Journal of Food Distribution Research
Volume 56, Issue 1, pp. 27–42

An Assessment of Profitability Using Monte Carlo Simulation Approach: A Case of Georgia Blueberry Industry

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Abstract

Our study assesses the profitability of producing blueberries using a drip irrigation system by addressing the price and yield variability. We use deterministic and stochastic budgeting approaches. We extend the deterministic budget to the stochastic budget using Monte Carlo simulation and applying triangular distributions to blueberry prices and yield in Georgia. The net present value (NPV) of returns from a blueberry investment under a deterministic budget is 1 to 3 times greater than under a stochastic budget. Under the stochastic approach, we study returns from blueberries by classifying growers based on their performance; thus, the study has direct implications particularly for Georgian and southeast growers in making investment decisions. Furthermore, the results will be helpful to farmers, researchers, and farm risk analyzers in assessing agricultural investment.

Keywords: blueberry, budget, Monte Carlo simulation, price, stochastic

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Introduction

The stochastic nature of key parameters, such as policy, production, and economic variables inherently complicates agricultural decision making. This complexity is accentuated in the agricultural sector due to its unique and diverse risks, including institutional (policy and regulations), production (disease and weather), and economic (input and output prices) risks (Harwood et al., 1999; Thorne and Hennessy, 2007). These risks introduce volatility in pricing and production outcomes, necessitating a comprehensive approach to uncertainty management in agricultural business decisions.

Variability in prices and yields represents significant risks in agriculture, impacting the predictability of farm income (Goodwin and Ker, 2002). Traditional methods that rely on historical averages may not capture the full spectrum of potential outcomes, making them insufficient in today's variable markets (Carter and Dean, 1960; Grant, 1985). Consequently, adopting a probabilistic approach to account for uncertainties in yield and price provides a more reliable basis for decision making, accommodating the unpredictable nature of factors like market demand fluctuations and climatic conditions.

This study enhances the traditional enterprise budgeting tool, a critical decision-making resource developed by extension teams at land-grant universities for various agricultural commodities and practices. Traditionally, these budgets have utilized a deterministic approach, tailored to specific growing conditions and inputs but have failed to account for the inherent variability in key factors, such as output quantity and price. By introducing stochastic elements into the budgeting process, this research adapts enterprise budgets to reflect better the uncertainties faced by blueberry growers in Georgia, providing a more robust framework for financial planning and risk assessment in agriculture.

Blueberry is one of Georgia's top 10 fruits and nuts commodities in terms of farm gate value, with a share of 42.3%, and contributed 2.45% of the total Georgia agricultural farm gate value in 2022 (University of Georgia, 2024). According to the 2022 Georgia Farm Gate Value Report (2024), the total farm-gate value of blueberries was $449.4 million from 27,192 acres, produced from 118 out of 159 counties in the state. Bacon County has been the top producer in the state, with the highest farm gate value in the past eight years.

Deterministic and Stochastic Budget

A deterministic budget provides financial outcomes based on fixed parameter values and assumes stable economic conditions, often not reflective of real-world scenarios (Fonsah and Hudgins, 2007; Fonsah et al., 2010; Fonsah et al., 2018). In contrast, a stochastic budget incorporates uncertainty and randomness, evaluating potential outcomes across a spectrum of variables rather than relying on fixed inputs. This method is particularly effective in non-stationary environments where variability is inevitable. The stochastic model utilizes variable estimates to predict likely outcomes, thus integrating risk and uncertainty into financial projections (Elkjaer, 2000; Richardson, 2006). Employing the Monte Carlo simulation technique, stochastic budget extends beyond single-point estimates to offer a probabilistic view that reveals the distribution of potential outcomes, providing deeper insights into the dynamics of agricultural economics.

Georgia blueberry growers suffer price and output changes due to the cultivar used in production, production area, aggregate productivity, market, and timing (Fonsah and Hudgins, 2007; Fonsah et al., 2007; Fonsah et al., 2011). However, despite pricing and output variations, Georgia blueberry growers usually rely on deterministic enterprise budgets, which are usually the type of enterprise budgeting decision tools made available by extension specialists at land-grant universities. Awondo, Fonsah, and Gray (2017) found that the grower's profit is overestimated by at least three times in a deterministic budget. Thus, we aim to incorporate risk associated with random variables like price and yield into Georgia's blueberry budget and present a probabilistic approach to evaluating returns on blueberry investment in Georgia. Our specific objectives are to (i) revisit the deterministic blueberry budget for Georgia, (ii) transform the deterministic budget to a stochastic budget, and (iii) compare net present values (NPV) from the two budget systems.

Several studies have used a probabilistic approach in farm enterprises. For example, Gummow and Patrick (2000), Rayburn (2009), Shalloo et al. (2004), and Werth et al. (1991) have utilized probabilistic approaches in the animal sector, whereas Elkjaer (2000), Ludena et al. (2010), Clancy et al. (2012), and Awondo, Fonsah, and Gray (2017) used them in the plant sector. Elkjaer (2000) recognizes Stochastic Budget Simulation (SBS) as a tool to estimate the overall cost to avoid statistical dependencies between variables. Ludena et al. (2010) present a greenhouse stochastic budgeting model incorporating risk to compare the production costs of flowers, taking pricing and flowering into account as stochastic components. Clancy et al. (2012) use nontraditional budgeting to estimate returns from willow and miscanthus in Ireland. Similarly, Awondo, Fonsah, and Gray (2017) consider price and yield as associated risk variables and provide the probability distribution of net present value and break-even year from producing muscadine grapes in Georgia.

For the past five years (2018–2023), the University of Georgia College of Agricultural and Environmental Sciences Extension (UGA-CAES) prepared deterministic budgets for southern highbush blueberry. Fonsah et al. (2007) and Kunwar and Fonsah (2022) introduced the risk-rated budget analysis approach for southern highbush blueberries, whereas Fonsah (2008, 2011) developed one for rabbiteye blueberries. These papers use sensitivity analysis to evaluate the effect of price and yield fluctuations that capture the risk component that could affect trends in blueberry production. The what-if analysis allows us to evaluate net returns in a few different price-yield scenarios; however, it does not allow us to project the whole range of net returns (in between and out of the designated case). Building upon the deterministic budgets in Kunwar and Fonsah (2022), we develop a stochastic budget for blueberry growers in Georgia to set a new, more realistic standard for enterprise budgeting in blueberry production.

Methodology

Deterministic Budget

To develop a deterministic budget, we considered two components, costs and returns, based on an acre of producing Southern Highbush blueberries in Georgia for a fresh market. We developed the budgets for a production system using a drip irrigation system and plant density of about 1,210 per acre and a planted distance of 12 feet apart in a row and 3 feet between rows.

A newly planted orchard will be fully productive in its fourth year. However, approximately 25% of blueberries can be harvestable from the second year of establishment (Fonsah et al., 2007; Kunwar and Fonsah, 2022). For the analysis of costs and returns in different years of production, we used the first three years as orchard establishment and the fourth and subsequent years as the full productive years. We collected input prices from farmers and agricultural vendors during the 2020 Annual Blueberry Growers Meeting. The input price information is private and confidential, making accessing comprehensive data from farmers challenging. Therefore, we consulted with extension county agents who maintain close relationships with the farming community. We calculated average prices for our analysis to address the variability in input prices, which may arise due to factors, such as the purchase volume, the vendor's relationship with the grower, or the payment terms (cash versus credit).

Total production costs were determined by estimating fixed and variable costs. Variable costs encompass land preparation, planting, fertilizers, weed and pest control, interest on operating capital, and harvesting and marketing expenses. Fixed costs include expenditures on tractors and equipment, overhead, management, and irrigation systems. Harvesting and marketing costs cover harvesting, custom packing, cooling, handling, and brokerage fees, which may vary annually depending on yield fluctuations. However, we assumed these costs would remain constant once the orchard reaches the full productive years, as we adopted a fixed yield for those years.

To estimate costs associated with machinery and other equipment, we used standardized practices recommended by the Agricultural and Applied Economics Association (AAEA) Task Force on Commodity Costs and Returns (AAEA, 2000). We assumed machinery and equipment costs as of the price of 2020. We estimated the costs of machinery and equipment based on 10 acres because their full efficiency is not obtained if used under 4 acres (Fonsah et al., 2007; Bogati et al., 2023; Magar, Fujino, and Han, 2024). However, we later adjusted these costs by an acre to harmonize with other costs. We included parameters, such as percentage used for the crop, purchase price, salvage value, lifespan, depreciation, interest, tax, and insurance in all machinery and equipment costs. The calculation used a salvage value of 20%, an interest rate of 6.5%, and 1.5% as taxes and insurance (Kunwar and Fonsah, 2022). We assumed farmers would use all the new equipment when establishing a blueberry farm.

For the returns side of the blueberry production, we estimated the price per pound (lb.) and the yield per acre based on multiple meetings and focus group discussions with growers, county agents, and blueberry economists. We used 15 years of production to estimate costs and returns, although blueberries can be harvested from an orchard for more than 15 years by adopting good agricultural practices (GAP). We used the blueberry price of $3 per lb., assuming it would remain constant throughout production. The expected yields for the second and third years are 1,700 lbs. and 4,000 lbs./ acre, respectively, whereas from the fourth year onward, it is 7,000 lbs./acre. Accounting for a 5% loss during harvesting and packaging, adjusted yields in years 2, 3, and 4–15 are 1,615 lbs., 3,800 lbs., and 6,650 lbs./acre, respectively.

To appraise the investment in blueberry production in Georgia, we calculated the net present value (NPV) of cash flows for 15 years. NPVs were estimated at two discount rates of 2% and 5% to capture the variability in the personal discount rate of growers.

Stochastic Budget

Unlike the deterministic budget, we described blueberry yield and price as random components and defined their distributions. We allowed simulation to model blueberry price and yield in Georgia. The costs were derived from input prices while acknowledging the challenge of capturing the variability of all input prices (Shrestha, 2015). Thus, we did not incorporate variability in input prices and used single-point estimates from the deterministic budget. Finally, we calculated NPVs from the total costs and the simulated yields and prices and used a probabilistic approach to evaluate NPVs. We applied the Monte Carlo simulation using triangular distribution for both price and yield.

Monte Carlo Simulation Using Triangular Distribution

Defining the probability distribution to model the price and yield in crop production is noteworthy during risk assessment and management (Ramirez, McDonald, and Carpio, 2010). We fitted the triangular distribution to represent the yield and the price variability of blueberries in Georgia.[1] The triangular distribution is used when we have small sample data (Hardaker et al., 2015) and to model agricultural price and yield data because the time series price and yield data for long periods are rare (Ramirez, McDonald, and Carpio, 2010). Moreover, the triangular distribution can define yield and price distribution when experts identify the minimum, maximum, and most likely values (Back, Boles, and Fry, 2000). We used the inversion of the cumulative distribution function (CDF) of triangular distribution for the simulation, which we discuss below.

Probability density function ($f(x)$) and cumulative distribution function ($F(x)$) of a triangular distribution with the parameters a (minimum), b (maximum), and c (most likely) are given by,

$$f(x) = \frac{2(x-a)}{(b-a)(c-a)}, \qquad if\ x \in [a,c] \qquad (1)$$

$$= \frac{2(b-x)}{(b-a)(b-c)}, \qquad if\ x \in [c,b] \qquad (2)$$

$$F(x) = \frac{(x-a)^2}{(b-a)(c-a)}, \qquad if\ x \in [a,c], \qquad say\ P_1 \qquad (3)$$

$$= 1 - \frac{(b-x)^2}{(b-a)(b-c)}, \qquad if\ x \in [c,b], \qquad \text{say } P_2 \qquad (4)$$

[1] We assume independence between prices and yields to simplify the analysis, making it accessible for extension agents and growers. This assumption aligns with the practical scope of data collected from a select group of participants at an annual meeting, where individual production levels are unlikely to influence market prices significantly.

In Figure 1, $x_1 = c - a$, $x_2 = b - c$, and the area of *ΔT₁* gives the probability of x less than or equal to c.

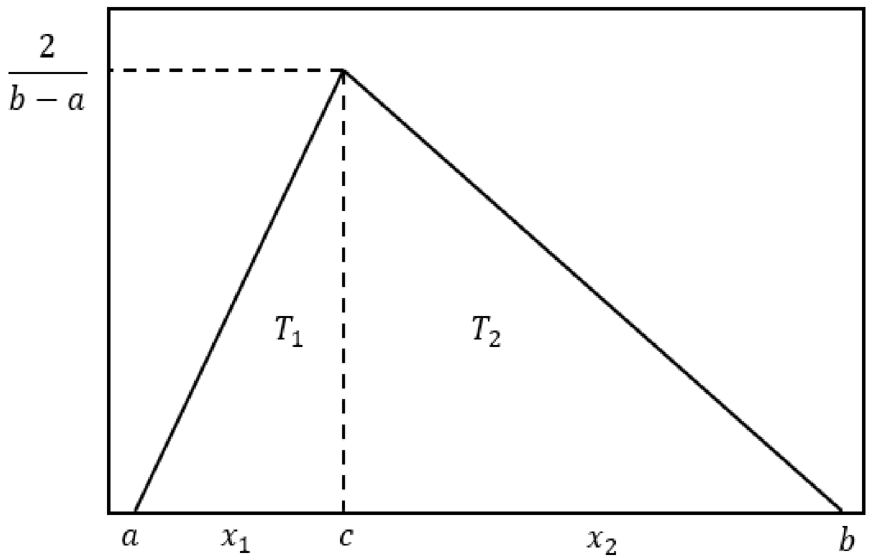


Figure 1. The Probability Distribution Function (PDF) of the Triangular Distribution

Mathematically,

$$P(x \le c) = area\,of\;\; \Delta T_1 = \frac{1}{2} \times (c-a) \times \frac{2}{(b-a)} = \frac{c-a}{b-a} \tag{5}$$

Now, taking equation (5) as a reference, if any random probability is smaller than *P (x ≤ c)*, we use the inverse function of equation (3) to get x_1 and, if any random probability is greater than *P (x ≤ c)*, we use the inverse function of equation (4) to get x_2.

$$\begin{gathered} P_1 = \frac{(x-a)^2}{(b-a)(c-a)} \\ or, x = a + \sqrt{P_1 \times (b-a) \times (c-a)} \end{gathered} \qquad if\ x \in [a, c] \tag{6}$$

$$\begin{gathered} P_2 = 1 - \frac{(b-x)^2}{(b-a)(b-c)} \\ or, x = b - \sqrt{(1-P_2) \times (b-a) \times (b-c)} \end{gathered} \qquad if\ x \in [c, b] \tag{7}$$

P(x) is a random probability between 0 and 1. So, for *P(x) ≤ P (x ≤ c),* we use $P_1 = P(x)$ and $x_1 = x$ from equation (6) and for *P(x) >P (x ≤ c)*, we use $P_2 = P(x)$ and $x_2 = x$ from equation (7).

Simulation Step

For the simulation process in this study, the price and the yield were the input variables, and the NPV was the output variable. We allowed for the simulation of the yield from years 4 to 15 and the price from years 1 to 15. We obtained NPVs following the steps mentioned below.

i. For each year from 4 to 15, we defined triangular distribution for yield by using maximum, minimum, and most likely yield to generate random yields in Equations (6) and (7).
ii. We applied step (a) for the price for each year from 1 to 15.
iii. To calculate the revenue for the corresponding years, we randomly selected yield and price in different years.
iv. From the net cash flows derived using the revenue generated above in (c), we computed NPVs at 2% and 5% discount rates.
v. We iterated the process from (a) to (d) 10,000 times.

Survey Design

A questionnaire was distributed to blueberry growers via email and personal meetings at the Annual Blueberry Growers Meeting in Alma County, Georgia, on January 8, 2020. A total of 40 responses were obtained; 5 responses were received through email, and 35 were gathered from personal interviews at the grower's meeting. The questionnaire asked respondents to provide historical annual yield and price data for up to 15 years if the farmers were able to keep historical records. If not, it asked the farmers to provide the expected maximum, minimum, and most likely price and yield if they were to grow blueberries for the next 10 years, given their experience growing blueberries in Georgia.

Results and Discussions

Deterministic Budget

The total cost of plants per acre (with a density of 1,210/acre) was $2,783 due to the $2.30 cost each for healthy and ready-to-plant blueberry bushes. Labor cost/acre was $242, and the total land preparation cost was $2,773/acre. In the first year of the establishment, the total operating costs were $6,947/acre.[2] The total operating costs in the second and third years of the establishment were $1,458 and $1,437 per acre, respectively. The total harvesting and marketing costs in the second and third years were $3,375 and $7,942 per acre, respectively. In full production years, the total operating cost was estimated at $1,646/acre, and the harvesting and marketing costs were estimated at $13,899/acre.

[2] For a comprehensive breakdown of these costs across different years, see Kunwar and Fonsah (2022). This reference provides an extensive categorization of costs and is a complementary resource to our analysis.

In the first three establishment years, the total variable costs were estimated at \$6,947.26/acre, \$4,833.65/acre, and \$9,379/acre, respectively. The total variable costs were estimated at \$15,544.24/acre for each full productive year. The observed decrease in the total variable costs in the second year from the year can be attributed to a lack of costs for land preparation, planting, and planting materials. Also, there is an increase in the total variable costs from the second to the third year. The yield in the third year increased compared to the second year, making the harvesting and marketing/packaging costs higher in the third year. Similarly, the total fixed costs estimated for years 1, 2, 3, and 4–15 were \$2,849.46/acre, \$2,026.11/acre, 2,022.92/acre, and \$2,054.23/acre, respectively, which included a fixed machinery cost of \$1,521.3/acre every year.

Table 1 shows the cash flows for the 15 years of production and the calculated NPVs at 2% and 5% discount rates. The investment in blueberry production begins to yield positive returns from the third year and covers the original cost of the investment in the ninth year. The net present value at both discount rates was positive, implying that NPVs at discount rates between 2% and 5% are positive. Thus, the returns from blueberry production are profitable, making the investment attractive for Georgia growers.

Table 1. Cash Flows and NPVs of Blueberry Production in Georgia, 2020

Year	Yield	Price	Return	Variable Cost	Returns over Variable Cost	Total Cost	Returns over Total Cost (Net Cash Flow)
1	0	3	0	6,947.26	-6,947.26	9,796.72	-9,796.72
2	1,615	3	4,845	4,833.65	11.35	6,859.77	-2,014.77
3	3,800	3	11,400	9,379.00	2,021.00	11,401.92	-1.92
4–15	6,650	3	19,950	15,544.24	4,405.76	17,598.47	2,351.53

NPV at a discount rate of 2% (NPV@2%) = 12,128.70
NPV at a discount rate of 5% (NPV@5%) = 7,187.17

Note: Yield is measured in lbs. per acre, and returns, costs, and price are measured in dollars per lb. Values for years 4 to 15 are the same; thus, we do not report to save space.

Stochastic Budget

Table 2 shows the average maximum, minimum, and most likely yields and prices obtained from the blueberry growers. Since the variation in maximum and minimum prices and yields were high, we classified blueberry producers into different categories based on prices and yields obtained.

Table 2. Summary Statistics of Expected Maximum, Minimum, and Most Likely Yield and Price of Blueberry Growers in Georgia, 2020

	Mean	Standard Deviation	Minimum	Maximum
Minimum yield	3,456.76	1,980.40	900.00	8,000.00
Most likely yield	6,459.46	2,514.90	2,000.00	12,000.00
Maximum yield	10,910.81	4,415.87	4,000.00	20,000.00

Minimum price	1.42	0.98	0.20	4.00
Most likely price	2.39	1.25	0.65	5.00
Maximum price	4.04	1.92	1.00	7.50

Note: Yield in lbs. per acre and price in dollars per lb. Source: Survey and authors' calculations.

Based on yield, we classified growers as "Top Producers" if their yield is above the average most likely yield and "Low Producers" if their yield is below the average most likely. Similarly, based on price, growers were categorized as "High-Price Receivers" if the received price was above the average most likely and "Low-Price Receivers" if the received price was below the average most likely. We calculated the average of maximum, minimum, and most likely yield and price for all categories. Interacting categories based on the price and yield, we have four groups of growers—"top producers receiving high prices (TPRHP)," "low producers receiving high prices (LPRHP)," "top producers receiving low prices (TPRLP)," and "low producers receiving low prices (LPRLP)," (see Table 3).[3] We also include the group "growers in general" without categorization. Figure 2 shows the CDFs for all the groups after simulation.

Table 3. Categorization of Georgia Blueberry Growers Based on the Price Received and the Yield, 2020

Panel A:

			Yield					
			Top Producer			**Low Producer**		
		Price	**a 4,833.33**	**c 8,638.89**	**b 13,777.78**	**a 2,152.63**	**c 4,394.74**	**b 8,194.74**
High price receiver	a	2.14						
	c	3.57	TPRHP (27.27%)			LPRHP (18.18%)		
	b	6.00						
Low price receiver	a	0.48						
	c	1.52	TPRLP (24.24%)			LPRLP (30.30%)		
	b	2.60						

Panel B:

	TPRHP	**LPRHP**	**TPRLP**	**LPRLP**
Yield range	8944.45	6042.11	8944.45	6042.11
Price range	3.86	3.86	2.12	2.12

Note: a, b, and c denote average minimum, average maximum, and average most likely, respectively. TPRHP represents top producers receiving high prices, LPRHP represents low producers receiving high prices, TPRLP represents top producers receiving low prices, and LPRLP represents low producers receiving low prices. Figures in the parentheses are the percentage of growers belonging to the group based on the most likely price and the most likely yield.

Higher prices for greater yields give more returns, so there was a 100% chance of obtaining positive NPV at 2% and 5%. Therefore, for the TPRHP, blueberry production in Georgia is highly

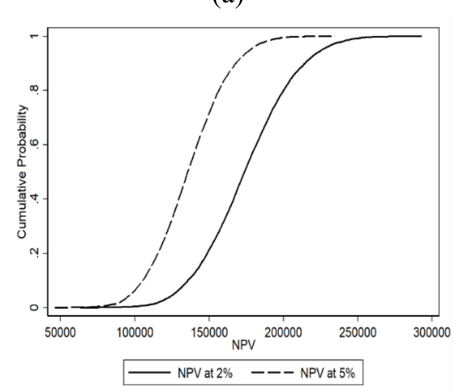
[3] Our study categorizes growers based on yield and price but does not explicitly link these categories to their risk preferences. Understanding the risk aversion of different groups could enhance the analysis, and we recommend this as an avenue for future research.

profitable. Figure 2a presents the cumulative distribution function of NPV respectively at two different discount rates. Unlike the TPRHP, blueberry production for the TPRLP is not conducive to investment. The chance of getting a positive NPV during the 15 years of production is almost 0% at 2% and 5% discount rates (see Figure 2b).

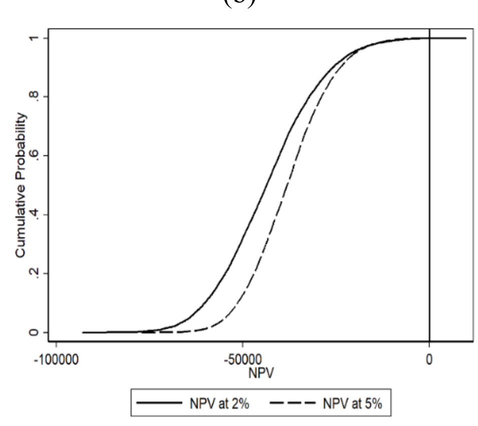
The chance of a positive NPV decreases from 100% to 67.72% and 63.63% at the discount rate of 2% and 5%, respectively, if a producer belongs to LPRHP fails to maintain the productivity of the farm (see Figure 2c). Because the probability is greater than 50%, the investment in the production of blueberries is favorable.[4] Growers in the category LPRLP do not obtain positive NPV during the 15 years of blueberry production. This category of farmers has a 0% chance of paying back the cost of their original investment (see Figure 2d).

The probability of getting a positive NPV for the "growers in general" at a 2% discount rate is 30.24%, and at 5%, it is 23.85% (see Figure 2e). These probabilities incorporate all the possible combinations of yields and prices. As the chance of a positive NPV is below 50%, the investment in blueberry production does not seem favorable in Georgia.

(a)



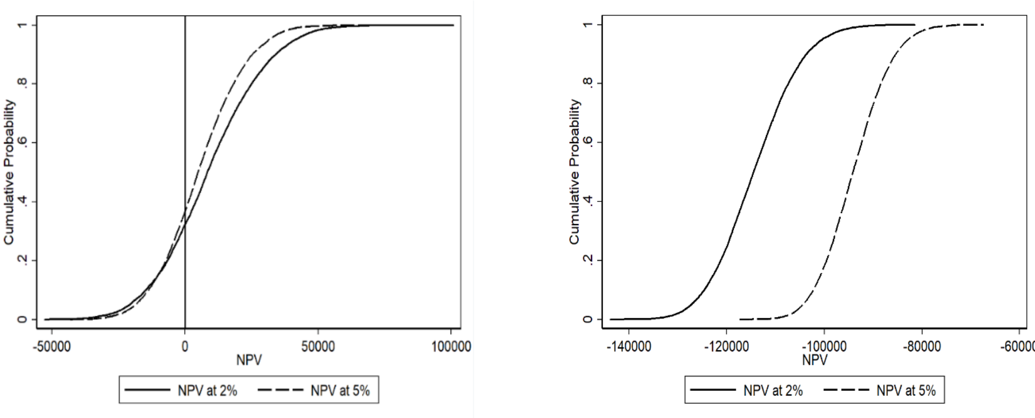
(b)



(c)

(d)

[4] The 50% threshold used in this analysis is a conventional benchmark, where an investment is considered favorable if the likelihood of achieving a positive NPV exceeds the likelihood of a loss. These standards balance risk and potential return and are suited to the moderate risk tolerance typical in agricultural investments. We leave it to future studies to explore alternative probability thresholds for evaluating investment favorability under conditions of uncertainty.



(e)

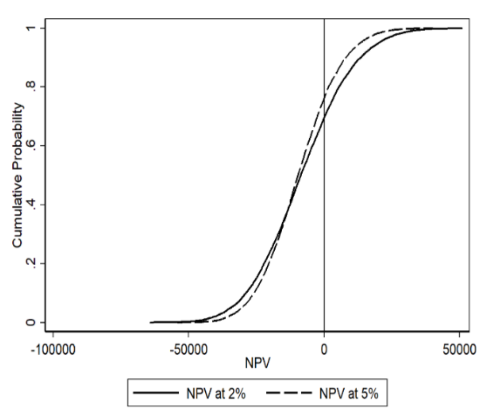


Figure 2: Cumulative distribution functions of net present values for blueberry producers in Georgia, 2020 (a) top producers receiving high prices (b) top producers receiving low prices (c) low producers receiving high prices (d) low producers receiving low prices (e) growers in general

Comparison and Discussion of Results from Deterministic Budget vs. Stochastic Budget.

Table 4 presents the expected NPV from the deterministic budget and stochastic budget for all categories of producers. The comparison shows that the expected NPV from the traditional budget is only possible if a grower falls in the "top producer receiving high price group." The expected NPVs from the deterministic budgets do not fall in any producers' 95% confidence interval, including the "growers in general." This discrepancy underscores a key distinction between the two budgeting approaches.

Table 4. Comparison of NPV from the Deterministic and Stochastic Budget in Georgia, 2020

	Discount Rate	Expected NPV	Lower Bound (95% CI)	Upper Bound (95% CI)	Chance of Positive NPV (%)
Deterministic budget	2%	12,129			100
	5%	7,187			100

Stochastic budget					
TPRHP	2%	174,579	173,987	175,172	100
	5%	136,449	135,975	136,924	100
TPRLP	2%	-43,387	-43,648	-43,127	0
	5%	-37,851	-38,059	-37,642	0
LPRHP	2%	9,122	8,754	9,491	67.72
	5%	5,567	5,270	5,864	63.63
LPRLP	2%	-114,231	-114,391	-114,070	0
	5%	-93,868	-93,997	-93,739	0
Growers in general	2%	-8,157	-8,480	-7,834	30.24
	5%	-9,174	-9,433	-8,915	23.85

Note: NPV in dollars per acre. TPRHP represents top producers receiving high prices, LPRHP represents low producers receiving high prices, TPRLP represents top producers receiving low prices, and LPRLP represents low producers receiving low prices.

There is a 100% chance of a positive NPV for the TPRHP and a 0% chance for the LPRLP. The results show no chance of a positive NPV for the TPRLP. However, there is a significant chance of a positive NPV for the LPRHP. Analyzing the difference between the maximum and minimum yields and prices within the TPRLP and the LPRHP categories can provide valuable insights into why LPRHP might exhibit a higher potential for positive NPV but not the TPRLP.

Table 3 shows that while the TPRLP has a yield range that is 1.48 times wider than the LPRHP (8,944.45 vs. 6,042.11 lbs. per acre), the LPRHP's price range is 1.82 times wider than that of the TPRLP ($3.86 vs. $2.12 per lb.). The TPRLP experiences high yield variability, which could buffer against low prices. However, the lower and narrow price range limits their potential profitability. Lower prices diminish the benefits of high yields because the returns per unit are reduced. The LPRHP has lower yield variability, suggesting consistent and predictable production. The higher and wider range of prices compensates for its lower yields. This signals that high prices ensure substantial net revenue even with modest yields. Thus, growers need to focus on determinants of blueberry prices such as the berries' quality, harvesting time, strategic marketing windows, and bargaining power (Kader, 2002; Yeh et al., 2023).

To contrast traditional and nontraditional budgets, comparing the expected NPV from the conventional budget to the expected NPV from the stochastic budget for the "growers in general" group makes more sense because both are estimated for all the blueberry producers in Georgia. The expected NPV in the deterministic budget is 248.70% more than the expected NPV in the stochastic budget at a 2% discount rate and 178.34% at a 5% discount rate. The considerable difference in expected NPVs from different budget systems shows that the result from the traditional budget is unrealistic and unjustifiably optimistic. Our results align with those of Awondo et al. (2017), who depicted that the chance of getting a positive NPV from the non-stochastic budget is 3 to 4 times greater than that from the stochastic budget. The chance of a positive NPV for the "top producers receiving high prices" (100%) is close to the findings of Fonsah et al. (2007), establishing a 92% estimated chance for profit in southern highbush blueberry production in Georgia. Similarly, the estimated chances of a positive NPV for the "low producers receiving high prices" (67.72% and 63.63% at the discount rate of 2% and 5%) are close to the figures obtained by Kunwar and Fonsah (2022), whereby an estimated 69% chance for profit was prescribed for southern highbush blueberry production using drip irrigation and frost protection in Georgia.

Conclusion

The paper discusses blueberry's profitability using two different kinds of budgets—deterministic and stochastic. For the simulation of prices and yields to develop a stochastic budget, we defined the triangular distribution using the minimum, maximum, and most likely values because the stochastic variable is better delineated by distribution. Thus, we interpreted the stochastic budget results using the chance (%) of getting a positive NPV at two discount rates, 2% and 5 %. Unlike the stochastic budget, the non-stochastic budget has a straightforward interpretation.

The expected NPV in the deterministic budget is $12,129/acre at a 2% discount rate and $7,187/acre at a 5% discount rate. Except for a group of producers with high production and who receive high prices, no other groups have NPV higher than in the deterministic budget with 100%. The NPVs at 2% and 5% for a group "top producer receiving high price" are expectedly high, constituting 27.27% of blueberry growers in Georgia. Also, no chance of positive NPVs for a group of producers with low production and receiving low prices was estimated. We found no chance of positive NPVs in a group of "top producers receiving low prices."

In contrast, a significant percentage of positive NPVs in a group "low producers receiving high prices" was observed, signaling price as a critical determining factor for higher returns on investment. Specifically, a more relevant comparison between NPVs for the group "growers in general" and NPVs from the deterministic budget shows that a deterministic budget projects notably higher (1 to 3 times) NPVs than the stochastic budget. Despite negative expected NPVs for a group of "growers in general," there is a certain chance (23.85%–30.24%) of getting a positive NPV.

This study was primarily focused on farmer-level prices and yield of blueberries, for which data from the primary source are critical. Any data from the secondary source could be used as a reference but is irrelevant to making farmer-level conclusions. Because the price and yield data of the commodity are confidential and growers are concerned about it, we found it difficult to obtain primary data for such kinds of studies.

A limitation of this study is that we do not consider costs (input prices) as stochastic variables. Considering input prices as random variables and applying a similar approach improves the study's findings and is a possible extension of our work. Finally, the takeaway message is that depending solely on the deterministic enterprise budget can mislead farmers regarding investment and returns. The estimates from the traditional assessment approach can underestimate or overestimate the real production scenarios of any farm crop. A better understanding of all the potential stochastic variables and proper definition of their distributions yields more accurate and precise estimates of the outcome variables.

While stochastic budgeting helps model uncertainty in agricultural economics, its adoption across the farm industry is restricted by computational complexity and a widespread lack of specialized training. Recognizing these barriers, it is crucial for Extension Agricultural Economists at land-grant universities to elevate their educational offerings, emphasizing training in stochastic budgeting techniques. Developing a stochastic budget that complements the traditional partial enterprise budgets produced annually for various horticultural crops can improve decision making among growers.

Our study is based on data from specific grower categories in Georgia, which may not fully reflect the broader variability in agricultural practices or market dynamics. As such, the findings are primarily applicable within similar environmental and economic contexts. Future research should explore these dynamics across more diverse regions to enhance the generalizability of our results.

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