new retail customers and provides on-going sales and marketing support. MaterCo takes ownership of the SuperT tomatoes when they leave the farmer's field until they are sold and delivered to the grocery retailer. They also oversee the SuperT supply chain to ensure that the brand standards are being upheld, in terms of quality, consistency, and environmental consciousness. In addition, MaterCo organizes and facilitates the SuperT in-store merchandising support at the retail level and takes full ownership and stewardship responsibility of the SuperT brand on each package of tomatoes.

To be an effective agriculture and food supply chain integrator, MaterCo's primary challenge is to spread the risk and profits of the system fairly among the supply chain participants. Many coordinated supply chains in food and agriculture fail because of imbalances of risk and reward among the supply chain participants. The farmers need an incentive to change their traditional production practices. They must also be compensated for the augmented yield risk, as the specialty variety is not as hardy in the field as traditional varieties. Furthermore, the farmer faces the potential market risk that the demand for the specialty tomato does not meet expectations. The repacker is also risking their valuable and long-standing relationships with growers and grocery retailers if the new venture fails. Damaging these relationships could also potentially damage the remainder of the repacker's business. The repacker, therefore, deserves to be compensated for their change of behavior and increased risk as well. At the same time, MaterCo must determine an appropriate level of risk and return from the new venture that they are willing to accept.

Arguably the most important supply chain participant in this premium fresh produce system is the grocery retailer. Without sufficient sales of the new product to consumers, the new venture would never even start. For the grocery retailer to support the SuperT supply chain, they also need a financial advantage to deviate from their traditional suppliers and products. This advantage can be a higher retail margin on the product, or in the case of SuperT, extensive retail merchandising support. On the other hand, premium branded products also bring new customers into the store and can enable the retailer to maintain higher price points and sales throughout the entire retail merchandising category. Quantifying these externalities is an area in need of further research. It may be the case that a grocery retailer can accept lower margins on a premium branded product due to the positive revenue effect on the category as a whole.

2.3 Current production planning practices

To test the validity of the proposed approach, it is important to understand how current supply decisions, i.e. production plans, are made within MaterCo. Similar to other agriculture-based businesses, planning decisions are made primarily with industry accepted heuristics and knowledge based on past experience. Though this may seem like simple gut-level decision making, the years of experience and expansive knowledge influencing production decisions should not be underestimated. Many agricultural production businesses have been successful at managing the inherent business risks for generations. Nevertheless, while the current decision-making framework appears to work, it may not be finding optimal solutions in all cases. Though risks are recognized and managed under the current decision-making systems, they are seldom quantified enough to be used in making even more effective decisions. Often, current production planning practices neither quantify risk on the demand side nor the supply side.

The SuperT sales forecasts are currently extracted from the business plan. The business plan is used to justify investment in the new product venture, and the assumptions and data used to forecast SuperT's sales are the best available. Since SuperT is a new product, no historical sales data is available. Once a sales history is established, more sophisticated demand forecasting techniques may be employed, but that is not the focus of this thesis. The primary issue with the business plan's sales forecast is that it is a point forecast.

On the supply side, yield forecasts and simple heuristics are used to determine the appropriate planted acreage to meet forecast demand. The weekly yield forecasts are point forecasts derived from the average weekly yield of growing trials. The number of potential harvest weeks, since this is an indeterminate variety, is also derived from the trial data. To account for yield variability from week to week and the uncertainty of a large scale crop failure because of unpredictable weather, a common heuristic used by production managers is to plant redundant acreage. Often this "double" acreage is in another location of the same latitude. The tomato producers call this "pairing" because plantings occur in pairs, starting on opposite coasts of Florida and moving up the Eastern U.S. in parallel. For example, plantings in Tennessee and North Carolina occur roughly on the same dates, as well as plantings in Michigan and New York State. Doubling may also occur within the same geography. As long as the redundant acreage is not in the same field, the chance of the entire crop being destroyed is reduced. Although this is the observed practice, more sophisticated models do exist for production planning in agriculture.

3 Literature Review

Many mathematical programming approaches to production planning are suggested in academic literature, but it is unclear how many of them, if any, are widely used in industry. This may be due to the complexity of the modeling approaches, lack of computing power available to producers, or lack of reliable data for inputting into the models. Most likely, limited acceptance of mathematical programming by farm-level production managers is because of few widely known practical applications that demonstrating the financial benefits. The majority of theoretical math programming approaches suggested in literature are not applied pragmatically for relevance to producers.

This research is builds upon mathematical programming theory in literature and provides a practical tool that production managers can use. The suggested approach adds to existing literature by taking a holistic supply chain view of production planning and incorporating real life uncertainties in both demand and supply. Profit maximizing production plans, for supply chain integrators (e.g. MaterCo), are tied to customer service levels at the grocery retail level. In this way, the two stage planning algorithm, on which this research is based, provides production managers an understanding of the trade-off between expected profit and customer service for better decision-making. Previous research in this area either lacks the inclusion of both agriculture supply and demand risk, or ignores the impact of production decisions on customer service.

3.1 Operations research in production planning

It is now over 50 years since Thornthwaite (1953) published a practical operations research approach to production planning. His approach survives the test of time, as Kreiner suggests in 1994 that practices based on Thorntwaite's methodology "have remained in use unchanged for over forty years" (Kreiner, 1994, p. 987). Thornwaite (1953) proposed using information of downstream demand to determine appropriate planting dates, based on measured growth rates and environmental factors. His approach is sound, but self-proclaimed to be limited by the exclusion of uncertainty.

3.2 Incorporating uncertainty

This thesis seeks to include uncertainty (random variables) in the production planning process to demonstrate the potential impact of uncertainty on profitability and the trade-offs between various production planning decisions. By recognizing and quantifying uncertainties, it is argued that management will be able to make better decisions. This approach is supported in literature. For example, Antle argues with his risk-efficiency hypothesis that "it is necessary to model and measure the dynamic structure of agricultural production to be able to evaluate the effects risk has on agricultural production and income" (Antle, 1983, p. 1102). Jolly concurs, by advocating agricultural managers' thinking in a "distributional" sense, but stresses the difficulty of estimating the relevant probability distributions, and the danger of overconfidence in a manager's ability to judge variance (Jolly, 1983, pp. 1110-1111).

The suggested two-stage planning algorithm in this thesis represents the probability distributions of demand and yield by their means and standard deviations. Demand and yield are represented with a normal distribution, where expected values are used to approximate the means and the variances are derived from empirical analysis of similar products. Other authors suggest that the random variables can be better approximated using more advanced analysis techniques and empirical data, such as Gaussian Quadrature (Lambert & McCarl, 1985; Preckel & DeVuyst, 1992). This can be particularly helpful with non-linear optimization models. Though using Gaussian Quadrature is arguably a more accurate approach, the product modeled in this thesis research is a new product and lacks the empirical data to perform this analysis. In the future, when adequate historical data exists, more accurate distributions for demand and yield can be substituted. Furthermore, maintaining simplicity of the suggested approach is important to achieve management buy-in. Therefore, the use of normal distributions can be justified.

3.3 Game theory

Some literature suggests a game theoretical approach to production planning, where a number of states of nature are defined and the optimal farm plan is determined for each potential state of nature. The payoff matrix can be used by the production manager (i.e. farmer) to evaluate the production plans based on their performance under the different states of nature, as well as the production manager's risk tolerance and business obligations (Tadros & Casler, 1969). Essentially, this is the suggested approach of this research thesis. The states of nature are different levels of demand and yield, determined by various certainty levels on their respective cumulative distribution functions. In the suggested two-stage planning algorithm, the production strategies (i.e. planting quantity, timing, and location) are determined in the first stage of the algorithm as the result of mixed integer linear programming optimization for each demand and yield level combination. In the second stage of the algorithm, the pay-off for each of the different potential production strategies is determined using simulation, which allows the user to evaluate each strategy's probability-weighted performance across all states of nature, as opposed to each state of nature discretely.

3.4 Risk programming

Other literature for farm planning under uncertainty suggests a risk programming approach, using different utility maximizing functions to determine the optimal farm plan among alternative solutions based on assumed risk-neutrality or risk-aversion of farmers. Examples of these risk programming approaches include Quadratic Risk Programming, MOTAD, Target MOTAD, and Mean-Gini programming. In these methods, a set of solutions are generated that meet a certain output criteria, such as minimum income or utility, and then the solution is selected with the least variance around the expected outcome (Hardaker, Pandey, & Patten, 1991).

Other literature suggests an approach that directly maximizes the producer's utility through non-linear programming, such as the Utility Maximization approach, if the farmer's utility function is known, and the Utility-Efficient Programming method if the utility function is not exactly known (Hardaker et al., 1991). Both of these approaches attempt to determine the optimum solution by modeling the producer's attitude towards risk.

Discrete Stochastic Programming (DSP) appears to be an approach to risk modeling much favored by literature, because it can incorporate sequential decisions (Hardaker et al., 1991). The problem noted with DSP is how the size of the problem can quickly become unmanageable.

An alternative to DSP, while still incorporating sequential decisions, is a combination of simulation and stochastic programming, suggested by Trebeck and Hardaker (1972). They utilize stochastic linear programming, simulation, and parametric stochastic programming to make optimal cattle production decisions regarding sequential stocking and pasture utilization decisions.

Though the tomato production planning researched in this thesis could similarly be analyzed as a sequential decision problem, it is instead suggested that the planting decisions be considered as a single-period problem. The model can then be re-run multiple times throughout the actual year with updated inputs, as better demand and yield information become available. This makes the model simpler to program and use.

The purpose of this research is not to provide a tool that predicts the future profit for the manager, but aid the manager to make a set of profit maximizing decisions. The suggested approach in this research does not attempt to determine the optimum production plan for the producer, but instead provides the information necessary for the manager (i.e. producer) to make a better decision based on their own individual circumstances and objectives, similarly to Tadros and Casler's (1969) suggested approach. This point is also made in Antle's (1983) paper, where he argues that it is not as important to determine the exact risk profile of the producer, but that tools should be developed to help the producer better understand the risks, so they can make better decisions based on a set of individual preferences, regardless of those exact preferences.

3.5 Chance constrained programming

Another method suggested is chance-constrained programming, where critical levels of probabilities are chosen for each random variable, thus rendering the random variables deterministic for inputting in to the optimization constraints (Charnes & Cooper, 1959). Hardaker et al. (1991) dismisses this approach because selections of the critical levels of probabilities are part of the decision input, and considered arbitrary. On the other hand, these critical probabilities don't have to be arbitrary, as this thesis suggests correlating the critical probabilities to meaningful customer service levels through simulation in the second stage of the algorithm. Yano and Lee (1995) voice surprise at the fact that more "constraints on various measures of service have not been considered in lieu of shortage costs," especially considering how important a measure this is in literature when considering situations of random demand.

3.6 Newsvendor approach

In fact, customer service levels were chosen as the primary constraints in the suggested approach, because of their importance in maintaining customer relationships and the difficulty of the alternative newsvendor approach. A newsvendor-model approach assumes that the overage and underage costs can be estimated. The overage costs for perishable item can be estimated easily, but estimating the life-time value of a lost customer due to poor service levels (i.e. underage) is very difficult.

Nevertheless, Jones, Lowe, Traub, and Kegler (2001) use a newsvendor-model approach with seed corn planting decisions and estimate the underage cost as two years of lost sales (Jones, Lowe, Traub, & Kegler, 2001; Jones, Kegler, Lowe, & Traub, 2003). The Jones et al. (2001) model is interesting, as it also involves allocating production acreage optimally between multiple regions, including the different costs involved between production regions. It is the only model that appeared in the reviewed literature to determine the optimum location and quantity of planted acreage for one crop, similar to the problem addressed in this research.

Allen and Schuster (2004) also use a newsvendor approach to determine the appropriate harvest rate of grapes. The Allen and Schuster (2004) article is important because it is unique in considering the risk of harvest failure. Risk is addressed in their model through the analysis of joint probability distributions. This research seeks to build on the work of Allen and Schuster by incorporating the chance of harvest failure, but evaluating uncertainty through simulation.

3.7 Minimum customer service levels

In production planning decisions for a traditional farm, as most of the available literature appears to address, service levels are not of importance, because the producers are selling to the commodity market. In these cases, the uncertainty of price is more important than the uncertainty in demand. Perhaps the two most cited papers for stochastic programming in farm planning both include price or margin uncertainty, but neither include demand uncertainty (Cocks, 1968; Rae, 1971). In Lowe and Preckel's (2004) review of operations research applications in agricultural business, only the Jones et al. (2001) paper is cited as incorporating demand uncertainty, as opposed to price uncertainty. For niche premium agriculture, the focus of the problem is reversed. Prices are premium with these products and have less variance compared to commodity products, but consumer demand, at least in the initial growth stages of the product life-cycle, is more unpredictable. Plus demand is limited, which is not usually the case with traditional commodity agriculture.

Many case studies exist in literature that use risk modeling techniques to evaluate farm production planning decisions, but most are concerned with cropping mix decisions under price uncertainty. For example, Manos and Kitsopanidis (1986) look at the appropriate cropping mix for Central Macedonian farms using a quadratic programming model. Musshoff and Hirschauer (2007) actually use empirical data to test the performance of risk programming as a decision tool for crop mix decisions as compared to traditional heuristics on German farms. A well publicized case, since it was submitted to the Edelman competition, is the Jan de Wit optimization of greenhouse space to the production of different lily flowers (Caixeta-Filho, van Swaay-Neto, & de Padua Wagemaker, 2002). In the Jan de Wit case straight linear programming is used, with no inclusion of uncertainty in the model.

Alternatively, Trebeck and Hardaker (1972) focus on one commodity and look at cattle stocking levels and pasturing decisions using a mix of simulation and stochastic programming. Ludena, McNamara, Hammer, and Foster (2003) look at a single cultivar, for greenhouse flower production, to demonstrate the benefits of simulation for decision analysis and budgeting. None of the farm planning research reviewed, however, considers customer service levels as a constraint in the programming.

3.8 Adding to the literature

Recognizing that this is not a comprehensive review of risk programming literature as it applies to agricultural production planning, the research in this thesis is considered unique in terms of the focus and constraints. First, no mathematical farm planning models in the reviewed literature address the case of premium fruit and vegetable production. This is probably because of the recent development of this market. Therefore, none of the proposed models truly consider limited demand of a perishable product. Even the Jones et al. (2001) research allows the seed corn to be carried over for one year and sold in the next planting season.

Without considering limited demand, the existing research does not provide production plans that target specific customer service levels. By recognizing customer service as a planning goal, the suggested two-stage planning algorithm takes a unique holistic supply chain view for agriculture production planning. Increasingly agricultural production managers must understand and consider the needs of their downstream customers. The farm-level focus of risk programming, as covered in existing literature, still has value for commodity producers, but premium crop producers need broader planning tools.

Furthermore, the existing literature typically suggests single stage models for problem solving, whereas this research suggests a two-stage mixed integer linear programming (MILP) and Monte Carlo simulation. The simulation, as a second stage to the proposed algorithm, is a relatively simple way to test the expected customer service levels of production plans output from the first stage MILP. The complexities of including customer service constraints into a one-stage optimization did not appear practical for widespread application by agricultural production managers. In addition, instead of trying to define a particular production manager's optimal solution based on their perceived risk preferences, the suggested two-stage planning algorithm allows production managers to determine their own acceptable risk levels. Details of the suggested two-stage planning algorithm follow in the next section.

4 Methodology

The core of this research is a two-stage planning algorithm, but preliminary work is necessary to understand and model the SuperT supply chain, as well as populate the model with relevant data.

First, information is gathered about the existing supply chain structure from production managers at MaterCo, particularly the dynamics and risks.

Second, the understanding gained in the first step is used to develop a model of the SuperT supply chain. Through the model building process, the production managers must quantify the cost and volume relationships in the fresh produce supply chain, including the uncertainties. The core of the modeling approach is to incorporate the random nature of demand, yield, and harvest failure and understand their impact on realized customer service levels.

Third, the inputs are defined for the model. The inputs include relative costs for different production decisions. The distributions of demand and yield are represented in the model by their respective means and standard deviations.

Fourth, an algorithm is used that alternates between a mixed integer linear program (MILP) and a Monte Carlo simulation until a desired level of customer service is reached. In the first stage of the algorithm, certainty levels are chosen for the random demand and yield. These certainty levels are probabilities on their respective cumulative distribution functions. The corresponding targeted levels of demand and yield are used as deterministic inputs in the optimization model.

Fifth, in the second stage of the algorithm, the solution from the optimization model is run through a simulation where the realized Type I Customer Service Level can be observed. The Type I CSL is the percentage of demand cycles where demand is expected to be met in full.

The process is repeated with an adjustment to the certainty levels until desired customer service is achieved. This idea is illustrated in Figure 2.

The following steps are a broad outline of the proposed process:

1. Understand the current supply chain dynamics and risks
2. Model the supply chain dynamics and risks
3. Define necessary inputs and assumptions
4. Stage One of Algorithm: Find optimal solution based on critical levels of demand and yield
5. Stage Two of Algorithm: Run solution through a simulation to develop probability distribution of customer service and profitability
6. Repeat steps 4 and 5 until desired customer service level is achieved

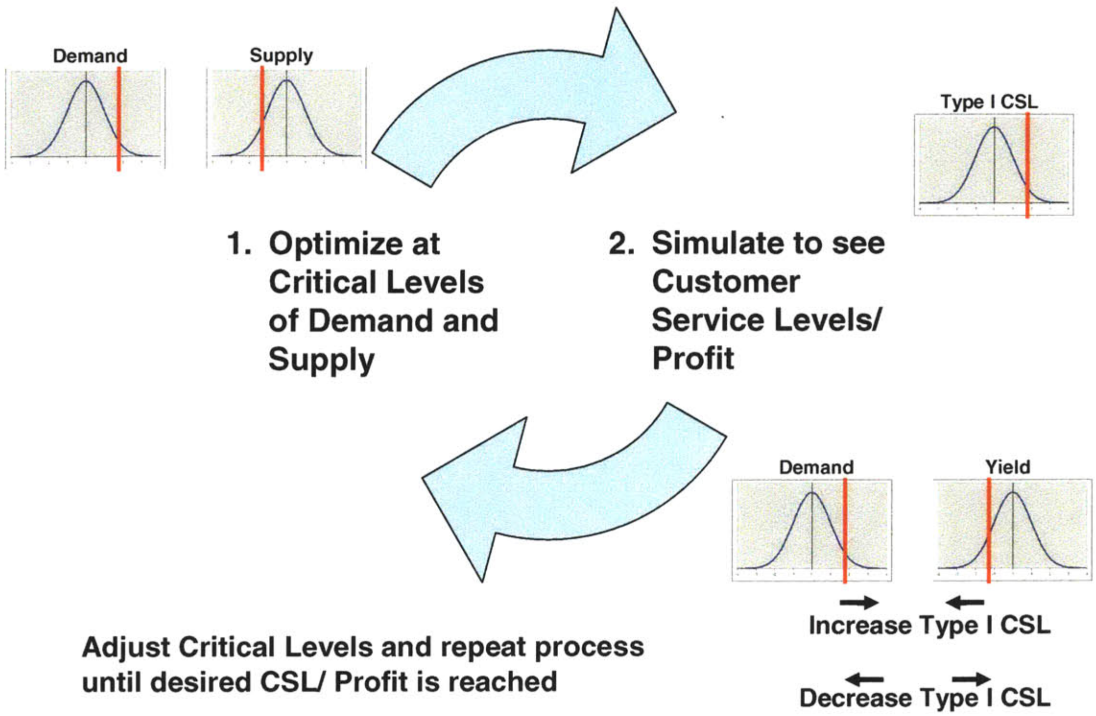


Figure 2: Two-stage planning algorithm

4.1 Understanding the current fresh produce supply chain dynamics and risks

The first step in developing a better solution to the challenges in the fresh produce supply chain is to gain a deeper understanding of how the supply chain is structured and operates. This is best accomplished starting with a thorough mapping of the physical supply chain. Following the mapping, information on the decision-making process and cost and service trade-offs can be gathered from supply chain participants. It is also important to understand how costs, risks, and profits are distributed among supply chain participants. For this thesis, all the information regarding the SuperT supply chain was gained through conversation with MaterCo management. Figure 3 is a representative map of the SuperT tomato physical supply chain. The dotted lines represent MaterCo's relationships. The solid lines represent the physical flow of product.

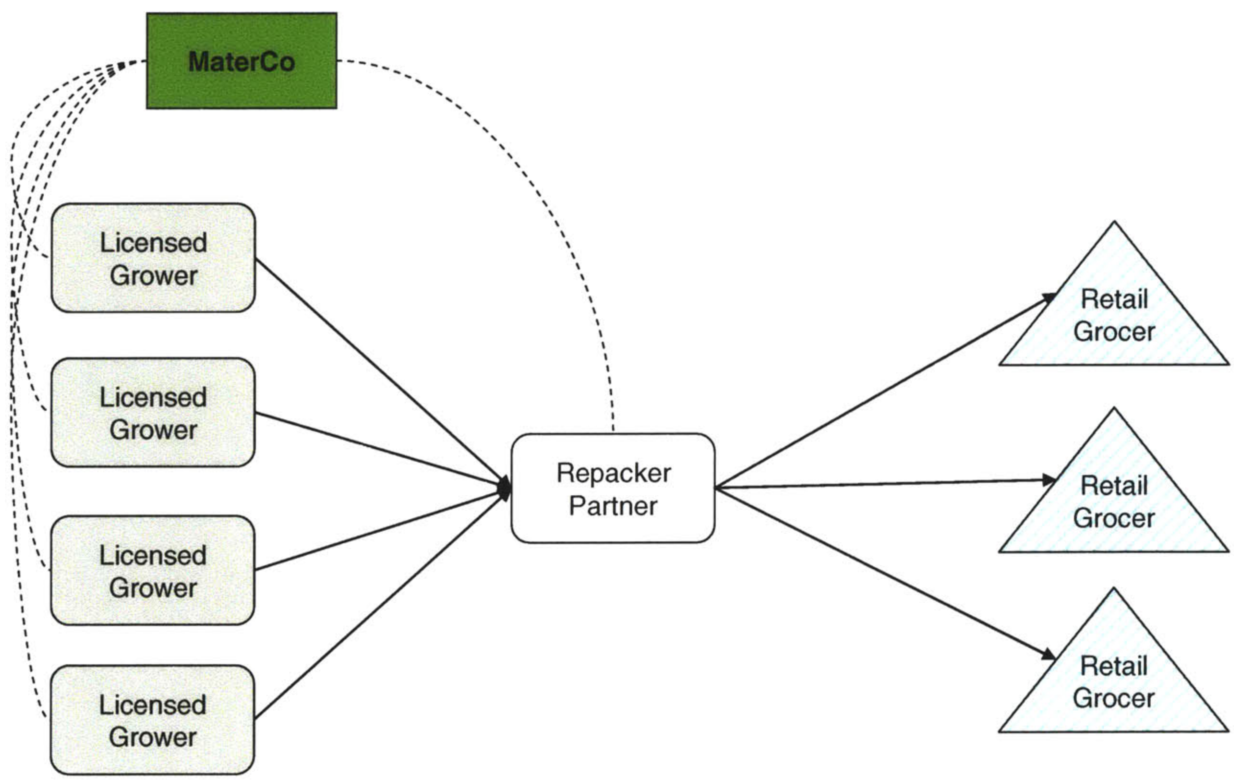


Figure 3: Overview of SuperT supply chain

4.2 Modeling the fresh produce supply chain

The second step is to develop a mixed integer linear programming model that represents the supply chain dynamics and risks, as accurately as possible. The model is input into Excel where the interaction between quantity, location, and timing of planted acres with costs, revenues, and satisfaction of demand can be programmed. This allows the user to both optimize the model for a given set of inputs and simulate uncertainty through random trials. A visual representation of the model is shown in Figure 4. The shaded figures are inputs. The clear figures are calculations. The striped figure is the objective function.

The number of acres to plant in a given geography is designated as the decision variables in the model. The model is formulated so that the planted acreage decisions will compute an expected pack out quantity, which has been adjusted for risk and shrink. Yield is input as a normally distributed random variable. Though yield may not be normally distributed in reality, it is assumed normal for simplification of the model. The expected yield level is calculated based upon a predetermined critical level, referred to as the Production Certainty Level (PCL), related to a probability on the cumulative distribution function of yield.

The Production Certainty Level (PCL) is not an existing convention in production planning decisions. Traditional production planning decisions are based upon a deterministic yield level approximating the average. This modeling approach attempts to capture both the reality of uncertain yields and the associated risks. The PCL gives the producer a yield level for decision making purposes at a pre-determined level of confidence.

(shaded = inputs, clear = calculations, striped = objective)

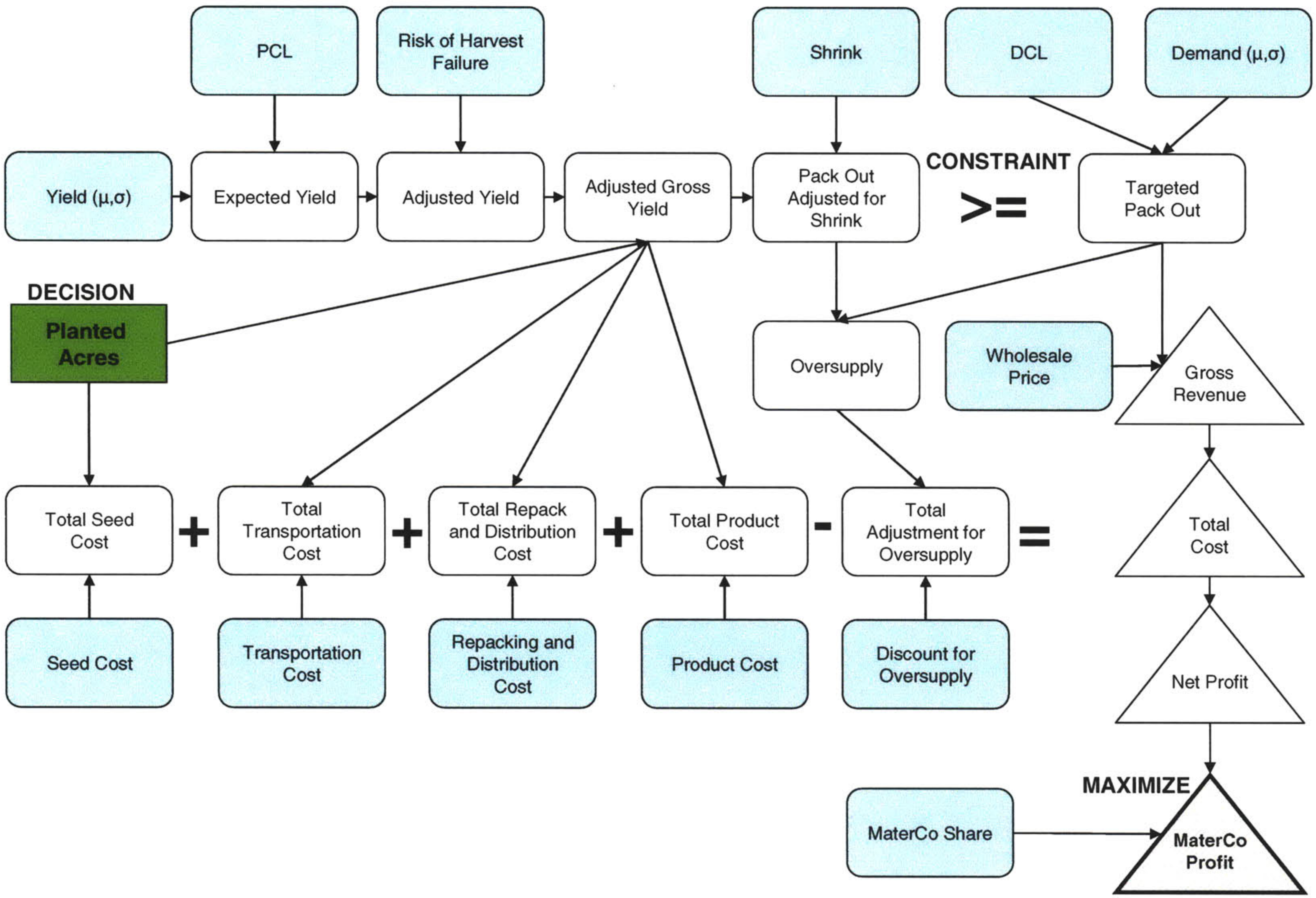


Figure 4: Overview of the model

This adjusted yield is multiplied by the acres planted to determine an expected pack out quantity. Eligible weeks of harvest are constrained by a Risk of Harvest Failure that adjusts the yield to zero in weeks outside of a realistic planting window. The expected pack out quantity is then compared to the quantity necessary to meet demand at a predetermined critical level, referred to as the Demand Certainty Level (DCL). Demand is also input as a normally distributed random variable. Though demand may not be normally distributed in reality, it is assumed to be normal for simplification of the model. The mathematical formulation follows:

Objective function

$$\begin{aligned}\text{max profit} = &\sum_{i=1}^{n} W_i S_i \\ &- \sum_{i=1}^{n}\sum_{j=1}^{m}\left[\left(P_{ij}+T_{ij}\right)\left(\sum_{b=1}^{n} E_{bij}X_{bj}+Z_{ij}\right)\right] \\ &- \sum_{i=1}^{n} U_i\left[(1\text{-}\delta)\sum_{j=1}^{m}\left(\sum_{b=1}^{n} E_{bij}X_{bj}+Z_{ij}\right)\right] \\ &- \sum_{b=1}^{n}\sum_{j=1}^{m} C_{bj}X_{bj} \\ &+ \sum_{i=1}^{n} O_i\left[(1\text{-}\delta)\sum_{j=1}^{m}\left(\sum_{b=1}^{n} E_{bij}X_{bj}+Z_{ij}\right)-S_i\right]\end{aligned}$$

Subject to:

(1.1) $\quad (1\text{-}\delta)\sum_{j=1}^{m}\left(\sum_{b=1}^{n} E_{bij}X_{bj}+Z_{ij}\right) \geq S_i \qquad \forall i$

(1.2) $\quad X_{bj} \geq 0 \qquad for\, b+L_j \leq\ i < b+L_j+H_j$

(1.3) $\quad X_{bj} \geq 0 \qquad \forall b, j$

(1.4) $\quad X_{bj} - MY_{bj} \leq 0 \qquad \forall b, j$

(1.5) $\quad X_{bj} - \gamma Y_{bj} \geq 0 \qquad \forall b, j$

Decision variables

$X_{bj} =$ acres planted in location j in week b
$Y_{bj} = 1$ if planting occurs in location j in week b, 0 if planting does not occur in location j in week b

Subscripts

i = harvest week of year (1 to 72)
b = planting week of year (1 to 72)
j = potential planting geography

Other Variables

$W_i =$ wholesale price in week i (per case)
$\delta =$ percent product volume shrink due to transportation and handling
$E_{bij} =$ adjusted yield per acre during harvest week i from location j for planting in week b (lbs)
$Z_{ij} =$ harvested quantity expected in week i from plantings occuring in prior year from location j (lbs)
$P_{ij} =$ product cost in week i in location j (per lb)
$T_{ij} =$ transportation cost from field to repacker in week i from location j (per lb)
$U_i =$ cost to repack product and distribute from repacker to retail customers in week i (per finished case)
$C_{bj} =$ cost of seed in week b at location j (average per acre)
$O_i =$ cost adjustment for oversupply quantity in week i (per case)
$S_i =$ targeted total system wide packout quantity in week i (cases)
$H_j =$ harvest length in location j (weeks)
$L_j =$ lead time for plant growth in location j (weeks)
M = a sufficiently large number to ensure logic constraints for binary variable Y
(M should be at least as large as the maximum number of acres for each planting)
$M = \max \left[X_{bj}\right] \qquad \forall b,j$
$\gamma =$ a minimum quantity of acres required for a planting to occur

The objective of the model is to maximize total profit over the planning horizon. The objective function has five terms. The first term captures the revenue gained from produce harvested and sold. The second term captures the product and transportation costs associated with harvested produce. The third term captures the cost of distribution from the repacking facilities to the actual customer locations, as well as a shrinkage factor. The fourth term captures the cost of seed for growing the produce. The fifth and final term is a cost adjustment for excess production that is purchased at a discounted price, and never sold, transported, or repacked.

Constraints (1.1) ensure that the total quantity of produce grown meets the quantity demanded for each week. Constraints (1.2) ensure that planting and harvesting for a specific location follows prescribed harvest windows and lead times. Constraints (1.3) ensure non-negativity.

Constraints (1.4) ensure the binary logic, that Y will equal 1 if a planting occurs. Constraints (1.5) ensure that any planting meets a minimum quantity of acres. This threshold acreage level is based on realistic production practices.

Following is a detailed description of how the elements are developed.

Description of Objective Function

The objective of the model is to maximize profit. The total revenue is calculated from the targeted packout quantity, based on demand. It is not calculated on total production, because in cases of oversupply not all of the product will be sold. Furthermore, the model is constrained so that demand is met in each week. Total cost includes the seed cost, product cost at farmgate price, the transportation cost from the field to repacker, the repacking cost, and the cost to distribute from the repacker to the retail customers (payment to re-packer).

The product cost and transportation cost to the repacker are multiplied by the production from each region in a given week of harvest(i). In contrast, the cost to repack the product and distribute to the retail customer is multiplied by the finished cases that are delivered to the retail customer. Finished cases include a shrink factor. The seed cost is the cost of seed per acre multiplied by the number of acres (i.e. decision variable) in a given week of planting (b).

The last cost is the adjustment for oversupply. Oversupply is determined by the difference in the total adjusted packout quantity and the targeted pack out quantity. The adjustment for oversupply is equal to a discount of the average grower price and average costs of transportation, repacking, and distribution. The grower price is included at a discount because producers will likely demand a payment close to what they would have received if their product were actually sold. The oversupply adjustment is in dollars per finished case.

Description of Decision Variables

The primary decision variable is how many acres to plant in each geography (j) in which planting weeks (b). The second decision variable is a binary integer that indicates whether or not a planting has occurred. The binary variable is necessary for constraining the minimum number of acres for each planting. The minimum acreage threshold ensures that the model outputs more realistic planting patterns.

Description of Subscripts

This is an indeterminate tomato variety (multiple weeks of harvest) so the planting week is separate from the harvest week in order to determine the sequential week of harvest. The weeks go to 72, instead of 52, to allow a cool down period to the model. Without the extra weeks, the model would not plant any acres in the last part of the current year and result in inadequate supply for the following year (i.e. weeks 53-72).

Description of Demand Inputs

D_i = forecast demand in week i
$f(D_i)$ = p.f. of demand in week i with mean, μ_{D_i}, and standard deviation σ_{D_i}
DCL = Demand Certainty Level
$p_{u\geq}(k) = 1 - DCL$
S_i = targeted packout quantity in week i, based on DCL
$S_i = \mu_{D_i} + k\sigma_{D_i}$

The targeted pack out quantity is defined based on a random, but normally distributed, demand and a desired Demand Certainty Level (DCL). The level of demand is from a predetermined sales forecast.

Description of Price and Cost Inputs

W_i = Wholesale price in week i (per case)
P_{ij} = product cost in week i in location j (per lb)
T_{ij} = transportation cost from field to repacker in week i from location j (per lb)
U_i = cost to repack product and distribute from repacker to retail customers in week i (per finished case)
C_{bj} = cost of seed in week b at location j (average per acre)

The wholesale price is the price that the firm receives from the retailer during weekly price negotiations in week i. This price is dollars per case.

The product cost is the price that the firm must pay to the growers to procure the tomatoes in harvest week i. This cost is dollars per pound.

The transportation cost from the field to the repacker is the amount of money that the firm must reimburse the repacking partner for transporting the crop from the field to their repacking facilities in harvest week i. This cost is dollars per pound. In this model, transportation cost is assumed to be deterministic.

The repacking and distribution cost is the money paid to the repacking partner to reimburse them for repacking the product and distributing to the retail customers. The repacking cost includes the cost of the materials (e.g. boxes, stickers, clamshells) and the cost of labor. This cost is paid to the repacker per finished case.

The cost of seed is the internal cost of the seed that the firm gives free to growers as an incentive to produce. This cost is dollars per acre in planting week b. This can also be representative of any "setup" cost that a firm must pay to a supplier for a production run.

O_i = cost adjustment for oversupply quantity in week i

$O_i = \alpha\beta\overline{P}_i + \beta\overline{T}_i + \overline{U}_i$

α = % of average product cost (grower market price) discounted on oversupply purchases

β = number of lbs in one case

$\overline{P}_i$ = average product cost (grower market price) in week i (per lb)

The adjustment for oversupply subtracts those costs that would not be incurred for excess production that is left in the field. This cost is dollars per case. First, only a proportion of the average product cost, i.e. average market price in harvest week i, which the grower would have received if the crop had been actually sold to retailers, is paid to growers. An average market price is used across all regions, because it is not possible to allocate oversupply to a particular region. Secondly, the transportation, repacking, and distribution costs are subtracted, as they would not be incurred. An average across all regions is also used for these costs to avoid the need to allocate oversupply to a particular region.

Description of Supply Inputs

H_j = harvest length in location j (weeks)
L_j = lead time for plant growth in location j (weeks)
week i (of D_i) $-$ 1 = harvest week i $\forall$ j
n_{bij} = sequential week of harvest for planting in week b and harvesting in week i in location j
n_{bij} = i(harvest week) - L_j $-$ b(planting week of X_{bj})
$0 < n_{bij} \leq H_j \ \forall \ n_{bij}$
$\Pr[H_{bij}]$ = probability of successful harvest in harvest week i
from location j for planting in week b (100% for all eligible weeks)

The probability of a successful harvest depends on the eligible weeks of harvest. The eligible weeks must have a sequential week of harvest greater than zero and less than or equal to the maximum harvest length. The sequential week is calculated based on the planting week (b), harvest week (i), and the lead time needed for plant growth (L).

A_{ij} = yield per acre during harvest week i in location j (lbs)
$f(A_{ij})$ = pdf of yield per acre during harvest week i in location j with mean $\mu_{A_{ij}}$,
and standard deviation $\sigma_{A_{ij}}$
PCL = Production Certainty Level
$p_{u\geq}(k) = 1 - PCL$
B_{ij} = assured yield level during harvest week i from location j, based on PCL
$B_{ij} = \mu_{A_{ij}} - k\sigma_{A_{ij}}$ where $n_{bij} > r_j$
$B_{ij} = \lambda\left(\mu_{A_{ij}} - k\sigma_{A_{ij}}\right)$ where $n_{bij} \leq r_j$
r_j = length of ramp-up period where full yield is not achieved in location j (weeks)
λ = ramp-up factor (percentage of full yield potential achieved during ramp-up period)

The yield used for the planning purposes of the model is based on a normally distributed yield and a desired Production Certainty Level (PCL).

The assured yield is a level that the firm can be assured of achieving at the desired level of certainty. The units for this are lbs per acre. A ramp-up period is included to account for the reduced yield during the initial weeks of harvest.

E_{bij} = adjusted yield per acre during harvest week i from location j for planting in week b (lbs)

$E_{bij} = \mathrm{B}_{ij} \Pr[H_{bij}]$

The assured yield is multiplied by the probability of a successful harvest to give an adjusted yield per acre for all planting week-harvest week combinations. The units for this are lbs per acre.

$\delta =$ percent product volume shrink due to transportation and handling

Total assured quantity packed out during harvest week i from all locations

$$= (1\text{-}\delta)\sum_{j=1}^{m}\left(\sum_{b=1}^{n} E_{bij} X_{bj} + Z_{ij}\right)$$

The adjusted yield for that planting week-harvest combination is multiplied by the number of acres planted in that location for that planting week. Then, the harvested quantities in that location, from all plantings that can be harvested that week, are summed. This includes any expected harvest quantities from plantings occurring in the prior year. Finally, the total assured quantity packed out during a given harvest week is the sum of the assured quantities harvested from all locations, discounted for estimated product shrink.

4.3 Inputs and Assumptions

The data for this model is from management at MaterCo. The data is transformed for reasons of confidentiality. The data is categorized into four primary pieces: demand, supply, costs, and revenue.

Demand

The demand data is taken directly from the SuperT sales forecast (Figure 5). Analysis of the sales forecasting process is not in the scope of this research, so the expected sales volumes per week are input directly into the model as the mean demand. The standard deviation of demand is derived from historical sales of a similar premium tomato, since there was no sales history for the SuperT at the point in time that this thesis was written. The coefficient of variation for this similar product is calculated and applied to the mean demand for SuperT to determine an appropriate standard deviation. This model considers a single aggregate demand input, because tomatoes from different geographic locations are mixed at the repacker to meet customer demand.

Target Demand Certainty Level (DCL) 70.0%

DCL= probability on cumulative demand distribution

	Demand				
Week #	**Demand Forecast (mean)**	***Demand Forecast (standard deviation)**	**Targeted pack out quantity**	**Targeted pack out quantity (cases)**	**Wholesale Price (per case)**
1	150	10	**155**	32	$ 13.00
2	330	20	**340**	69	$ 13.00
3	400	10	**405**	82	$ 10.00
4	500	15	**508**	102	$ 14.00

Figure 5: Disguised demand inputs

Supply

On the supply side, the mean and standard deviation for yield, as well as the expected harvest length, is based on trial data for the SuperT. Since limited trials were completed, it is assumed that the tomato plant would have similar yield distribution in all geographic locations. This is not likely to be accurate, but management does not believe that yield differences between geographies are significant enough to justify a more sophisticated yield forecasting approach. In the future, these inputs can be based upon actual historical data for the SuperT.

To account for the different growing periods in the various geographies, yield data is only input for potential harvest weeks appropriate for the latitude of the growing region. All non-eligible weeks of the year for the geography (i.e. not included in the harvest window) have yield inputs of zero. Harvest windows in this model were determined based on management and grower experience within the geographies. These potential harvest weeks, i.e. harvest windows, are primary dictated by climate, but can also be decided by picking crew schedules. The majority of the harvest weeks within the pre-determined window have such a high probability of success that the chance for harvest failure is ignored.

When using the model for the second stage simulation, however, a Bernouli distribution is utilized to represent the chance of harvest failure occurrence. The simulation tool generates a 1 (100 percent) for a successful harvest or a 0 (zero percent) for a harvest failure in each week, according to the probability for a successful harvest that is input into the model. The chance of harvest failure is only significant in the first and last few weeks of the harvest window.

The length of harvest, i.e. number of potential weeks of harvest for each planting, is assumed to be the same across all geographies because data does not exist to indicate otherwise. In the trial data, the yield within the first two weeks of harvest is approximately half of the full expected yield potential, so this ramp-up period length and a ramp-up factor is also included in the calculations. An example of the supply inputs into the model is in Figure 6.

The last supply estimate is for the percentage of shrink that occurs to the product volume during transportation and repacking. During distribution from the repacking facility to the grocery retailer, the product is packed in small plastic clamshells which offer a high degree of protection and therefore shrink after repacking can be effectively ignored. The estimated percentage of shrink is based on management experience.

Production Certainly Level (PCL) 70.0%

PCL= probability on cumulative yield distribution

	Name	City	State	
Geography	HGA	Hazard Co	GA	

Region 1

	# of weeks
Harvest Length (mean)	7
Lead time for plant growth	11
Harvest RampUp	2
Yield During RampUp	50%

		Yield (Lbs)			
Calendar Week	**Harvest Week**	Yield Forecast (mean)	Yield Forecast (standard deviation)	Expected Yield at Certainty Level	Probability of Harvest Failure
1/1/2007	1	3000	500	2737.8	0.80
1/8/2007	2	3000	500	2737.8	0.40
1/15/2007	3	3000	500	2737.8	-
1/22/2007	4	3000	500	2737.8	-

Figure 6: Disguised supply inputs

<u>Costs</u>

Cost inputs for the model are estimates from the MaterCo management team (Figure 7). In the case of SuperT, the tomato seed is given to the growers at no expense to control the distribution of the proprietary genetics. This also serves as an additional incentive for growers to grow the new unproven product. Growers are very concerned with the yield risk since they have no experience growing this tomato variety. The cost of the seed is based on an internal transfer price at MaterCo.

The product cost, which is the payment to the growers for their harvested produce, is estimated based on historic regional market prices for a similar product. All the transportation and repacking costs incurred by the repacking partner are reimbursed by MaterCo and are estimated using historical data. The transportation costs from the field to the repacking facility are estimated using known costs per pound per loaded truck mile, and an estimate of the road mileage between the fields and the repacking facility. The costs for physically repacking the product, i.e. boxes, clamshells, stickers, labor, etc., are based on historic costs. Historic average distribution costs are also used to determine the amount paid per finished case to distribute SuperT to grocery retail customers.

In oversupply situations, where the quantity supplied is in excess of the retail demand, growers are reimbursed partially for the product they would have sold. Since the SuperT growers have no alternative channels to sell these specialty tomatoes, MaterCo shares the risk of oversupply. MaterCo agrees to pay growers a percentage of the product price they would have received if the product had been sold. The product price is determined based on the average among all the growing regions at that time. This is because it is not fair to allocate the oversupply volume to a specific region, since tomatoes are mixed at the repacking facility to meet an aggregate demand. In reality, there may be certain weeks of the year where supply is only coming from one region. In those cases, a specific local market price can be used. The price discount percentage used in this model for oversupply situations is from MaterCo management. Oversupply volume also does not have any associated transportation, repacking, or distribution costs. In an oversupply situation, the product is disposed of at the farm.

An alternative method for addressing the oversupply situation is to discount the product through promotions at the retail level, in order to bring demand and supply back into alignment. Depending on the degree of oversupply this may be the preferred method for handling these situations. In reality, the wholesale price is negotiated weekly with the grocery retail customers in order to ensure that the maximum product is sold profitably. These techniques are considered demand management. Since demand management is not in the scope of this thesis research, these price and volume adjustments are not included in the model.

	Costs		Region 1			Region 2		
Week	Cost of Seed/Input (per acre)	Adjustment for Oversupply	Product Cost (per lb)	Transportation to Repacker (per lb)	Repacking and Distribution (per case)	Product Cost (per lb)	Transportation to Repacker (per lb)	Repacking and Distribution (per case)
1	$ 500	$ 8.10	$0.50	$0.020	$6.35	$0.54	$0.035	$6.35
2	$ 500	$ 8.10	$0.50	$0.020	$6.35	$0.54	$0.035	$6.35
3	$ 500	$ 8.10	$0.50	$0.020	$6.35	$0.54	$0.035	$6.35
4	$ 500	$ 8.10	$0.50	$0.020	$6.35	$0.54	$0.035	$6.35
5	$ 500	$ 8.10	$0.50	$0.020	$6.35	$0.54	$0.035	$6.35
6	$ 500	$ 8.10	$0.50	$0.020	$6.35	$0.54	$0.035	$6.35
7	$ 500	$ 8.10	$0.50	$0.020	$6.35	$0.54	$0.035	$6.35
8	$ 500	$ 8.10	$0.50	$0.020	$6.35	$0.54	$0.035	$6.35
9	$ 500	$ 8.10	$0.50	$0.020	$6.35	$0.54	$0.035	$6.35
10	$ 500	$ 8.10	$0.50	$0.020	$6.35	$0.54	$0.035	$6.35

Figure 7: Disguised cost inputs

Revenue

Estimates for the wholesale price, paid by grocery retail customers to MaterCo are based on MaterCo management's discretion and the competitive environment for similar premium tomatoes. Analysis of historic data for premium tomato prices shows less seasonal fluctuation than comparable "commodity" tomatoes, such as rounds. It is assumed by MaterCo management that SuperT tomato prices will remain fairly stable over the calendar year, except during promotional periods.

4.4 Optimization (Initial Stage of Algorithm)

After development of the model and determination of appropriate inputs, the model is optimized to determine the most profitable quantity, timing, and location of planted acres. The optimization is constrained so that demand is met in any given week and planted acres are positive. The optimization is a mixed integer linear program (MILP) and is solved using What's Best® [2]. Run time is less than five minutes. In order to account for horizon issues with the model, an additional 20 weeks into the following year are also optimized, so that the model accurately suggests planting towards the end of the calendar year to meet demand in the beginning of the following year. The planted acreage decisions are constrained by a minimum quantity threshold.

Multiple optimizations are run for this research to compare the current deterministic planning process and a planning process that incorporates uncertainty in yield and demand. The current deterministic planning process is tested by setting the standard deviation for demand and yield to a low enough number that the variability is washed out during rounding. This represents the current practice of using point estimates of demand and yield for planning purposes.

[2] What's Best® is a product of Lindo Systems, Chicago, Illinois

The optimization model is also run at different certainty levels of demand and yield (DCL and PCL) based on their estimated distributions. This is the first stage of the suggested algorithm. The corresponding levels of demand and yield are used as deterministic inputs into the optimization model. Table 1 shows the demand and yield certainty levels (DCL and PCL) that were tested in the stage one optimization. The solutions from the optimization are input into the simulation to observe the resulting Type I Customer Service Level and profitability. The optimization is repeated with adjusted DCL and PCLs dependent on the outcome of the simulation.

Table 1: Optimization runs

Inputs for Optimization Runs	
Run	**Demand and Yield Certainty Levels**
A	*Avg Yield and Demand (DCL = 50%, PCL = 50%)*
A2 (Doubling)	*Same inputs as A (with acreage output doubled)*
B	DCL = 70%, PCL = 70%
C	DCL = 75%, PCL = 75%
D	DCL = 80%, PCL = 80%
E	DCL = 85%, PCL = 85%
F	DCL = 86%, PCL = 86%
G	DCL = 87%, PCL = 87%
H	DCL = 88%, PCL = 88%

4.5 Simulation (Second Stage of Algorithm)

The next step in the modeling analysis is to perform a simulation on the optimal production planning solution at a given DCL and PCL. The simulation provides the management of MaterCo a more realistic distribution of possible outcomes, as opposed to a point estimate forecast. This information is used to compare the risk and robustness of various solutions. The primary attributes of the various solutions under evaluation are the forecasted profit to MaterCo and the resulting customer service levels to the grocery retailers. Type I Customer Service, which is the percentage of weeks that demand is met in full, is considered.

To run a simulation, one of the resulting solutions from the optimization model is entered into the simulation model as a fixed input. With the planting acres fixed, the demand, yield, and probability of harvest failure are replaced with random variables adhering to the established mean and standard deviation parameters. The simulation is run using Crystal Ball® [3] with 500 iterations. The resulting distributions for profit and customer service (Type I) are evaluated. If a desirable Type I CSL is not achieved, the optimization is repeated with adjusted DCL and PCLs, and the new solution is run through the simulation.

For this research, the following potential production plan solutions were compared:

1. The outcome of the optimization model with deterministic assumptions of average demand and yield (Run A)
2. The outcome of the optimization model with deterministic assumptions of average demand and yield, with each suggested acreage multiplied by two to represent the current risk management heuristic of planting redundant acreage (Run A2)
3. The outcome of the suggested production planning algorithm, where the optimal solution for various PCL and DCLs is simulated, until a desired Type I CSL is achieved (Runs B-H).

The resulting profit and customer service level distributions from the suggested algorithm are compared to the outcome of the simple "doubling" heuristic. The hypothesis is that the suggested

[3] Crystal Ball® is a product of Decisioneering, Inc., Denver, Colorado

algorithm can outperform the simple heuristic by achieving an acceptable level of customer service with higher profitability. Though the desired level of customer service will vary for different business cases, a Type I Customer Service Level of 90 percent is considered adequate for grocery retail customers.

5 Results and Analysis

The results of various optimizations are first analyzed to observe differences in planting patterns resulting from different certainty levels of demand and yield. Even though harvest windows are relatively fixed in the model, subtle differences in planting patterns emerge, as well as predictable changes in planted acreage. The production plans from the various optimization runs are then simulated to see if an acceptable level of customer service can be achieved with less planted acres than the industry heuristic of doubling the acreage. The more sophisticated two-stage risk-incorporating algorithm demonstrates significant savings to MaterCo, when compared to the doubling heuristic.

5.1 Optimization Results (Stage One of Algorithm)

The results of the optimization models (i.e. feasible solution set) are analyzed for differences in planting patterns, only. The integrator's (MaterCo) share of profit and the resulting customer service level distributions are explored through simulation.

The planting patterns across the feasible solution, in terms of timing and geography, do change as certainty levels are increased. As higher levels of certainty are desired, intuitively, the planted acreage increases, as well as the optimal planting locations and timing. The relative change in planted acreage and planting patterns is illustrated for a few of the optimization runs in Tables 2, 3, and 4.

It is also interesting to observe the total planted acres required under the various solution sets (Table 5). When average demand and yield are used, 13.15 acres total are required to be planted during the year. To follow the simple risk management heuristic of the industry, this is doubled to a requirement of 26.29 acres. The production plan for Optimization Run H, however, achieves the target 90 percent Type I Customer Service Level with approximately 20 percent less acres, i.e. 20.95 acres (Table 5).

The acres required to meet the minimum service level will increase as the variability of demand or yield (input into the model) is increased. It is more likely, however, that demand and yield variability will decrease as more historical data is collected for growing and selling the SuperT.

Table 2: Production plan for Optimization Run A (Average Demand and Yield)

	Planting Decisions (acres)					
Week	Region 1	Region 2	Region 3	Region 4	Region 5	Total Acres Planted
Last week of Previous Year						
1	0.47	-	-	-	-	0.47
2	-	-	-	-	-	-
3	-	-	0.28	-	-	0.28
4	-	-	-	-	-	-
5	-	-	-	-	-	-
6	0.48	-	-	-	-	0.48
7	-	-	-	-	-	-
8	0.51	-	-	-	-	0.51
9	-	-	-	-	-	-
10	-	-	-	-	0.34	0.34
11	-	-	-	-	-	-
12	-	-	-	-	-	-
13	-	-	-	-	0.28	0.28
14	-	-	-	-	-	-
15	-	-	-	0.46	0.28	0.74
16	-	-	-	-	-	-
17	-	-	-	-	-	-
18	-	-	-	-	-	-
19	0.93	-	-	-	-	0.93
20	0.56	-	-	-	-	0.56
21	-	-	-	-	-	-
22	-	-	-	0.37	-	0.37
23	-	-	-	0.37	-	0.37
24	-	-	-	-	-	-
25	-	-	-	0.37	-	0.37
26	-	-	-	-	-	-
27	-	-	-	0.74	-	0.74
28	-	-	-	-	-	-
29	-	-	-	-	-	-
30	-	-	-	0.74	-	0.74
31	-	-	-	-	-	-
32	-	-	-	-	-	-
33	-	-	-	-	-	-
34	-	1.49	-	-	-	1.49
35	-	-	0.49	-	-	0.49
36	-	-	0.25	-	-	0.25
37	-	-	0.49	-	-	0.49
38	-	-	0.25	-	-	0.25
39	-	-	-	-	-	-
40	-	-	-	-	-	-
41	-	-	-	-	-	-
42	-	-	1.12	-	-	1.12
43	-	-	0.37	-	-	0.37
44	-	-	-	-	-	-
45	-	-	-	-	-	-
46	0.74	-	-	-	-	0.74
47	-	-	-	-	-	-
48	0.74	-	-	-	-	0.74
49	-	-	-	-	-	-
50	-	-	-	-	-	-
51	-	-	-	-	-	-
52	-	-	-	-	-	-

Table 3: Production plan from Optimization Run B (DCL & PCL = 70%)

Week	Region 1	Region 2	Region 3	Region 4	Region 5	Total Acres Planted
	Planting Decisions (acres)					
Last week of Previous Year						
1	0.58	-	-	-	-	0.58
2	-	-	-	-	-	-
3	-	-	0.26	-	-	0.26
4	-	-	-	-	-	-
5	-	-	-	-	-	-
6	0.77	-	-	-	-	0.77
7	-	-	-	-	-	-
8	0.46	-	-	-	-	0.46
9	-	-	-	-	-	-
10	-	-	-	-	0.62	0.62
11	-	-	-	-	-	-
12	-	-	-	-	-	-
13	-	-	-	-	0.31	0.31
14	-	-	-	-	-	-
15	-	-	-	0.31	0.29	0.61
16	-	-	-	-	-	-
17	0.63	-	-	-	-	0.63
18	-	-	-	-	-	-
19	0.63	-	-	-	-	0.63
20	0.59	-	-	-	-	0.59
21	-	-	-	-	-	-
22	-	0.63	-	-	-	0.63
23	-	-	-	0.25	-	0.25
24	-	-	-	0.25	-	0.25
25	-	-	-	0.25	-	0.25
26	-	-	-	-	-	-
27	-	-	-	0.92	-	0.92
28	-	-	-	-	-	-
29	-	-	-	0.42	-	0.42
30	-	-	-	0.50	-	0.50
31	-	-	-	-	-	-
32	-	-	-	-	-	-
33	-	-	-	-	-	-
34	-	1.84	-	-	-	1.84
35	-	-	0.67	-	-	0.67
36	-	-	0.25	-	-	0.25
37	-	-	0.67	-	-	0.67
38	-	-	0.25	-	-	0.25
39	-	-	-	-	-	-
40	-	-	-	-	-	-
41	-	-	-	-	-	-
42	-	-	1.38	-	-	1.38
43	-	-	0.46	-	-	0.46
44	-	-	-	-	-	-
45	-	-	-	-	-	-
46	0.92	-	-	-	-	0.92
47	-	-	-	-	-	-
48	0.92	-	-	-	-	0.92
49	-	-	-	-	-	-
50	-	-	-	-	-	-
51	-	-	-	-	-	-
52	-	-	-	-	-	-

Table 4: Production plan from Optimization Run H (DCL & PCL = 88%)

Week	Region 1	Region 2	Region 3	Region 4	Region 5	Total Acres Planted
	Planting Decisions (acres)					
Last week of Previous Year						
1	0.63	-	-	-	-	0.63
2	-	-	-	-	-	-
3	0.25	-	-	-	-	0.25
4	-	-	0.25	-	-	0.25
5	-	-	-	-	-	-
6	0.93	-	-	-	-	0.93
7	-	-	-	0.25	-	0.25
8	0.42	-	-	-	-	0.42
9	-	-	-	0.00	0.28	0.28
10	-	-	-	-	0.45	0.45
11	-	-	-	-	-	-
12	-	-	-	-	-	-
13	-	-	-	-	0.40	0.40
14	-	-	-	-	0.55	0.55
15	-	-	-	-	0.39	0.39
16	-	-	-	-	-	-
17	0.51	-	-	-	-	0.51
18	-	-	-	-	-	-
19	1.11	-	-	-	-	1.11
20	0.77	-	-	-	-	0.77
21	-	-	-	-	-	-
22	-	0.51	-	0.34	-	0.85
23	-	-	-	0.35	-	0.35
24	-	-	-	0.25	-	0.25
25	-	-	-	0.35	-	0.35
26	-	-	-	-	-	-
27	-	-	-	1.20	-	1.20
28	-	-	-	-	-	-
29	-	-	-	0.50	-	0.50
30	-	-	-	0.70	-	0.70
31	-	-	-	-	-	-
32	-	-	-	-	-	-
33	-	-	-	-	-	-
34	-	2.39	-	-	-	2.39
35	-	-	0.90	-	-	0.90
36	-	-	-	-	-	-
37	-	-	1.20	-	-	1.20
38	-	-	-	-	-	-
39	-	-	0.30	-	-	0.30
40	-	-	-	-	-	-
41	-	-	-	-	-	-
42	-	-	1.80	-	-	1.80
43	-	-	-	-	-	-
44	-	-	0.60	-	-	0.60
45	-	-	-	-	-	-
46	1.20	-	-	-	-	1.20
47	-	-	-	-	-	-
48	1.20	-	-	-	-	1.20
49	-	-	-	-	-	-
50	-	-	-	-	-	-
51	-	-	-	-	-	-
52	-	-	-	-	-	-

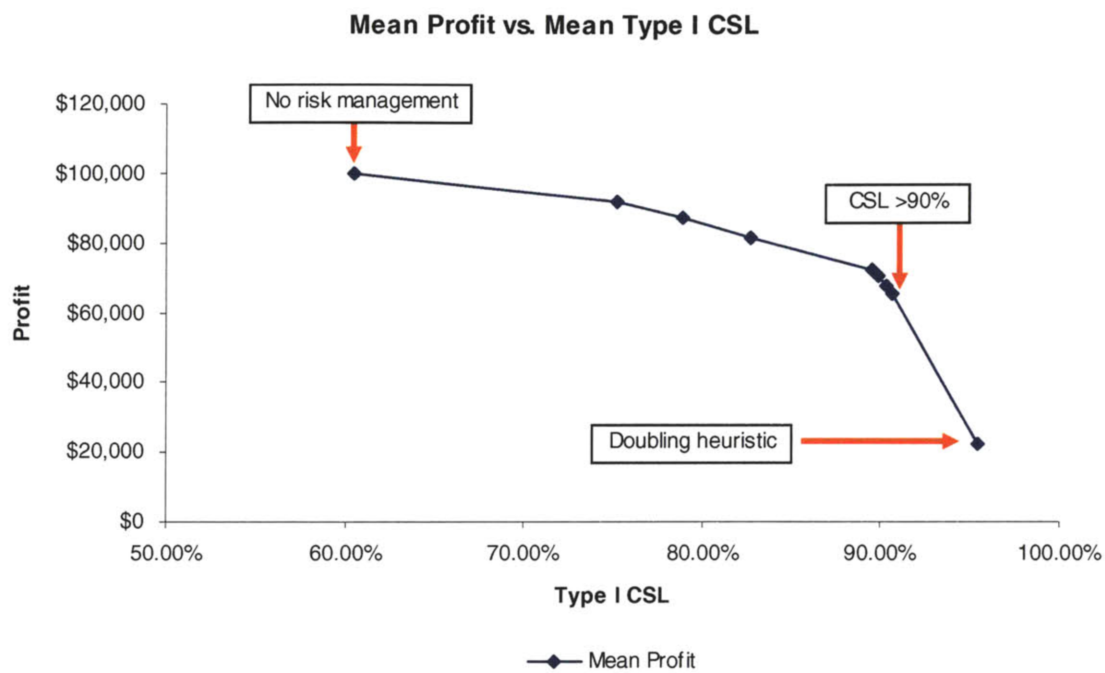
5.2 Simulation Results (Stage Two of Algorithm)

The solutions from the stage one optimization are run through a simulation where they can be evaluated on two primary dimensions: profit to the integrator (i.e. MaterCo) and Type I Customer Service Level (percentage of weeks where demand is met in full). Running the solutions through the simulation gives a forecast distribution of the range and probability of various profit and customer service levels occurring.

5.3 Integrator profit and customer service levels

The highest profits are observed for the lowest customer service levels. Figure 8 shows how the mean profit decreases as mean customer service levels are increased. It also illustrates the gap in service levels and profitability between the production plan based on expected (average) demand and yield and any of the risk-inclusive optimizations that were tested. Though the profitability is attractive, the customer service levels are not realistically acceptable if no risk management measures are taken. In the current model formulation, there are no negative consequences for low customer service. Poor service in one week does not impact the ability to sell product in the following week. This is an area for further development of the model.

Figure 8: Mean profit versus customer service trade-off curve



Intuitively, the risk of poor service to the customer decreases as the planted acreage base increases. Nevertheless, as the customer service level increases, the profitability decreases because a higher level of production is required to service the tails of the demand distribution and to account for the tails of the yield distribution. Furthermore, the variability of profit increases along with the higher customer service levels (Table 5). With the simple doubling heuristic, there is even the possibility of losing money, which is not the case for Optimization Run H (Figures 9 and 10). This reinforces the importance of finding the right balance between customer service and profitability.

Given a minimum customer service level of 90 percent, the optimal production plan suggested from the algorithm is from Optimization Run H. This production plan achieves at least 90 percent customer service with the least amount of acres. Compared to the doubling heuristic, the mean profit from Optimization Run H is approximately $40,000 more. Therefore, higher profitability can be achieved in this instance using the suggested production planning algorithm and models, versus the simple doubling heuristic. Statistical tests validate the significance of the results.

Test 1: Is the Type I Customer Service Level from Optimization Run E above 90 percent?

$H_O : \mu_{CSL_H} < .9$
$H_A : \mu_{CSL_H} \geq .9$

$$\text{Test Statistic (z)} = \frac{.9 - \mu_{CSL_H}}{\frac{\sigma_{CSL_H}}{\sqrt{500}}} = -4.09$$

P value of -4.09 < .001
Can reject the null hypothesis

The P value is very significant. Therefore, the Type I Customer Service Level from Optimization Run H is higher than 90 percent. The production plan from Optimization Run H is a feasible solution.

Test 2: Is the profit from Optimization Run H greater than the profit from Optimization Run A2 (i.e. Doubling Heuristic)?

$H_O : \mu_{\text{Profit}_H} - \mu_{\text{Profit}_{A2}} = 0$
$H_A : \mu_{\text{Profit}_H} - \mu_{\text{Profit}_{A2}} \neq 0$

$$\text{Test Statistic (z)} = \frac{0 - \left(\mu_{\text{Profit}_H} - \mu_{\text{Profit}_{A2}}\right)}{\sqrt{\left(\frac{\sigma^2_{\text{Profit}_H}}{n_H} + \frac{\sigma^2_{\text{Profit}_{A2}}}{n_{A2}}\right)}} = -118.70$$

P value of -118.70 < .001
Can reject the null hypothesis

The P value is very significant. Therefore, the profit from Optimization Run H is greater than the profit from the doubling heuristic. The production plan suggested by the algorithm is preferred to the production plan resulting from the simple industry heuristic.

This test shows that MaterCo can save unnecessary production expenses while still providing acceptable service to their retail customers. With better understanding of the trade-off between profitability and customer service, MaterCo can also make more informed promises to customers. A further benefit of this approach is that it can give managers better information around the expected distribution of profitability for a given production plan, allowing them to make better budget decisions.

Table 5: Acres, profit, and customer service levels

Run	Acres	Mean Profit	St. Dev. Profit	Mean CSL	St. Dev. CSL
A	*13.15*	$99,736	$7,422	60.49%	5.72%
B	16.05	$91,679	$8,913	75.24%	5.03%
C	17.03	$87,345	$9,366	78.92%	4.74%
D	18.22	$81,486	$9,876	82.75%	4.33%
E	19.89	$72,613	$10,786	89.53%	3.82%
F	20.22	$70,409	$10,872	89.88%	3.73%
G	20.58	$67,952	$10,963	90.25%	3.68%
H	20.95	$65,330	$11,050	90.64%	3.50%
A2	26.29	$22,639	$12,349	95.47%	2.50%

Figure 9: Histogram of Profit from Optimization Run A2 (Doubling Heuristic)

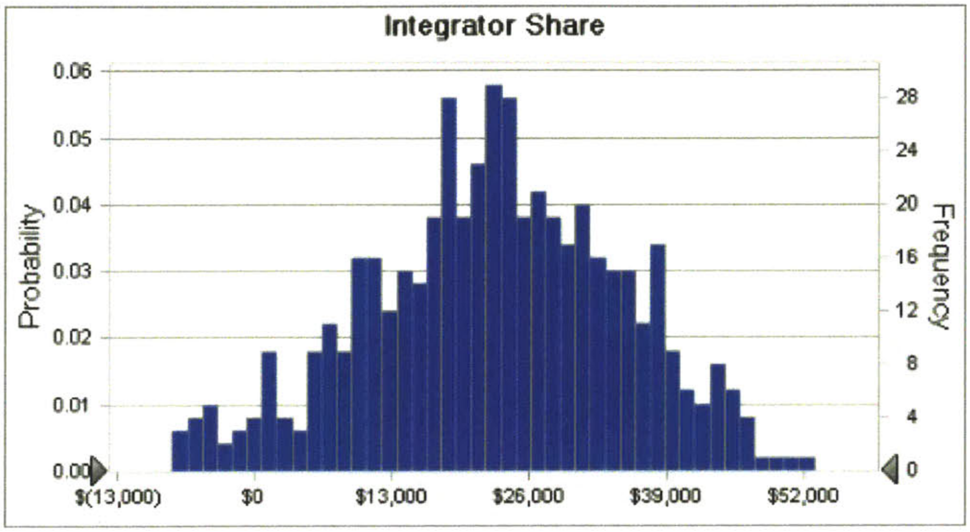
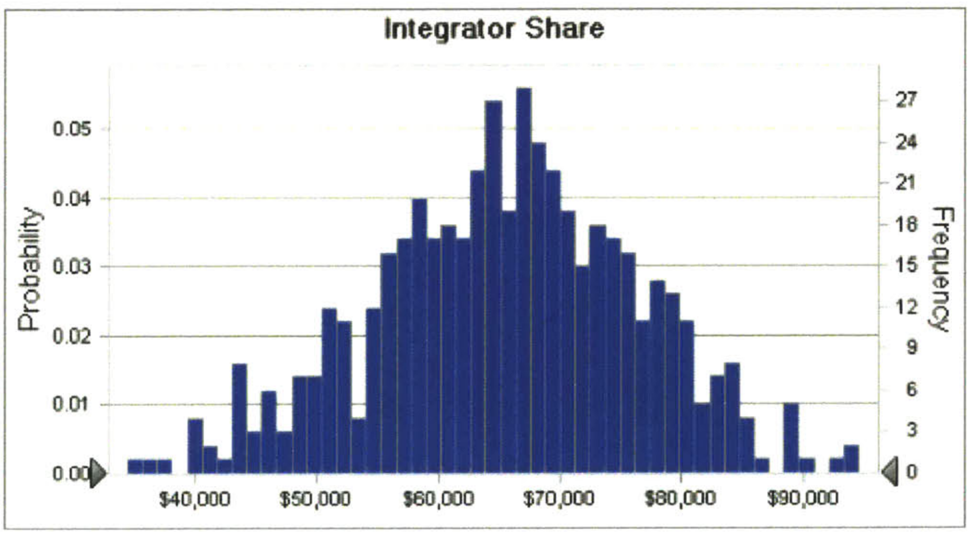


Figure 10: Histogram of Profit from Optimization Run H (DCL & PCL = 88%)



6 Conclusion

The primary objective of this thesis is to find the optimal production plan (i.e. timing, quantity, and location) for planting a premium tomato. The optimal production plan is defined as that which maximizes profitability while recognizing the inherent uncertainty in the fresh produce supply chain. These are mainly yield, demand, and harvest failure risks. The optimal solution depends upon the level of uncertainty in service that the retail customer is willing to accept. Lower customer service levels will result in higher profitability to the integrator, but it may be impossible to maintain business relationships.

The most basic value that the two-stage planning algorithm provides is determination of the optimal planting pattern (amount, location, timing), which can be difficult to calculate manually in a complex planning environment. If the demand level is constant and few planting geographies are available, it may be possible to determine the planting pattern by hand or with simple spreadsheets. On the other hand, when many planting location choices exist, with varying harvest windows, and varying levels of demand, determining a feasible planting pattern is difficult without optimization. Not only does the amount of acres need to be considered, but also the staggered timing of plantings, and the relative costs of each decision. It is relatively easy to foresee production planning situations where the number of variables to consider is beyond the scope of unaided decision making.

The primary contribution to agricultural decision making from the suggested two-stage planning algorithm is the incorporation of risk into the premium fruit and vegetable production planning process. Through modeling and quantification of the inherent uncertainties in both supply and demand, these risks can be better managed to more efficiently match supply with demand. This brings more sustainable profitability to premium agriculture supply chains. In the case of MaterCo, a better understanding of these uncertainties, alone, is already improving the company's ability to make supply chain decisions. With the tools provided, management can find the production planning solution that maximizes their potential profit while meeting the risk profile of their customers, in terms of acceptable service levels. These tools also allow management to better prepare for worst-case and best-case scenarios by indicating both the potential consequences and the probability of occurrence.

Some limitations in the suggested models are that they do not consider variability in fuel prices or commodity prices. In the simulation runs documented in this thesis, the price of fuel, farm-gate tomato prices, and wholesale tomato prices (to grocers) were considered to be deterministic, for purposes of simplification. They can, however, be entered in separately for each individual week. Nevertheless, it would not be a difficult adjustment to the simulation model to substitute random variables in the place of these inputs.

The two-stage planning algorithm also does not consider the risk pooling benefit of planting redundant acreage in two different locations. If the yield distributions in each region can be considered identical and independent, less acreage will be needed in total to meet a predetermined customer service level, because variation in one location will offset variation in the other location.

It is important to note that significant efforts were made throughout this thesis research to develop a model and approach that maintain enough simplicity for practical use. Though the proposed additions mentioned above could be incorporated in the models, the models could become too complex for regular use by production managers. It is suggested that this production planning algorithm is used repeatedly throughout the growing season to adjust the production plan as new data becomes available. It is relatively simple for managers to fix values for planting decisions that have already been made, and rerun the algorithm to determine a new optimal solution.

7 Further Research

Further research can improve the optimization and simulation models to more accurately reflect reality. For example, the simulation model can be further developed to incorporate negative consequences for poor service, such as decreasing the level of potential sales following a week of shortages.

It may also be useful to quantify and incorporate the risk of complete crop failure (e.g. due to adverse weather conditions) in this model, if possible. This implies that no further harvest is conducted in a location after a complete crop failure occurs.

Further research also needs to be conducted regarding forecasting and demand management in fresh produce supply chains. More sophisticated demand and yield forecasting techniques will improve the accuracy and profitability of production planning decisions. Producers can also benefit from a better understanding of how pricing decisions impact sales, which they can use to institute better price negotiation processes. In addition, research is lacking that helps grocery retailers understand the true value that a premium branded product brings to their entire produce category.

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