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Optimal Land Allocation and Production Timing for Fresh Vegetable Growers under Price and Production Uncertainty

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Production timing is an essential element in fresh vegetable growers' efforts to maximize profitability and reduce income risks. The present study uses biophysical simulation modeling coupled with a dual crop (tomatoes, sweet corn) whole-farm economic formulation to analyze the effects of growers' risk aversion levels and price consideration (seasonal or annual price consideration) in expected net returns and production practices. The findings indicate that consideration of seasonal price trends results in higher expected net returns and greater opportunities to mitigate risk. Furthermore, risk aversion levels substantially influence production timing when seasonal price trends are considered.

Key Words: biophysical simulation, farm management, mean variance, price seasonality, vegetable production

JEL Classifications: C61, C63, D81

Growers' decisions (i.e., choice of inputs, land allocation, production mix, etc.) in the uncertain environment created by production and price variability are a subject that has attracted scholars for more than five decades. Babcock, Chalfant, and Collender (1987) and Mapp et al. (1979) provide a discussion and review of the early research endeavors in this topic. Following the work of Chavas and Holt (1990), growers' risk behavior became an important element in the study of their allocation choices (i.e., Liang et al., 2011; Nivens, Kastens, and Dhuyvetter, 2002; Wang et al., 2001).

In addition to the production and price variability, fresh vegetable growers face increased uncertainty as a result of the special characteristics of their product. For instance, the high perishability of most fresh production results in limited storage opportunities; thus, the vegetable supply in the short run is highly inelastic (Cook, 2011; Sexton and Zhang, 1996). As a result, growers are compelled to accept the price during or close to the harvesting period. Consequently, planting and harvest timing plays an important role in the income received from vegetable production. Furthermore, the impact of quality on the prices of fresh vegetables should not be understated. Specifically, if the vegetable produced does not reach the quality standards expected by the buyer (i.e., consumers, retailers, intermediaries, etc.), then the growers have to accept a lower price (Hueth and Ligon, 1999).[1]

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[1] The present research does not incorporate the quality attribute in the economic analysis. The reason for that lies on data limitation issues discussed later in the study.

Despite an abundance of research regarding growers' decisions under uncertainty and the increased risk faced by vegetable growers, the literature regarding how 1) growers' risk aversion levels; and 2) consideration of price seasonality[2] impact the production decisions, particularly timing of planting and harvest, is limited. A notable exception is Simmons and Pomareda (1975). The research presented is an effort to fill this gap.

The objectives of this study are threefold. First, the study seeks to develop a dual-crop vegetable farm model with a land allocation and production timing decision interface focusing on economic optimization. Second, it examines the effect of price/production variability and of growers' risk preferences on their decisions regarding the optimal production practices (land allocation, transplant timing). Third, the study investigates potential alterations in optimal production practices and in the economic results with and without considering seasonal price trends, a factor that may influence growers' production timing decisions. Mathematical programming modeling in conjunction with biophysical simulation techniques are used to achieve these goals.

The focus area for the present article is Fayette County, Kentucky. The following two reasons dictated the selection of Fayette County as the study region: 1) it is among the top vegetable-producing counties in Kentucky (U.S. Department of Agriculture, National Agricultural Statistics Service, 2010); and 2) the abundance and availability of weather and soil data. These data are essential requirements for the biophysical simulation.

Kentucky was ranked 42 out of 50 states within the United States based on the 2010 value of farm cash vegetable receipts. However, the importance of vegetable crops in the overall agricultural economy of the state is rising. Two facts highlight the growing role of vegetable production in Kentucky. First, in contrast to the overall decline of farm numbers in the state, there is an increase in the number of farms with some type of vegetable crop from 1086 (1997) to 2123 in 2007 (2007 Census of Agriculture). Second, there is a steady growth in the annual farm cash receipts from \$8.7 million (1997) to \$24.7 million in 2007 (U.S. Department of Agriculture–Economic Research Service, 2011).

The latter fact indicates an additional opportunity for enhanced growth, because it represents a 51% increase in cash receipts per acre over a ten-year period, which annualizes to a modest growth of just over 4% annually or slightly more than the inflation rate. Looking at the demand side, the percentage of adults who consumed vegetables three or more times per day in Kentucky is higher than the national average (29.4% compared with 26%; Centers for Disease Control and Prevention, 2010). This increased demand is coupled with growing interest among consumers for local products, attributable in part to the success of the Kentucky Proud program. These factors highlight a great range of opportunities for benefiting producers.

Tomatoes and sweet corn are the crops included in the whole-farm economic model. These vegetables were selected because they are among the top ten vegetables produced in Kentucky, both in number of farms and in acres. Specifically, sweet corn was ranked first among vegetables in terms of acres and second in number of farms. Tomatoes were ranked first in terms of farm number and third in acres planted (2007 Census of Agriculture). In addition to their overall importance in the agricultural sector of Kentucky, tomatoes and sweet corn were selected because growers can easily rotate among them (Coolong et al., 2010).

The comparison of economic outcomes and the estimation of optimal production timing for vegetables, with and without consideration of seasonal price trends, constitute the main contribution of the study to the literature. Furthermore, it is among the first research endeavors that uses the Decision Support System for Agrotechnology Transfer[3] (Hoogenboom et al., 2004; Jones et al., 2003) to overcome data

[2] Price seasonality is defined as the price patterns occurring within a "crop marketing period."

[3] DSSAT Version 4.0 has been used in the present study.

limitations for economic studies that include multiple vegetables.

Data Collection and Yield Validation

The present section has the following three objectives: 1) discuss the biophysical simulation model used for the estimation of yield data; 2) illustrate how the biophysical simulation model was validated; and 3) describe the sources of data used in the study.

DSSAT Data Requirements and Data Sources

One interesting strand of the applied economic/agricultural literature relates to efforts made by scholars with the goal of developing the most accurate possible model for yield forecasting. Two of the most widely cited techniques for yield forecasting are statistical regression equations and simulation methods (Kaufmann and Snell, 1997; Walker, 1989). The advantages and shortcomings of these two approaches have been widely discussed (Jame and Cutforth, 1996; Kaufmann and Snell, 1997; Tannura, Irwin, and Good, 2008; Walker, 1989). Among the advantages of the biophysical simulation[4] are: 1) that there is no need to specify a functional form; 2) it can provide yield data for different weather and production practices; 3) the use of biological principles for crop growth; and 4) the use of shorter time periods to estimate growth. However, it is more difficult to use simulation techniques for large geographical areas.

A lack of yield data for the examined vegetables, the need to estimate the effects of different production practices and soil types on yields, the focus on a specific geographical area, and the overall objective of using these data for economic modeling suggest the use of biophysical simulation as the most appropriate yield estimation technique for the present study (Dillon, Mjelde, and McCarl, 1991).

Biophysical simulation techniques have been extensively applied in the literature (e.g., Archer and Gesch, 2003; Barham et al., 2011; Deng et al., 2008; Shockley, Dillon, and Stombaigh, 2011). Among the several biophysical models that have been developed and used, the present study uses the Decision Support System for Agrotechnology Transfer (Hoogenboom et al., 2004; Jones et al., 2003). DSSAT was selected for the following reasons: 1) it is well documented; 2) it has been used and validated in numerous studies over the last 15 years; and 3) it is well suited for the present study because it incorporates modules for the two examined vegetables (tomatoes and sweet corn).

The minimum data set required to generate yield estimates using DSSAT includes weather data, soil data, and production practices information for the examined region (Fayette County, Kentucky). Daily weather data for 38 years (1971–2008)[5] were obtained from the University of Kentucky, College of Agriculture–Economic Research Service (2011). The data set includes information regarding daily minimum/maximum temperature and rainfall. The weather data collection was finalized with the calculation of solar radiation from the DSSAT weather module.

Soil data were gathered from the U.S. Department of Agriculture–Natural Resources Conservation Service (2011). According to the soil maps, the most common soil type in Fayette County is silt loams. Following Shockley (2010), the percent slopes from the soil maps are used as a criterion for distinguishing between deep and shallow soils. Specifically, if the slope is between 0% and 6%, then the soil is characterized as deep. If the slope is between 6% and 20%, then the soil is characterized as shallow. Based on these scales, 65% of the land is classified as deep silt loam and 35% as shallow. Furthermore, the default soil types of DSSAT were modified to better depict the characteristics of Fayette County soil conditions. Soil color, runoff potential, drainage, and percent soil slope were among the parameters modified. Table 1 reports the exact specifications of the used soil types. Lastly, the seasonal analysis option of DSSAT is used for the yield simulation. Under this option the soil water conditions, nutrients

[4] Biophysical simulation is a special case of the simulation models (Musser and Tew, 1984).

[5] These years of weather data were available when the biophysical model of the study was constructed.

Table 1. Characteristics of Soils Included in Farm Simulation Model

Soil	Color	Drainage	Runoff Potential	Slope (%)	Runoff Curve No.	Albedo	Drainage Rate
Deep silty loam (65%)	Brown	Moderately well	Lowest	3	64	0.12	0.4
Shallow silty loam (35%)	Brown	Somewhat poor	Moderately Low	9	80	0.12	0.2

Source: Shockley, 2010.

and organic matter are reset to initial levels every year on January 1.

Information regarding the following production practices: 1) irrigation levels, 2) nitrogen requirements, 3) plant population, 4) planting depth, 5) transplant age, 6) planting/transplanting periods, and 7) harvesting periods for the examined crops were obtained from the University of Kentucky Extension Service Bulletins (Coolong et al., 2010). One cultivar was examined for each of the two crops under consideration because only one was available from DSSAT Version 4. For the purposes of the present study, planting/transplanting period and harvesting dates vary in the model.

Tomatoes in the examined region are transplanted from early May (spring crop) through early August (fall crop). Regarding sweet corn, planting period extends from April 20 to July 20. In addition, 65–80 days after transplant and 70–95 days after planting are the typical harvest periods for tomatoes and sweet corn, respectively. Including all the combinations of transplanting/planting days and harvesting periods requires modeling for 9500[6] treatments, the inclusion and evaluation of such is beyond the scope of this study. The production practices examined here included eight biweekly transplanting days for tomatoes (starting May 1) and nine weekly planting days for sweet corn (starting April 25). Four weekly harvest periods for each crop were initially included in the model.[7]

Detailed information regarding the production practices included in the simulation model is reported in Table 2. The validation process, discussed in the next section, explains why the harvest periods included in Table 2 are less than the ones initially examined.

Yield Data Simulation and Validation

The aforementioned data sets (soil, weather, production practices) were incorporated in the DSSAT tomato and sweet corn modules to estimate the yield data under the different transplanting/planting periods for the 38 years of weather data. Table 3 reports summary statistics for the simulated yields. Figures 1 and 2 provide a graphical representation for the simulated yields under the different transplanting/planting periods included in the model.

A required step following yield data simulation is the validation of the estimated yields. As a result of data limitations,[8] two nonstatistical validation methods were used in this study. First, the estimated yields were presented to Dr. Timothy Coolong[9] (2012) and he was asked whether or not they were a reasonable representation of expected yields in central Kentucky for the crops evaluated based on his experience and observations. Based on the simulated yield results and on Dr. Coolong's suggestions (2012), three harvest periods (63, 70, 77 days) for tomatoes and one (84 days) for sweet corn are kept in the final model formulation[10] instead of the four initially included. The simulated yields

[6] (120 transplanting days * 15 harvesting days for tomatoes) + (120 planting days for sweet corn * 25 harvesting days) * 2 for the two soil types examined.

[7] 63, 70, 77, and 84 days after transplant for tomatoes and 70, 77, 84, and 91 days after planting for sweet corn.

[8] The historical yield data available was too limited to do a validation through regression.

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[10] Eighty-four days harvest period for tomatoes and 70, 77, and 91 days for sweet corn are excluded from the final formulation because the simulated yields, for these periods, are not achievable in the examined area.

Table 2. Summary of Production Practices Used in the Biophysical Simulation Model

1) Tomato Production Practices	
Transplanting date	May 1, May 15, May 29, June 12, June 26, July 10, July 24, August 7
Harvesting period	63, 70, 77 days after transplant
Cultivar	BHN 66
Actual N/week (lbs/acre)	10
Irrigation	Drip irrigation, one inch water/week
Plant population (plants/acre)	5000
Transplant age	42 days
Planting depth	2.5 inches
Assumptions	Dry matter = 6%, cull ratio = 20%
2) Sweet Corn Production Practices	
Planting Date	April 25, May 2, May 9, May 16, May 23, May 30, June 7, June 14, June21, June 28
Harvesting period	84 days after planting
Cultivar	Sweet corn cultivar of DSSAT Version 4
Actual N/week	Two applications of ammonium nitrate; one preplant (90 lb. actual N/acre) and a second four weeks after planting (50 lb. actual N/acre)
Irrigation	Drip irrigation, one inch water/week
Plant population (plants/acre)	20,000
Planting depth	Two inches
Assumptions	Dry matter = 24%, cull ratio = 3%, ear weight = 0.661 pounds

were considered higher than what an average vegetable grower can achieve but not unreasonable for the best producers.

Second, the simulated yields were compared with findings from previous studies. Specifically, for tomatoes, consistent with past research (i.e., Hossain et al., 2004; Huevelink, 1999; Schweers and Grimes, 1976), the simulated yields are substantially influenced by transplant period. Furthermore, consistent with the aforementioned studies, simulated yields had approximately a bell-shaped form (Figure 1). Similarly, in agreement with previous research (Williams, 2008; Williams and Lindquist, 2007), our findings illustrate that sweet corn planting date plays an important role in production with yield decreasing substantially during the later planting periods after May (Figure 2). There is no comparison of absolute values between the simulated yields and yields in the previous studies as a result of the differences in soil and weather conditions.

Finally, the simulated yields were compared with four experimental trials for tomatoes (Coolong et al., 2009; Rowell et al., 2005, 2006; Rowell, Satanek, and Snyder, 2004) and one for synergistic sweet corn (Jones and Ferguson Sears, 2005) conducted in Fayette County and eastern Kentucky, respectively. Regarding tomatoes, the biophysical simulation results compare favorably to the highest yielding cultivars. For sweet corn, the average simulated yields are slightly lower than the best yellow cultivar of the experimental trial.

Economic and Resource Data Estimation

In addition to the data requirements for the biophysical simulation model, the following supplementary data were needed to achieve the objectives of the present study: 1) price data for the examined vegetables; 2) suitable field hours per day; 3) land availability; and 4) input requirements and input prices.

Weekly price data for 13 years (1998–2010) were obtained from the USDA Agricultural Marketing Service (AMS). Specifically, the Atlanta terminal market prices are used. AMS

Table 3. Summary Statistics of Simulated Yields and Detrended Atlanta AMS Prices for Tomatoes and Sweet Corn by Size[a]

Tomato Yields by Size (simulated)			
	Medium	Large	Extralarge
Average (pounds/acre)	6,580	26,321	10,967
Standard deviation	1,976.92	7,907.67	3,294.86
Coefficient of variation	30.00	30.00	30.00
Maximum yield	10,425	41,700	17,375
Minimum yield	0	0	0
Tomato Prices by Size			
	Medium	Large	Extralarge
Average ($/25 pound boxes)	$15.04	$15.56	$16.31
Standard deviation	3.12	3.48	3.84
Coefficient of variation	20.74	22.36	23.54
Maximum price ($/25 pound box)	29.55	30.58	30.70
Minimum price ($/25 pound box)	8.99	9.77	9.68
Sweet Corn Yield (simulated, one size)			
Average (ears/acre)	22,687		
Standard deviation	6,140		
Coefficient of variation	27.00		
Maximum yield	28,579		
Minimum yield	903		
Sweet Corn Price			
Average ($/crate)	$13.04		
Standard deviation	3.94		
Coefficient of variation	30.21		
Maximum price ($/crate)	33.78		
Minimum price ($/crate)	6.56		

[a] The maximum and minimum yields reported on the table refer to different production practices; thus, one is not expected to add the minimum yield of medium, large, and extralarge to obtain maximum yield per acre.
Source: DSSAT model yield results, Atlanta Agricultural Market Station prices.

terminal market reports are created using price data on vegetables traded at the local wholesale markets for 15 major cities. The price information is received by wholesalers for vegetables that are of "good merchantable quality" (U.S. Department of Agriculture, 2012). The tomato data set used in the study includes information for different variety (mature greens, immature greens, vine-ripe), crop size (medium, large, extra large), and package size (20- and 25-pound boxes). However, DSSAT Version 4.0.2 does not differentiate yield based on product variety and tomato size. To overcome this difficulty, following Dr. Coolong's recommendations, two assumptions are made: 1) 90% of yield is assumed to be mature green (the remaining 10% is immature greens or vine-ripes); and 2) the simulated yield is divided into three sizes based on the following distribution: 15% medium, 60% large, and 25% extra large. The prices were transformed in a $/pound base. Considering that the price data set provides limited information regarding quality and the same is true for the biophysical simulation model, no specific quality assumptions are made. Thus, the whole harvest (after a 20% reduction for cull tomatoes) was considered of good merchantable quality. The hypothetical

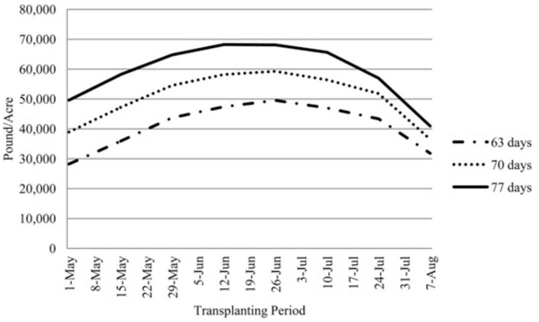

Figure 1. Simulated Tomato Yields (Note: The graph depicts average tomato simulated yields across years and soil types. Source: Biophysical simulation results)

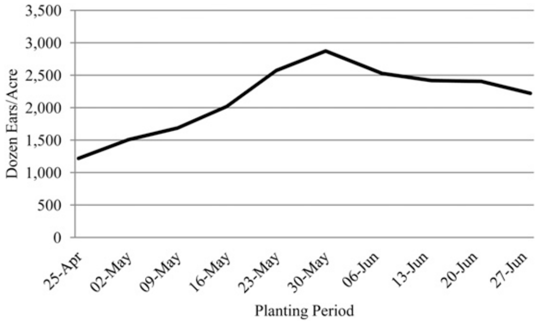

Figure 2. Simulated Sweet Corn Yields (Source: Biophysical Simulation Results)

grower of the study is assumed to discard the cull tomatoes. For sweet corn, prices are transformed to a $/dozen basis. The price set used is for yellow sweet corn.

Because there was a yearly trend detected in the price data set, to avoid overestimating the price variance, the Hodrick and Prescott filter is used to remove the trend movements. Following Ravn and Uhlig (2002), a smoothing parameter (λ) of 6.25 is used. Table 3 reports summary statistics for the price data set. The combination of 13 years of price data with 38 years of simulated yield generates 494 (13*38) different states of nature. This approach for determining the underlying revenue distribution assumes a perfectly competitive environment wherein the producer does not impact prices received. Furthermore, it is consistent with low correlation between prices and yield calculated for the data used.

Field conditions dictate whether a given time is suitable or not for fieldwork. Following Shockley, Dillon, and Stombaigh (2011), the probability of not raining more than 0.15 inches per day over weekly periods for the 38 years of weather data available is first calculated. This probability was multiplied with the days worked in a week and the hours worked in a day to determine expected suitable field hours per week to estimate labor availability regarding field conditions. It was assumed that any quantity of labor up to this amount could be hired. The information regarding the cost of labor has been obtained from the University of Kentucky Extension Service Vegetable Budgets (Woods, 2012). The land constrained was set at five acres based on average acre of operation obtained in the 2010 Kentucky Produce Planting and Marketing Intentions Grower Survey and Outlook (Woods, 2010).

The Mississippi State Budget Generator (MSBG) is used to estimate weekly labor requirements and input cost per acre for tomatoes and sweet corn. MSBG (Laughlin and Spurlock, 2007) is a software tool developed by Mississippi State University that uses machinery costs, input prices (i.e., fertilizer, fuel, etc.), and labor cost to calculate a per-acre cost for a field operation (Ibendahl and Halich, 2010). For the present study, the 2012 vegetable budget files of MSBG were modified to depict the Fayette County specifications. In detail, input requirements and prices were modified following the suggestions of Dr. Coolong and the 2008 vegetable budget developed by the University of Kentucky extension service publications.[11] A detailed representation of the included costs is reported in Table 4.

Theoretical Framework

This section provides the theoretical background for the economic model that will be implemented in the study. Whole-farm economic

[11] Available at: www.uky.edu/Ag/CDBREC/vegbudgets08.html.

Table 4. Production Costs per Acre

Tomato Expenses		Sweet Corn Expenses	
Type of Expense	$ Cost	Type of Expense	$ Cost
Fertilizer	319.67	Fertilizer	194.16
Herbicide	2.33	Herbicide	21.16
Insecticide	97.47	Insecticide	208.10
Seed and planting supplies	1575.08	Seed and planting supplies	126.00
Labor	3688.26	Labor	116.58
Machinery expenses	139.69	Machinery expenses	66.76
Other expenses (i.e., boxes)	1600.00	Other expenses (i.e., crates)	580.00
Interest on capital	76.00	Interest on capital	10.58
Irrigation supplies	627.00	Irrigation supplies	410.00

analysis has been used by scholars to answer important questions such as: What is the optimal crop mix? Should I invest in new technologies? What is the best rotation strategy? A review of related work is presented by Lowe and Preckel (2004).

An interesting modeling aspect of the whole farm analysis is associated with the efforts made to incorporate risk in the objective function. Among the most frequently implemented techniques to cope with this issue is the mean variance (E-V) formulation originally developed by Markowitz (1952). One of the following conditions must be satisfied for the results of E-V analysis to be equivalent to expected utility theory: 1) the utility function of the decision maker is quadratic; 2) normal distribution of outcomes (net returns); and 3) Meyer's location-scale (L-S) condition (Dillon, 1992). The first two conditions are overly restrictive and have well-documented theoretical deficiencies. For instance, quadratic utility functions have the unrealistic characteristics of wealth satiation and increasing absolute risk aversion (Bigelow, 1993).

Considering the previously mentioned limitations, the more general L-S condition is adopted for the present study. Because yields and price for sweet corn and tomatoes are the stochastic elements of net returns, it is sufficient to illustrate that they satisfy the L-S condition. Following Dillon (1992), a sufficient condition to meet the L-S requirements is for the ranked yields to be linear function of one another. The minimum correlation for the ranked yields was 97% and for ranked prices 87%. Thus, the use of mean variance analysis is considered legitimate for this study. Quadratic programming is commonly used to produce efficient E-V frontiers. The present study uses a formulation consistent with Freund (1956).

Empirical Framework

This section discusses in detail the formulation of the economic model that is used in this article. Specifically, an E-V formulation is implemented to depict the economic environment of a hypothetical fresh vegetable farm in Fayette County, Kentucky. In line with Dillon (1999), the proposed model incorporates accounting variables as well as endogenous calculation of net returns variance instead of a variance–covariance matrix.

The objective of the grower is the maximization of net returns above selected variable costs less the absolute risk aversion coefficient multiplied by the variance of net returns. The hypothetical farm is assumed to have five acres of cropland available and grow tomatoes and sweet corn in rotation with 50% of acres in any year devoted to each crop. This represents a two-year crop rotation, which is commonly followed by growers in the examined region (Coolong et al., 2010). This will lead to a maximum of 2.5 acres with tomatoes, which is close to the average acres cultivated with tomatoes in Kentucky reported from an unpublished survey of wholesale tomato growers (Vassalos, 2013). Rotation is required to prevent pathogen

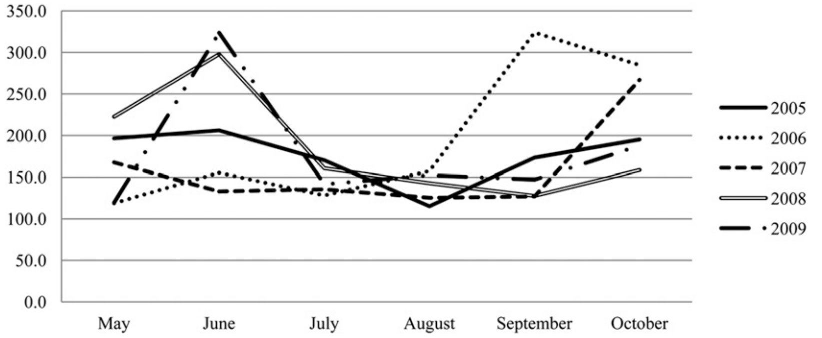

Figure 3. Fresh Tomatoes Monthly Producer Price Index (1982 = 100; Source: USDA, ERS Fresh Tomato Monthly Producer Price Index, U.S. Tomato Statistics)

build-up in the soil and control certain insects such as corn rootworms (Coolong et al., 2010). In addition to land limitation and rotation, the model includes the following constraints: 1) ratio of soil type; 2) marketing balance; 3) input purchases by input; and 4) weekly labor resource limitation. Specifically, the first constraint guarantees that 65% of the number of acres, selected as optimal from the model, is classified as deep silty loam and 35% as shallow silty loam. The second constraint ensures that the hypothetical grower cannot sell more pounds of tomatoes and/or ears of sweet corn than the amount produced. The third constraint guarantees that the hypothetical grower will purchase the amount of inputs required for the production of each crop. Lastly, the amount of weekly hours for agricultural activities is limited by the estimated suitable field days per week (weekly labor resource limitation constraint).

The model is estimated for the following two scenarios: 1) the grower considers seasonal price trends; and 2) the grower considers only annual average prices. The aforementioned scenarios do not necessarily reflect growers with different price information knowledge. They examine the conscious decision of a grower to adjust, or not, the production timing decisions based on the historical price trends. More precisely, the seasonal price trend scenario incorporates an interaction of seasonal price movement with yield differences associated with the alternative production practices examined.

The reason for examining these two scenarios vis-à-vis lies on the importance of production timing discussed earlier. Presumably, one of the factors that can drive optimal timing decisions is whether the growers consider historical price trend information. This is especially true for fresh vegetable marketing, which is characterized by substantial price seasonality (Figure 3).

The 13 years of weekly price data for tomatoes and sweet corn from AMS are used for the estimation of the first scenario (seasonal price trends). A two-step experimentation process is adopted for the latter scenario (annual average price). First, the optimal management decisions are identified when only considering the average weekly price for each AMS year. Second, these optimal decisions are imposed in the optimization model with the complete weekly historical price information to ascertain actual economic outcome. It is important to mention that the model in the present study is a steady-state equilibrium model and that the decision variables do not alter by state of nature under both scenarios.

In addition to the risk-neutral case, the two specifications of the model were estimated for nine different risk aversion coefficients. These coefficients were calculated using the McCarl and Bessler (1989) approach. Based on this approach, a grower is said to maximize the lower limit from a confidence interval of normally distributed net returns (Dillon, 1999). Specifically, the formula used to estimate the risk aversion coefficient (Φ) for each case is:

(1) $$\Phi = {}^{2Z_a}\!/_{S_y}$$[12]

where Z_a is the standardized normal Z value for a level of significance and S_y is the standard deviation of expected net returns for the risk-neutral case. Each one of the nine examined risk aversion levels in this study corresponds to a 5% increment from the previous significance level, starting from 50% (risk neutral) and ending with 95%. The mathematical specification of the model follows.

The grower's objective is to maximize net returns above selected variable costs less the risk aversion coefficient multiplied by the variance of net returns and is given by:

(2) $$\bar{Y} - \Phi\sigma_y^2$$

subject to land availability constraint, given by:

(3) $$\sum_C \sum_D \sum_H X_{C,D,H.S} \leq ACRES_s \forall S$$

weekly labor resource limitation, given by:

(4) $$\sum_C \sum_D \sum_H \sum_S LAB_{C,D,H,WK} X_{C,D,H,S} \leq FLDDAY_{wk} \forall WK$$

marketing balance:

(5) $$\sum_D \sum_H \sum_S YLD_{C,D,H,TS,S} X_{C,D,H,S} - SALES_{C,YR,WK,TS} = 0 \forall C,TS,WK,YR$$

input purchases by input:

(6) $$\sum_C \sum_D \sum_H \sum_S REQ_{I,C} X_{C,D,H,S} - PURCH_{I,C} = 0 \, \forall I$$

soil depth ratio constraint:

(7) $$CSOILRATIO_{\text{``shallow''}} X_{C,D,H,\text{``deep''}} - CSOILRATIO_{\text{``deep''}} X_{C,D,H,\text{``shallow''}} = 0 \forall C,D,H$$

and crop rotation constraint:

(8) $$\sum_C \sum_D \sum_H \sum_S ROTATE_C X_{C,D,H,S} \leq 0.5 \; ACRES_S \forall S$$

Net returns by year are given by:

(9) $$\sum_I IP_I PURCH_{I,C} - \sum_{WK} \sum_C \sum_{TS} P_{C,WK,TS} SALES_{C,YR,WK,TS} + Y_{YR} = 0 \forall YR$$

Expected profit balance is given by:

(10) $$\sum_{YR} \frac{1}{N} Y_{YR} - \bar{Y} = 0$$

The optimization model is solved with the use of General Algebraic Modeling System (GAMS). The solver option adopted is MINOS (GAMS, 2013). Table 5 provides the description of the activities, indices, and coefficients included in the whole farm economic model formulation.

Results and Discussion

The results obtained from the mean variance quadratic formulation, in conjunction with a discussion about them, are presented in this section. Tables 6 and 7 report results for three of those nine risk levels: low (65% significance level), medium (75% significance level), and high (85% significance level) risk aversion as well as the risk-neutral case. The selection of the mentioned risk aversion attitudes was made to better depict the changes that take place in the optimal decisions (i.e., transplant/plant and harvest timing) and the economic outcomes as the risk aversion level increases.

Optimal Production Management Results

To achieve the best possible economic outcome, and reduce their risk exposure (if they are risk-averse), growers need to take into consideration production timing. This is especially true for fresh vegetable production where even the most basic decisions such as when to plant can lead to significant improvement or decline of economic results as a result of: 1) the price variability; and 2) the seasonal and perishable attributes of fresh produce. Table 6 reports the model results

[12] Based on this formula, the nine risk aversion levels used in the study are: 1) 0.00001203; 2) 0,00002417; 3) 0.00003677; 4) 0.00005005; 5) 0.00006447; 6) 0.00008042; 7) 0.00009905; 8) 0.00012245; and 9) 0.00015712.

Table 5. Description of the Activities, Indices, and Coefficients Included in the Whole-Farm Economic Model Formulation

Activities	Indices	Coefficients
$\bar{Y}$: Expected net returns above selected variable cost	C: Crop S: Soil depth	Φ: Risk aversion Coefficient
$X_{C,D,H,S}$: Production of crop C, under transplanting/planting period D, harvesting period H, and soil depth S	TS: Tomato Size (medium, large, extralarge); there is only one size for sweet corn	$P_{C,WK,TS}$: Weekly price for different tomato sizes in \$/pound and for sweet corn in \$ per ear
$PURCH_{I,C}$: Purchases of input I	H: Harvesting period (1 for sweet corn)	$YLD_{C,D,H,TS,S}$: Expected yield of tomatoes by size in pounds and of sweet corn by ears
Y_{YR} : Net returns above selected variable cost by year	YR: Year	
$SALES_{C,YR,WK,TS}$: Tomato sales by size (medium, large, extralarge in pounds and sweet corn sales in dozens of ears by week and year, respectively	D: Transplant date for tomatoes, planting date for sweet corn	$FLDDAY_{WK}$: Available field days per week
	WK: Week	$ROTATE_C$: Rotation matrix by crop C
	I: Input	$P_{C,WK,TS}$: Weekly price in \$/pounds per tomato size and in \$/ear for sweet corn
	N: State of nature (13 * 38)	$CSOILRATIO_{``S"}$: Ratio of total acres allocated to depth S

regarding three possible production strategies: 1) land allocation/production mix; 2) planting schedule; and 3) harvesting schedule.

As far as land allocation choice is concerned, as a result of the rotation constraint, 50% of the available acres are devoted to tomato production and 50% to sweet corn for all risk aversion levels and for both scenarios examined. Furthermore, all the available acres (five) are used by the hypothetical farm.

Regarding the optimal transplant/plant and harvest timing, two strategies are observed from Table 6 depending on risk aversion levels. Under the seasonal price trend scenario, a risk-neutral grower who seeks to maximize expected net returns should focus on a combination of late tomato transplanting (July 10, July 24) and late sweet corn planting (June 21) as well as late tomato harvest (77 days after transplant). Under this plan the grower can receive higher prices, on average, for tomato and sweet corn. However, these production periods are associated with lower yields (Figures 1 and 2).

As risk aversion levels increase and growers are willing to accept lower but more certain net returns, two risk-mitigating strategies are suggested from the findings. First, risk-averse growers should focus on an earlier tomato transplanting period compared with risk-neutral farmers (June 12 instead of July 24). Specifically, the higher the risk aversion level, the greater the transition to earlier transplant in terms of acres cultivated with tomatoes (Table 6). This transition indicates a movement from a focus on higher prices to focus on higher yields and more stable prices. Specifically, the price coefficient of variation drops from 19% (July 24, 77 days harvest) to 10% (June 12, 77 days harvest) and the weighted average price declines from approximately \$16.30 per 25-pound box to \$13.40.

A similar strategy (transition to earlier planting period for a risk-averse grower compared with risk-neutral) is observed for sweet corn (Table 6). In antithesis to tomato production, the land allocation for sweet corn does not change further with higher risk aversion levels. Besides reducing the price variation, an additional benefit of earlier planting for sweet corn is the reduced ear worm pressure.

Regarding the optimal production practices under the second model formulation (annual average price scenario), three main observations are elicited from Table 6. First, irrespective of

Table 6. Summary of Optimal Production Practices by Risk Attitude

Model 1: Seasonal Price Trend

	Tomatoes[a]			Sweet Corn		
		Acres (% of total)			Acres (% of total)	
Risk Levels	Transplanting Date	DSL[b]	SSL[c]	Planting Day	DSL	SSL
Risk-neutral	July 10	27.0%	14.7%	June 21	32.5%	17.5%
	July 24	5.2%	2.8%			
Low risk aversion	June 12	5.4%	3.0%	May 23	32.5%	17.5%
	July 10	27.0%	14.6%			
Medium risk aversion	June 12	16.6%	9.0%	May 23	32.5%	17.5%
	July 10	16.0%	8.6%			
High risk aversion	June 12	23.0%	12.4%	May 23	32.5%	17.5%
	July 10	8.4%	4.4%			
	July 24	1.2%	0.6%			

Model 2: Annual Average Prices

	Tomatoes			Sweet Corn		
		Acres (% of total)			Acres (% of total)	
Risk Levels	Transplanting Date	DSL	SSL	Planting Day	DSL	SSL
Risk-neutral	June 12	26.8%	14.4%	May 30	32.5%	17.5%
	June 26	5.7%	3.0%			
Low risk aversion	June 12	15.0%	8.2%	May 30	32.5%	17.5%
	June 26	17.4%	9.4%			
Medium risk aversion	June 12	14.4%	7.8%	May 30	32.5%	17.5%
	June 26	18.0%	9.8%			
High risk aversion	June 12	14.2%	7.6%	May 30	32.5%	17.5%
	June 26	16.8%	9.0%			
	July 10	1.4%	0.8%			

Source: Economic Model Results.

[a] Optimal harvesting period for tomatoes, for all the risk aversion levels and for both models, is 77 days after transplanting.

[b] DSL, deep silty loam.

[c] SSL, shallow silty loam.

risk aversion level, the selected combination of tomato transplanting dates is earlier in the growing season compared with the seasonal price trend scenario. Specifically, June 12 and June 26 is the preferred transplanting date combination for risk-neutral, low- and medium-risk aversion levels instead of seasonal price trends scenario's later a combination of July 10 and July 24 (risk-neutral) or June 12 and July 10 (low and medium risk aversion). For the high-risk aversion level, in line with the seasonal price trend scenario, the optimal transplanting periods increase from two to three. However, as can be seen from Table 6, there is a transition toward earlier transplanting periods with the combination of June 12, June 26, and July 10 being preferred to June 12, July 10, and July 24. Second, only minor changes in the selected tomato production practices occur as risk aversion levels increase. Third, risk aversion levels do not influence the optimal planting period for sweet corn.

Justification for these findings lies in the estimation process adopted in the second scenario. In detail, the use of annual average prices to obtain the optimal production practices (first step in the second scenario) disregards seasonal price fluctuations. Thus, the optimal solution emphasizes the production periods with higher yields (Figures 1 and 2). Furthermore, greater

Table 7. Net Returns by Risk Attitude

Model 1: Seasonal Price Trend				
Economic Results	Risk Neutral	Low Risk Aversion	Medium Risk Aversion	High Risk Aversion
Mean ($)	84,573	81,492	77,192	74,391
Min ($)	42,064	48,676	48,216	46,497
Standard deviation ($)	20,939	16,914	14,120	12,816
Coefficient of variation	24.76	20.76	18.29	17.13
Certainty equivalent	84,573	70,972	64,338	58,122

Model 2: Annual Average Prices				
Economic Results	Risk Neutral	Low Risk Aversion	Medium Risk Aversion	High Risk Aversion
Mean ($)	71,827	71,429	71,407	71,994
Minimum ($)	41,807	40,282	40,202	40,970
Standard deviation ($)	12,453	12,562	12,582	12,783
Coefficient of variation	17.34	17.59	17.62	17.76
Certainty equivalent	71,827	65,626	61,200	55,808

Source: Economic Model Results.

focus on the yield variability component of net return risk leads to little reason to alter much from these high-yielding but stable production practices.

Regarding tomato harvesting, the model always recommends as the optimal schedule harvesting 77 days after transplant (Table 6). The higher yields and prices associated with these periods (in contrast with 63 and 70 days after transplant) explain this choice (Figures 1 and 2).

Economic Results

The economic results associated with the previously mentioned production strategies are reported in this section. As can be seen from Table 7, the average net returns above selected variable costs, the coefficient of variation, and the minimum possible net returns vary substantially between the different risk aversion levels and among the two model formulations.

Specifically, a risk-neutral grower under the seasonal price trend consideration scenario has an average net return above selected variable costs of $84,573 combined with a coefficient of variation (CV) of 24.7%. As the level of risk aversion increases, in line with the underlying theory, a decline in both average net returns and CV is noticed. For instance, the mean net returns for a highly risk averse grower correspond to 88% of the risk-neutral case, whereas those for the low-risk aversion scenario corresponded to 96%. However, the risk-neutral case is associated with higher levels of standard deviations and CV (almost 7% greater than the highly risk-averse case).

The importance and impact of a farm manager's conscious consideration of price seasonality is investigated as a primary objective of this study. This is accomplished by calculating the economic outcomes that would result from a suboptimal solution ignoring the weekly fluctuation in prices. This depicts a more naïve production strategy that disregards within-season market timing. Under this scenario, three substantial differences are identified regarding the economic outcomes (Table 7).

First, a grower who schedules production with consideration of seasonal price variation enjoys 3–15% higher expected net returns, depending on risk aversion level, compared with one who disregards the ability to exploit production timing based on price information. Furthermore, minimum net returns are also higher under the first scenario (Table 7). These findings validate the hypothesis that the consideration of seasonal price trends has the potential to increase net returns.

Regarding income risk levels, with the exception of a highly risk-averse grower, the CV is larger under the seasonal price trend scenario (Table 7). This result indicates that consideration of seasonal price trends can increase the net returns but it will also increase income variability. This is observed on both an absolute (standard deviation) as well as relative (CV) basis at all risk aversions and under risk neutrality. However, this counterintuitive result does not imply that risk efficiency under the annual average price scenario is superior. To compare the tradeoffs between risk and returns among the two strategies appropriately, one can compare the certainty equivalent (CE) at each risk aversion level. The CE, which depicts the certain amount that the decision-maker would be indifferent in accepting in lieu of the stochastic returns, may be calculated under the mean variance formulation as mean net returns less the product of the risk aversion coefficient and variance of net returns. The greater level of CE for every risk attitude under the seasonal price trend strategy (Table 7) demonstrates its superior economic performance over the annual average price scenario. Furthermore, it is worth noting that the high-risk aversion results for seasonal price trend consideration enjoy mean net returns that are nearly $2400 greater than any annual average price results coupled with a CV that is lower than any annual average price result.

An important aspect for every decision-maker is the risk management ability. For the purposes of the present study, risk management is defined as the potential to reduce income risk under the two scenarios. Based on this definition, a greater opportunity to manage risk is permitted under the seasonal price trend scenario. Specifically, the CV for this scenario ranges from 17.13% to 24.76%. On the other hand, under the annual average price scenario, CV has a substantially lower span from 17.34% to 17.76%. A counterintuitive result is that income variability increases as risk aversion increases under the second scenario and that expected net returns are greater for a highly risk-averse grower. This result is attributed to the two-step estimation process used in the second model formulation[13] coupled with the observation that the more stable yielding planting date of July 10 enters the solution and is accompanied by the highest weekly prices. This emphasizes the economic advantage of timing planting date to extract the best selling price of the season.

Finally, a comparison of the estimated net returns above selected variable costs with a 2008 vegetable budget (Woods, 2012) resulted in some thought-provoking observations. Specifically, the estimated net returns (on a per-acre basis) are from one and a half (highly risk-averse) to two times (risk-neutral) greater than the ones reported on the 2008 vegetable enterprise budget. This difference can be attributed to the combination of the conservative price/yield estimations of the extension service in contrast to the higher prices (obtained from the Atlanta AMS) and yields (from the biophysical simulation) used in the study. Furthermore, these higher price levels might have a large influence on the optimal decisions and the economic results. However, our findings are closer to the estimations of Rowell et al. (2006) who indicate that for the best tomato cultivars that season, it is possible to achieve close to $16,000 per acre. The aforementioned discrepancy may be reduced if annual inflation rates are considered because the study results are in 2010 dollars.

Conclusions

The present study combines biophysical simulation and mathematical programming modeling to develop an economic model that will provide some guidelines regarding the optimal production mix and planting decisions for vegetable production. The area of study was Fayette County, Kentucky, and the enterprises of tomatoes and sweet corn were evaluated.

Considering the importance of production timing, as a result of the perishability of

[13] As a reminder, under this formulation, the optimal production practices are estimated using annual average prices and the economic outcomes are calculated based on the complete weekly historical price information.

vegetable production, and the role that seasonal price trends consideration may play in optimal transplant/planting and harvesting schedules, two distinct scenarios are examined. Under the first scenario, the hypothetical grower plans production timing considering seasonal price variation, whereas under the second one, the grower chooses a simpler but less complete focus of annual average prices only. Three risk aversion levels are examined for each scenario. The findings indicate that vegetable producers have the potential to improve their economic results if they follow a structured farm management plan. Specifically, under the first formulation (seasonal price trend), growers can achieve average net returns that are from 3% to 15% higher than the ones from the second formulation (annual average prices scenario). Furthermore, they have greater opportunity to manage risk as depicted by the range of CV values.

Limitations of this study are primarily associated with the nature of the biophysical simulation model used. Specifically, yield estimations were made only for one variety and there are no calibrations for locally grown cultivars. Examination of different varieties may lead to different results considering the different performance each variety has under different weather patterns and soil conditions. In addition to including more vegetables in the model, future work can investigate how the results are affected when multiple markets are examined simultaneously.

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