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Optimizing Multi-Crop Agricultural Production under Uncertainty: A Two-Stage Stochastic Approach

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ABSTRACT

Efficient crop planning is very important in agriculture because farmers need to allocate limited resources such as land, labour, and budget while facing uncertainty in crop yield, demand, and prices. In this research, deterministic and stochastic programming models are developed to determine the optimal land allocation and crop production plan that maximizes farmers' profit while meeting food scarcity. All parameters in the deterministic models are certain. To address the uncertain parameters, a 2-stage stochastic programming model is developed where the land allocation, demand, selling, and purchasing decisions are considered as uncertain. Primary data are collected from direct interviews with the farmers to validate the model. Secondary data collected from the Bangladesh Bureau of Statistics (BBS) Yearbook 2023 are also used. Uncertainty is analysed through a stochastic model with 4 scenarios. Both models are implemented and solved using the AMPL programming language. A comparative analysis indicates that although the deterministic model yields higher profit under fixed conditions, the stochastic model provides more robust and reliable decisions by incorporating uncertainty. Therefore, the proposed stochastic crop planning model can serve as an effective decision-support tool for farmers to manage agricultural risks and improve overall farm profitability.

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1. Introduction

Worldwide agricultural production plays a central role in ensuring food security, economic development, and rural livelihoods. Global demand for food continues to rise due to population growth, urbanization, and evolving consumption patterns, exerting increasing pressure on agricultural systems to enhance productivity while balancing environmental and economic goals [1,2]. However, agricultural systems face significant challenges due to climatic variability, soil degradation, pest outbreaks, and market fluctuations, which can drastically affect crop yields and farm incomes [3,4]. In countries like Bangladesh, where agriculture contributes significantly to the economy and employs a large share of the workforce, the adoption of modern agricultural machinery is crucial for improving productivity and reducing labour dependency. However, farmers often face challenges such as limited financial resources, small landholdings, and inadequate access to mechanization services, which restrict the widespread adoption of modern farming technologies [5]. Islam et al. show that conservation agriculture practices can enhance crop yields and water productivity, contributing to sustainable agricultural intensification for smallholders [6].

Traditional farm decisions are frequently based on experience or reactive responses rather than structured planning techniques, leading to overproduction, underproduction, and financial losses. Overproduction can saturate markets and depress prices, while underproduction can exacerbate food shortages and elevate prices, adversely affecting both farm profitability and consumer welfare [5,7]. These patterns highlight the importance of decision support tools that incorporate both economic objectives and real-world uncertainties.

Linear programming (LP) has been widely used in agricultural planning to allocate scarce resources under deterministic assumptions. Hazell et al. illustrate how LP models can optimize economic decisions in agriculture by incorporating cost structures and production constraints [7]. Sorin demonstrated the utility of linear programming in farm planning models to optimize crop structure and maximize income in vegetable agricultural farms [8]. Rajni et al. show how linear programming can support crop mix decisions, highlighting its practical value in real-world farm planning scenarios [9].

Birge et al. provide a comprehensive foundation for SP, detailing how uncertainty can be modelled using scenarios and probability distributions [10]. Shapiro et al. further develop the theory and computational aspects of SP, highlighting its applicability in planning problems where recourse actions are key [11]. Stochastic programming extends traditional optimization by incorporating uncertainty in parameters such as demand, prices, or yields. Accounting for this uncertainty allows for more robust and risk-aware decisions, with applications in agriculture, finance, and energy planning [10,11]. Applied studies show that SP can outperform deterministic models, especially in environments with high variability. Hardaker et al. review alternative programming models for farm planning under uncertainty, showing how stochastic, fuzzy, and chance-constrained approaches help farmers make decisions that balance expected returns with risk from variable yields, prices, and input availability [12]. Itoh et al. address the limitations of traditional linear programming in crop planning by incorporating uncertainty in profit coefficients caused by factors such as future weather. Their model treats these uncertain elements as both fuzzy and random variables, enabling farmers to make more informed and resilient decisions under variable agricultural conditions [13]. Ouattara et al. demonstrate that stochastic optimization can guide land allocation between annual and perennial crops, helping risk-averse farmers make decisions that balance income potential and production risk [14]. Backus et al. highlight how decision-making tools under risk and uncertainty can assist farmers in choosing optimal strategies, improving farm efficiency and reducing potential losses [15]. Nuthall emphasizes that enhancing farmers' managerial ability through psychological insights can improve decision-making, resource use, and overall farm performance [16]. Empirical analysis by Haile et al. demonstrates how international price changes and volatility influence farmers' acreage allocation and yield decisions for major crops such as wheat, rice, corn, and soybeans. Their dynamic panel data results highlight that higher prices encourage production expansion, while increased price volatility discourages farmers from making larger production investments due to uncertainty [17]. Müller et al. explore uncertainties in global crop yield projections using a large ensemble of crop models combined with CMIP5 and CMIP6 climate scenarios. The study shows that variations in climate models, emission pathways, and crop model structures contribute significantly to uncertainty in future global crop yield projections under climate change [18]. Schlenker et al. investigate the nonlinear effects of temperature on U.S. crop yields using historical yield and weather data. The study demonstrates that extreme heat events cause disproportionately large reductions in yields, indicating that climate change could severely damage U.S. corn and soybean production [19]. Gao et al. propose a general framework for sustainable supply chain design that integrates life cycle optimization with two-stage stochastic programming to account for both economic and environmental objectives under uncertainty. Their stochastic mixed-integer linear fractional programming (SMILFP) model addresses uncertainties in feedstock supply and product demand, and an efficient solution algorithm using a parametric and multi-cut L-shaped decomposition method is demonstrated through a county-level hydrocarbon biofuel supply chain case study in Illinois [20]. Rockafellar et al. introduce the concept of Conditional Value-at-Risk (CVaR) as a coherent risk measure applicable to general loss distributions, providing a more robust assessment of extreme losses compared to traditional Value-at-Risk (VaR) approaches [21]. Ahmed et al. present the Sample Average Approximation (SAA) method as an effective approach for solving stochastic programs with integer recourse, providing a practical way to approximate solutions under uncertainty while maintaining computational tractability [22]. Shapiro discusses how stochastic programming problems involve optimizing an expected value function that cannot be computed exactly and must be approximated, often using Monte Carlo sampling. He highlights the Sample Average Approximation (SAA) method as a practical and efficient approach for estimating expectations and solving stochastic programming problems in real-world applications [23]. Olsson et al. highlight the use of Latin Hypercube Sampling (LHS) as an efficient technique for structural reliability analysis, enabling more accurate estimation of failure probabilities with fewer simulations compared to traditional Monte Carlo methods [24]. Ashofteh et al. assess streamflow simulation and transition probabilities under future climate change scenarios, demonstrating how hydrological models can project changes in water availability and inform adaptive water resource management strategies [25]. Lee et al. analysed agro-economic time series from South Korea to show how fluctuations in crop prices and yields influence farmers' crop selection decisions, highlighting the importance of integrating economic and production uncertainties into agricultural planning [26]. Biswas et al. demonstrate that fuzzy goal programming can be applied to agricultural land use planning, enabling decision-makers to balance multiple, often conflicting objectives under uncertainty for more effective resource allocation [27]. Charnes et al. introduce chance-constrained programming as a method to handle uncertainty in optimization problems, allowing constraints to be satisfied with a specified probability and supporting more robust decision-making under risk [28]. Ben-Tal et al. present robust convex optimization as a framework for making optimization decisions that remain feasible under data uncertainty, enhancing solution reliability and performance in uncertain environments [29]. Bertsimas et al. explore robust optimization theory and its applications, demonstrating how optimization models can account for uncertainty in parameters to produce solutions that are reliable and effective across a range of possible scenarios [30].

Despite the rich literature on uncertainty modelling and optimization, many existing studies rely on synthetic or

aggregated data rather than real farm-level information, limiting their applicability to individual farmers' decisions. Integrating primary data collected through farmer interviews with secondary national statistics, such as those provided by the Bangladesh Bureau of Statistics Yearbook, enhances the relevance and practical utility of optimization models [2,31]. Nusser et al. emphasize that proper sampling and data collection methods are essential for obtaining reliable and representative agricultural survey data. Their research highlights how careful design and estimation techniques reduce bias and improve the accuracy of farm-level analysis for research and policy decisions [32]. Risk metrics such as the Value of the Stochastic Solution (VSS) and the Expected Value of Perfect Information (EVPI) have also been developed to quantify the value of accounting for uncertainty in optimization models. VSS measures the improvement in expected outcomes when uncertainty is incorporated compared to using a deterministic expected-value solution. EVPI estimates the theoretical value of knowing future states with certainty, providing an upper bound on the benefit achievable through uncertainty resolution [10,11]. Bai et al. illustrate how stochastic and deterministic models can be compared in agricultural production networks by examining differences in model behaviour and performance metrics under uncertainty, highlighting the advantages of stochastic approaches for capturing variability in agricultural systems [33].
The remainder of this study is organized as follows: the problem statement as well as the deterministic model and two-stage stochastic model are explained in Section 2. The computational results and analysis are presented in Section 3. Finally, conclusions and further research directions are discussed in Section 4.

2. Model formulation

This section presents the formulation of both the deterministic and stochastic programming models for crop planning. The two approaches differ primarily in the way they handle uncertainty in key parameters such as crop yield, demand, and selling or purchasing prices.
In the deterministic model, all parameters and decision variables are treated as fixed inputs. While this simplifies the modeling process and enables straightforward optimization, it has limited practical applicability because it does not account for the inherent variability and uncertainty in agricultural production. Consequently, solutions obtained from deterministic models may be less robust under real-world conditions and may fail to maximize profit when unexpected changes occur.
In contrast, the stochastic programming model explicitly incorporates uncertainty into the decision-making process. Some key variables are considered scenario-dependent random variables. By accounting for multiple possible outcomes and their associated probabilities, the stochastic model provides a more realistic and risk-aware framework for crop planning. This approach enables the farmer to make decisions that are robust to variability, minimizing potential losses and improving expected profitability under uncertain conditions.
The deterministic model serves as a baseline approach, while the stochastic model captures the dynamic and uncertain nature of agricultural production, providing more reliable and practical decision support for optimal resource management.

2.1 Problem statement

In agricultural production planning, farmers must decide how much land to allocate to each type of crop at the beginning of the planning period. These decisions are challenging because the key factors such as crop yield, market demand, and purchasing prices are intrinsically uncertain. The optimal strategy depends on multiple uncertain parameters, including variability in weather, market fluctuations, and production costs.

2.2 Mathematical notation

The mathematical notations used in the crop planning model are summarized in Table 1. The notations define the sets, parameters, and decision variables required to formulate the objective function and constraints.

Table 1: Notations for the deterministic model

Sets (subscripts):		
i	*1, 2, …, I*	Crop index
Parameters:		
L	Total available land (decimal)	
M	Total budget (Tk)	
LH	Total labor (hour)	
d_i	Demand of crop *i* per kg	
p_{x_i}	Purchase cost of crop *i* per kg	
c_{x_i}	Production cost for crop *i* per decimal	
y_{x_i}	Yield per decimal (kg)	
L_{x_i}	Labor hour needed for crop *i* per decimal	
s_{s_i}	Selling price of crop *i* per kg	
Decision Variables:		
x_i	Decimal of land devoted to crop *i*	
p_i	Purchasing amount of crop *i* (kg)	

s_i	Selling amount of crop i (kg)

2.3 Deterministic model

In the proposed deterministic crop planning model, all parameters are assumed to be known with certainty. That is, yields, demands, selling prices, purchase prices, labour availability, land, and budget are considered fixed and predictable.

The following assumptions are made in the deterministic model:

- No initial inventory: It is assumed that the farmer starts with zero stock of any crop at the beginning of the planning period.
- Resource limitations: Both land and labour are considered limited resources. Production is constrained by available land, labour hours, and the associated production costs. These resources are shared across all crops, and the model ensures that allocation does not exceed available capacity.

Under these assumptions, the deterministic model simplifies the stochastic crop planning problem into a single-scenario optimization, where the profit-maximizing land allocation, production, and purchasing decisions can be determined with certainty.

2.3.1 Objective function

The objective of the proposed crop planning model is to maximize the farmer's total profit by taking into account selling price, purchasing costs, and production costs. Each term of the objective function represents a distinct component of the overall profit.

Total Selling Price:

Firstly, the total revenue earned from selling crops is $\sum_{i=1}^{I} s_i * s_{s_i}$. This component captures the primary source of income for the farmer, reflecting how the harvested crops translate into monetary returns. By maximizing this term, the model encourages allocation of land to crops that have high revenue potential, taking into account both crop yield and market price.

Total Purchasing Price:

Secondly, the cost incurred to purchase crops to meet demand that exceeds the farmer's own production is $\sum_{i=1}^{I} p_i * p_{x_i}$. This term ensures that the model incorporates additional expenditures required to satisfy crop demand. It discourages over-reliance on market purchases, encouraging the farmer to produce sufficient quantities on their own land whenever feasible.

Total Production Cost:

Thirdly, the cost of producing each crop on the allocated land is $\sum_{i=1}^{I} x_i * c_{x_i}$. This term ensures that the model accounts for the resources and expenses associated with land cultivation. By including production cost, the objective function encourages efficient allocation of land, focusing on crops that provide higher net returns relative to their production cost.

The objective function can be interpreted as the net profit of the farming process, and considering all three components, it can be expressed as:

$$\max z = \text{total selling revenue} - \text{total purchasing cost} - \text{total production cost}$$
$$= \sum_{i=1}^{I} [s_i * s_{s_i} - p_i * p_{x_i} - x_i * c_{x_i}]$$

The model maximizes the difference between expected revenues and total costs, thereby providing an optimal land allocation strategy.

2.3.2 Constraints

The proposed crop planning model is subject to several practical and economic constraints that ensure feasibility and realism in the allocation of resources. Each set of constraints reflects a physical, financial, or agronomic limitation in the production process. The following constraints are considered in the proposed model:

Land constraints: $\sum_{i=1}^{I} x_i \leq L$ (1)

This constraint ensures that the total area allocated to all crops does not exceed the available land L. Land is a limited resource, and improper allocation can lead to infeasible production plans. By including this constraint, the model enforces that cropping decisions remain within the physically available land.

Demand constraints: $x_i * y_{x_i} + p_i - s_i \geq d_i, i = 1,2,3, \ldots ,13$ (2)

This constraint ensures that the total available quantity of each crop-consisting of production from allocated land and market purchases, minus the quantity sold-is sufficient to meet the required demand, d_i. Including this constraint ensures that the farmer meets crop demand under realistic production conditions, preventing shortages.

Cost constraints: $\sum_{i=1}^{I} p_i * p_{x_i} + \sum_{i=1}^{I} x_i * c_{x_i} \leq M$ (3)

The total cost of production and purchasing must not exceed the available budget M. The production cost includes all expenses associated with cultivating the crops, while the purchasing cost covers additional crop requirements. This constraint reflects the financial limitations of the farmer, ensuring that the cropping plan is affordable and within budget. It also prevents overproduction that could exceed financial capacity, which may reduce profitability.

Labor constraints: $\sum_{i=1}^{I} x_i * L_{x_i} \leq LH$ (4)

Agricultural production is labour-intensive, and the demand for labour increases during the production period.

This constraint ensures that the total labour required for all crops does not exceed the available labour hours LH. Including labour constraints reflects practical operational limits, preventing infeasible cropping plans due to labour shortages.

Upper Bound on land allocation: $x_i \leq Up, \; i = 1,2,3, \dots, I$ (5)

Certain crops cannot be cultivated beyond specific land limits due to agronomic, environmental, or operational considerations. For example, some crops may require special soil conditions, irrigation, or management practices that restrict maximum cultivation area. This constraint also prevents excessive production, which could lower market selling prices due to oversupply.

Non-negativity Constraints: $x_i, p_i, s_i \geq 0$ for $i = 1,2,3, \dots, I$ (6)

All decision variables are required to be non-negative, reflecting that negative land allocation, crop purchase, or sales quantities are not feasible in practice. This constraint ensures that the model only produces realistic and implementable cropping plans.

This framework provides a comprehensive and balanced approach, allowing the farmer to maximize net profit while efficiently managing resources and mitigating the risks associated with production and market uncertainties.

2.4 Two-stage stochastic programming model

To address uncertainty in agricultural production planning, a two-stage SP model is developed. The model determines the optimal land allocation for different crops while considering uncertain demand, yield, purchasing prices, and selling prices under multiple scenarios. The decision process is divided into two stages: first-stage decisions, which are made before the realization of uncertainty, and second-stage recourse decisions, which are made after the uncertain parameters are observed [10,11].

Table 2: Notations for the SP model

Sets (subscripts):		
i	*1, 2, …, I*	Crop index
s'	*1, 2, …, S'*	Scenario index
Parameters:		
L	Total available land (decimal)	
M	Total budget (Tk)	
LH	Total labor (hour)	
$d_{i,s'}$	Demand of crop *i* per kg at each scenario s'	
$p_{x_i,s'}$	Purchase cost of crop *i* per kg at each scenario s'	
c_{x_i}	Production cost for crop *i* per decimal	
$y_{x_i,s'}$	Yield per decimal (kg) at each scenario s'	
L_{x_i}	Labor hours needed for crop *i* per decimal	
$s_{s_i,s'}$	Selling price of crop *i* per kg at each scenario s'	
$\pi_{s'}$	Probability at each scenario s'	
Decision Variables:		
x_i	Decimal of land devoted to crop *i*	
$p_{i,s'}$	Purchasing amount of crop *i* (kg) at each scenario s'	
$s_{i,s'}$	Selling amount of crop *i* (kg) at each scenario s'	

2.4.1 Objective function of the 2-stage SP model

The objective of the SP model is to maximize the total profit, which is defined as the total selling revenue minus the purchasing cost and production cost with realization s'=*1, 2, …,* S'. The corresponding probability at each realization is $\pi_{s'} \geq 0$ and $\sum_{s'=1}^{S'} \pi_{s'} = 1$. Then,

$$\max z = \sum_{s'=1}^{S'} \pi_{s'} \sum_{i=1}^{I} s_{i,s'} * s_{s_i,s'} - \sum_{s'=1}^{S'} \pi_{s'} \sum_{i=1}^{I} p_{i,s'} * p_{x_i,s'} - \sum_{i=1}^{I} x_i * c_{x_i}$$

The first term represents the total revenue obtained from selling crops, the second term denotes the total purchasing cost of crops, and the third term represents the total production cost associated with land allocation decisions.

2.4.2 Constraints of the 2-stage SP model

The first-stage decisions correspond to strategic planning choices made before the realization of uncertain parameters. In this stage, the decision maker determines the amount of land allocated to each crop.

Let x_i denote the amount of land (in decimal) allocated to crop i, where *i=1,2,…,I*. These decisions incur production costs and utilize limited resources such as land and labor.

The following constraints must be satisfied, which are similar to a deterministic programming model.

Land constraints: $\sum_{i=1}^{I} x_i \leq L$ (7)

Labor constraints: $\sum_{i=1}^{I} x_i * L_{x_i} \leq LH$ (8)

Upper Bound Constraints: $x_i \leq Up, \; i = 1,2,3, \dots, I$ (9)

Second-stage decision (Recourse actions):

After the realization of uncertainty, represented by scenario s', the farmer observes the values of uncertain parameters. Based on these realized values, the farmer makes recourse decisions to balance supply and demand. The production quantity of crop i under scenario s' depends on the allocated land and scenario-dependent yield:

Production at each scenario = $x_i * y_{x_i,s'}$

For each crop and scenario, total available supply must satisfy the demand.

$$\text{Demand constraints: } x_i * y_{x_i,s'} + p_{i,s'} - s_{i,s'} \geq d_{i,s'}; \quad i = 1,2,3,\dots,I;\ s' = 1,2,3,\dots,S' \tag{10}$$

The total expenditure consisting of production cost and purchasing cost cannot exceed the available budget *M*.

$$\text{Cost constraints: } \sum_{s'=1}^{S'} \sum_{i=1}^{I} p_{i,s'} * p_{x_i,s'} + \sum_{i=1}^{I} x_i * c_{x_i} \leq M; \tag{11}$$

Non-Negativity Constraints:
All decision variables must be non-negative.

$$x_i, p_{i,s'}, s_{i,s'} \geq 0 \text{ for } i = 1,2,3,\dots,I;\ s' = 1,2,3,\dots,S' \tag{12}$$

3. Case study

To illustrate and validate the proposed models, a case study is conducted based on a crop production planning problem of a farmer in Bangladesh. Agricultural production planning is highly influenced by uncertain factors such as crop yield, demand for the crop, and price fluctuations. Therefore, farmers must carefully allocate their limited resources, such as land, labor, and budget, to maximize profit while managing these uncertainties.

In the considered case study, a farmer has a fixed amount of cultivable land, available labor hours, and a limited production budget. The farmer plans to cultivate several types of crops during a single production season. At the beginning of the planning period, the farmer must decide how much land should be allocated to each crop. However, the actual yield of crops, demand, selling price, and purchasing price may vary due to weather conditions, market fluctuations, and other external factors.

The crops produced by the farmer can either be sold in the market to generate revenue or used to satisfy the farmer's own demand. If the farmer's production is insufficient to meet the demand, additional quantities of crops may be purchased from the market, which increases the total cost. On the other hand, if production exceeds demand, the surplus crops may be sold in the market, contributing to additional profit.

The deterministic model assumes that all parameters such as yield, demand, and prices are known with certainty. However, in reality these parameters are uncertain, and therefore a stochastic programming approach is applied to incorporate multiple scenarios representing possible realizations of these uncertain parameters.

The case study demonstrates how the proposed deterministic and stochastic models can support efficient agricultural production planning and resource allocation under uncertainty.

3.1 Data sources

The data used in this study were collected from both primary and secondary sources to ensure the reliability and applicability of the proposed crop planning model.

First, primary data were obtained through direct interviews with local farmers. These interviews provided practical information related to crop production, such as land allocation, labor requirements, production costs, and other relevant farming practices. The information collected from the farmers reflects the real agricultural production environment and decision-making behavior at the farm level. The primary data collected from the interviews are presented in Table 3. The total available land, *L*= 700 decimal; total budget, *M* = 657970 Tk; total labor hours, *LH* = 1840 hours. In addition to the primary data, secondary data were obtained from the Yearbook of Agricultural Statistics 2023 published by the Bangladesh Bureau of Statistics [31]. This publication provides reliable and nationally recognized statistical information related to agricultural production and market prices. In this research, the statistical data were used to supplement and validate the collected field data. The crop production data obtained from this source are presented in Table 4. Furthermore, Table 5 presents the national average market price obtained by farmers, which is also collected from the same statistical yearbook [31]. These prices represent the average selling price received by farmers in the national market, and they are used in the model to estimate the potential revenue from crop sales. By integrating field-level primary data with official national statistical data, the dataset used in this study provides both practical relevance and statistical reliability, which strengthens the validity of the deterministic and stochastic crop planning models developed in this research. The upper-bound constraints data are represented by equation (13).

$$\text{Upper Bound Constraints: } x_1, x_{13} \leq 200;\ x_2, \dots, x_8, x_{11}, x_{12} \leq 50;\ x_9, x_{10} \leq 100; \tag{13}$$

Table 3: Primary data

Serial no.	Goods	Own demand (kg/ pieces)	Pur-chase price (Tk per kg/ pieces)	Land cultiva-tion (decimal)	Produc-tion cost (Tk per decimal)	Total produc-tion cost (Tk)	Yield (kg/ pieces per decimal)	Total yield (kg/ pieces)	Labor (hours per decimal)	Total labor (hours)	Produc-tion cost (Tk per kg)	Selling price (Tk per kg/ pieces)	Selling amount(kg)	Total selling price (Tk)	Total profit (Tk)
1	Potato	100	26	200	900	180000	112	22400	2.4	480	8.04	20	22300	446000	266000
2	Tomato	25	39	25	2000	50000	140	3500	6.4	160	14.29	30	3475	104250	54250
3	Brinjal	30	52	50	2000	100000	40	2000	4.8	240	50.00	40	1970	78800	-21200
4	Cauliflower	20	26	25	4000	100000	120	3000	3.2	80	33.33	20	2980	59600	-40400
5	Cabbage	18	32.5	25	4000	100000	120	3000	3.2	80	33.33	25	2982	74550	-25450
6	Radish	15	19.5	25	1000	25000	80	2000	3.2	80	12.50	15	1985	29775	4775
7	Other Vegetables	40	26	5	600	3000	80	400	8	40	7.50	20	360	7200	4200
8	Pepper	5	195	25	600	15000	12.8	320	4.8	120	46.88	150	315	47250	32250
9	Wheat	20	91	75	373	27975	16	1200	1.06	79.5	23.31	70	1180	82600	54625
10	Maize	10	28.86	25	400	10000	64	1600	3.2	80	6.25	22.2	1590	35298	25298
11	Bottle Gourd	15	39	12.5	400	5000	24	300	6.4	80	16.67	30	285	8550	3550
12	Onion	30	65	7.5	266	1995	32	240	10.7	80.25	8.31	50	210	10500	8505
13	Pumpkin	15	13	200	200	40000	80	16000	1.2	240	2.50	10	15985	159850	119850
				Total = 700		Total = 657970				Total =1840				Total = 1144223	Total = 486253

Table 4: Summary of crop production and cultivated area

Serial no.	Crops name	year	Area ‘000’ Acres	Production ‘000’ Metric Tons
1	Potato	2022-23	1125	10432
2	Tomato	2022-23	77	469
3	Brinjal	2022-23	86.4	445.8
4	Cauliflower	2022-23	56.4	343.8
5	Cabbage	2022-23	53.5	422.3
6	Radish	2022-23	67.4	340.7
7	Different other vegetables	2022-23	138	666.4
8	Pepper	2022-23	240	662
9	Wheat	2022-23	783	1170
10	Maize	2022-23	1227	4563
11	Bottle gourd	2022-23	49.7	284.3
12	Onion	2022-23	503	2547
13	Pumpkin	2022-23	44.9	227

Table 5: Harvest time market price of each crop 2022-2023 (100kg/100 pieces/80 pieces/per Tk)

Serial no.	Product Name	Annual Average
1	Potato	2320
2	Tomato	4834
3	Brinjal	2898
4	Cauliflower	2456
5	Cabbage	1744
6	Radish	1935
7	Other Vegetables	2500
8	Pepper	32241
9	Wheat	4552
10	Maize	3204
11	Bottle Gourd	2489
12	Onion	3621
13	Pumpkin	2238

3.2 Scenario generation

In agricultural production planning, several critical parameters like crop yield, demand, selling price, and purchasing price are uncertain due to weather variability, pests, and market fluctuations. To consider this uncertainty, a scenario-based SP approach is employed where each scenario represents a possible realization of these uncertain parameters, capturing the variability in production and market conditions. In this SP model, 4 types of scenarios are considered, which are the following:

- Average value: the typical expected level.
- 10% above average: a moderately favorable condition with slightly higher yield, demand, or price.
- 10% below average: a moderately unfavorable condition with slightly lower yield, demand, or price.
- 40% below average: a highly unfavorable condition representing extreme adverse events, such as poor weather, low market demand, or price drops.

These 4 scenarios are applied to crop yield. y_{x_i}farmer own demand d_i, selling price $s_{s_i}$and purchasing price p_{x_i}

to generate a comprehensive set of possible outcomes.
The scenario probabilities are assigned based on expert judgment using primary data from farmer interviews. These scenarios allow the stochastic model to evaluate the expected profit under different conditions and support decision-making that is robust against variability in yield, demand, and market prices.

3.3 Deterministic model results and analysis for primary data

The deterministic crop planning model was solved using the AMPL programming language, assuming that all parameters are known with certainty. The model was solved using primary data collected directly from farmer interviews, which reflects real agricultural practices and decision-making. The solution provides the optimal allocation of land, purchasing, and selling amounts for each crop to maximize the total profit. The optimal objective function value for this deterministic case is z = 739,956 Tk.
The results for land allocation x_i, purchasing amount p_i, and selling amount s_i for each crop are summarized in Table 6:

Table 6: Solution of the deterministic model using primary data

Land allocation(decimal)	Purchasing amount(kg)	Selling amount(kg)
x_1 = 200	p_1 = 0	s_1 = 22300
x_2 = 50	p_2= 0	s_2 = 6975
x_3 = 0	p_3 = 30	s_3 = 0
x_4 = 0	p_4= 20	s_4 = 0
x_5 = 0	p_5= 18	s_5 = 0
x_6 = 0	p_6 = 15	s_6 = 0
x_7 = 0.5	p_7 = 0	s_7 = 0
x_8 = 50	p_8 = 0	s_8 = 635
x_9 = 100	p_9 = 0	s_9 = 1580
x_{10} = 100	p_{10} = 0	s_{10} = 6390
x_{11} = 0	p_{11} = 15	s_{11} = 0
x_{12} = 13.7474	p_{12} = 0	s_{12} = 409.916
x_{13} = 185.753	p_{13} = 0	s_{13} = 14845.2

Land Allocation

- Potato (200 decimals) and pumpkin (185.753 decimals) receive the largest land allocation, reflecting their high contribution to profit per unit of land.
- Tomato (50 decimals), pepper (50 decimals), wheat (100 decimals), maize (100 decimals), and onion (13.7474 decimals) also receive moderate land allocations, showing that these crops are profitable but limited by land or budget constraints.
- Brinjal, cauliflower, cabbage, radish, and bottle gourd are not cultivated (x = 0), indicating that purchasing from the market is more cost-effective than production under deterministic assumptions.
- Other vegetables (0.5 decimals) receive a negligible allocation, showing low profitability but a minimal contribution to the solution.

Purchasing Amount

- Crops with zero land allocation (brinjal, cauliflower, cabbage, radish, and bottle gourd) have purchases made from the market to satisfy demand.
- No purchasing is needed for the remaining crops because one's own production is sufficient to meet demand.

Selling Amount

- Crops that receive substantial land allocation also have large selling amounts, e.g., potato (22,300 kg) and pumpkin (14,845.2 kg). Purchased crops are used entirely to satisfy demand and have no additional sales.

Based on farmers' interview data, the estimated profit is 486,253 Tk, reflecting real-world practices, local constraints, and traditional decision-making approaches. In contrast, the deterministic LP model produced a significantly higher profit of 739,956 Tk when primary data were used, representing an optimal allocation of land, purchasing, and selling quantities under fixed parameter assumptions. The difference of 253,703 Tk highlights the potential efficiency gains achievable through systematic optimization. The deterministic model identifies an ideal resource allocation, whereas decisions obtained from direct farmer interviews reflect practical limitations such as lack of systematic planning and possible inefficiencies in current farming practices.

3.4 Deterministic model results using secondary data

In this case, the model was solved using secondary data obtained from the *Yearbook of Agricultural Statistics*

2023 of the Bangladesh Bureau of Statistics, which provides reliable national-level production and market price information. This dataset enables an analysis that reflects broader market conditions rather than farm-specific practices.

The solution provides the optimal allocation of land, purchasing, and selling amounts for each crop, achieving a total profit of z = 1,017,700 Tk. The results are summarized in Table 7:

Table 7: Solution of the deterministic model using secondary data

Land allocation(decimal)	Purchasing amount(kg)	Selling amount(kg)
x_1 = 200	p_1 = 0	s_1 = 18446
x_2 = 0.410	p_2= 0	s_2 = 0
x_3 = 0	p_3 = 30	s_3 = 0
x_4 = 0	p_4= 20	s_4 = 0
x_5 = 0	p_5= 18	s_5 = 0
x_6 = 0	p_6 = 15	s_6 = 0
x_7 = 0	p_7 = 40	s_7 = 0
x_8 = 50	p_8 = 0	s_8 = 1374
x_9 = 85.92	p_9 = 0	s_9 = 1263.59
x_{10} = 100	p_{10} = 0	s_{10} = 3709
x_{11} = 50	p_{11} = 0	s_{11} = 2845
x_{12} = 13.67	p_{12} = 0	s_{12} = 662.403
x_{13} = 200	p_{13} = 0	s_{13} = 10097

The deterministic solution using secondary data demonstrates the profit-maximizing cropping plan under national-level production and market conditions, achieving a total profit of 1,017,700 Tk, which is higher than the profit obtained using primary data. This difference reflects the higher yields and selling prices at the national average level, compared to the local farm-level conditions captured in the primary data.

- High-profit crops: potato and pumpkin consistently receive the largest land allocations in both primary and secondary data cases, confirming their strong profitability across different data sources.
- Moderate allocation: Crops such as maize, wheat, pepper, bottle gourd, and onion are allocated moderate land areas, balancing resource constraints and profit contribution. Compared to the primary data case, bottle gourd receives more land in the secondary data scenario, indicating differences in national average yields and market prices.
- Minimal cultivation: Tomato and other vegetables receive negligible or very low land allocation, while brinjal, cauliflower, cabbage, and radish are entirely purchased from the market to meet demand. This is consistent with the primary data case, suggesting that for these crops, market purchases are more cost-effective than cultivation.
- Selling amounts: Crops with large land allocations, such as potato, pumpkin, and maize, have correspondingly high selling amounts. Purchased crops are used entirely to satisfy demand and are not available for additional sales.

The comparison indicates that while the optimal cropping pattern is broadly similar between the primary and secondary data cases, the total expected profit is significantly higher under secondary (national) data due to higher yields and selling prices. This highlights the sensitivity of deterministic solutions to input data. Decisions based on local farm-level data may yield more conservative profits, whereas national averages may overestimate achievable returns.

This analysis emphasizes the limitation of deterministic models, as both solutions assume certainty in all parameters. Real-world agricultural conditions are variable, and ignoring uncertainties in crop yield, demand, and prices can lead to risky decisions. This motivates the application of a stochastic programming approach, which incorporates uncertainty to provide more robust and risk-aware cropping plans.

3.5 Analysis for the stochastic case

In the stochastic programming framework, we consider land allocation as the first-stage decision, which must be made before the realization of uncertainties. The purchasing amount and selling amount of each crop are treated as second-stage recourse decisions, which can be adjusted once the uncertain parameters are realized.

To model uncertainty, four levels of crop yield are considered: the average yield, 10% above average, 10% below average, and a critical scenario of 40% below average. The 40% below-average scenario represents extreme events such as floods, erosion, tornadoes, or storm surges that can severely damage crop fields and significantly reduce production. These four cases are treated as different scenarios in the stochastic framework. The first scenario (average yield) is assigned a probability of 0.50, the second scenario (10% above average yield) has a probability of 0.10, the third scenario (10% below average yield) has a probability of 0.25, and the fourth scenario (40% below average yield) is assigned a probability of 0.15. These 4 scenarios are applied to crop yield y_{x_i}, farmer own demand d_i, selling price s_{s_i}, and purchasing price p_{x_i} to generate a comprehensive set of possible outcomes. The scenario probabilities are assigned based on expert judgment using primary data from farmer interviews.

Assuming independence between demand and yield is often unrealistic because both are driven by common factors such as weather and market conditions. This can misrepresent their joint behavior by ignoring correlation and extreme co-movements. As a result, risk may be underestimated and profit estimates biased. It can also lead to non-robust decisions and implausible scenario combinations, reducing model reliability and practical relevance. In this study, demand is assumed to vary proportionally with the respective yield scenarios, while the selling price changes in the opposite direction, reflecting the typical supply-demand relationship in agricultural markets: lower yields generally lead to higher prices, whereas higher yields tend to reduce prices. This scenario-based framework enables the stochastic model to represent both normal and extreme production conditions and to generate a more robust and risk-aware crop planning strategy that accounts for the inherent variability in agricultural production and market dynamics.

Tables 8, 9, 10, and 11 summarize the scenario-based data used in the stochastic model. Table 8 provides the crop yields for each scenario, Table 9 lists the corresponding selling prices, Table 10 shows the market demand, and Table 11 presents the purchasing prices. These tables serve as the input parameters for the stochastic analysis, capturing the variability across different scenarios and enabling systematic evaluation of crop planning decisions under uncertain conditions.

Table 8: Yield in different scenarios

Serial no.	Goods	Average yield (kg/pieces per decimal)	10% Above average yield (kg/pieces per decimal)	10% Below average yield (kg/pieces per decimal)	40% Below average yield (kg/pieces per decimal)
		Scenario 1	Scenario 2	Scenario 3	Scenario 4
1	Potato	112	123.2	100.8	67.2
2	Tomato	140	154	126	84
3	Brinjal	40	44	36	24
4	Cauliflower	120	132	108	72
5	Cabbage	120	132	108	72
6	Radish	80	88	72	48
7	Other Vegetables	80	88	72	48
8	Pepper	12.8	14.08	11.52	7.68
9	Wheat	16	17.6	14.4	9.6
10	Maize	64	70.4	57.6	38.4
11	Bottle Gourd	24	26.4	21.6	14.4
12	Onion	32	35.2	28.8	19.2
13	Pumpkin	80	88	72	48

Table 9: Selling price in different scenarios

Serial no.	Goods	Average selling price (Tk per kg/pieces)	10% below average selling price (Tk per kg/pieces)	10% above average selling price (Tk per kg/pieces)	40% above average selling price (Tk per kg/pieces)
		Scenario 1	Scenario 2	Scenario 3	Scenario 4
1	Potato	20	18	22	28
2	Tomato	30	27	33	42

3	Brinjal	40	36	44	56
4	Cauliflower	20	18	22	28
5	Cabbage	25	22.5	27.5	35
6	Radish	15	13.5	16.5	21
7	Other Vegetables	20	18	22	28
8	Pepper	150	135	165	210
9	Wheat	70	63	77	98
10	Maize	22.2	19.98	24.42	31.08
11	Bottle Gourd	30	27	33	42
12	Onion	50	45	55	70
13	Pumpkin	10	9	11	14

Table 10: Demand in different scenarios

Serial no.	Goods	Average demand (kg/pieces)	10% Above average demand (kg/pieces)	10% Below average demand (kg/pieces)	40% Below average demand (kg/pieces)
		Scenario 1	Scenario 2	Scenario 3	Scenario 4
1	Potato	100	110	90	60
2	Tomato	25	27.5	22.5	15
3	Brinjal	30	33	27	18
4	Cauliflower	20	22	18	12
5	Cabbage	18	19.8	16.2	10.8
6	Radish	15	16.5	13.5	9
7	Other Vegetables	40	44	36	24
8	Pepper	5	5.5	4.5	3
9	Wheat	20	22	18	12
10	Maize	10	11	9	6
11	Bottle Gourd	15	16.5	13.5	9
12	Onion	30	33	27	18
13	Pumpkin	15	16.5	13.5	9

Table 11: Purchasing price in different scenarios

Serial no.	Goods	Purchase price (Tk per kg/pieces)			
		Scenario 1	Scenario 2	Scenario 3	Scenario 4
1	Potato	26	23.4	28.6	36.4
2	Tomato	39	35.1	42.9	54.6
3	Brinjal	52	46.8	57.2	72.8
4	Cauliflower	26	23.4	28.6	36.4
5	Cabbage	32.5	29.25	35.75	45.5
6	Radish	19.5	17.55	21.45	27.3
7	Other	26	23.4	28.6	36.4

	Vegetables				
8	Pepper	195	175.5	214.5	273
9	Wheat	91	81.9	100.1	127.4
10	Maize	28.86	25.974	31.746	40.404
11	Bottle Gourd	39	35.1	42.9	54.6
12	Onion	65	58.5	71.5	91
13	Pumpkin	13	11.7	14.3	18.2

3.5.1 Stochastic model solution and interpretation

Finding the solution of the 2-stage SP model is very challenging. Because considering all scenarios, the number of variables and constraints becomes very large. The stochastic crop planning model of this study was solved using the AMPL programming language.

Table 12 presents the optimal values of the first-stage decision variables, which represent the allocation of land among different crops. The solution indicates that the largest portions of land are allocated to potato (200 decimals), pumpkin (185.753 decimals), wheat (100 decimals), maize (100 decimals), tomato (50 decimals), and pepper (50 decimals). A very small portion of land is allocated to other vegetables (0.5 decimals) and onion (13.7474 decimals), while brinjal, cauliflower, cabbage, radish, and bottle gourd receive no land allocation. These decisions are made before the realization of uncertainty and remain fixed across all scenarios.

Table 12: First stage solution

Decimal of land allocation
x_1 = 200
x_2 = 50
x_3 = 0
x_4 = 0
x_5= 0
x_6 = 0
x_7 = 0.5
x_8= 50
x_9 = 100
x_{10} = 100
x_{11}= 0
x_{12}= 13.7474
x_{13}= 185.753

Tables 13 and 14 show the optimal values of the second-stage decision variables for each scenario. Table 13 presents the selling quantities of crops for scenarios *i=1,2,3,4,* which correspond to different realizations of yield and market conditions. The results show that crops such as potato, tomato, pepper, wheat, maize, onion, and pumpkin are sold in significant quantities across scenarios, while the remaining crops have zero selling quantities because they are not cultivated or are not profitable under the given conditions. The selling quantities vary across scenarios because changes in yield and demand directly influence the amount available for sale.

Table 14 presents the purchasing quantities under different scenarios. Purchasing occurs mainly for crops that are not produced sufficiently by the farmer but are required to meet demand constraints. For example, brinjal, cauliflower, cabbage, radish, and bottle gourd show positive purchasing amounts, and these values vary across scenarios depending on the changes in demand and market conditions. In contrast, crops that are sufficiently produced, such as potato, tomato, wheat, maize, onion, and pumpkin, do not require purchasing.

The optimal objective function value of the stochastic model is z = 707826. This value represents the expected profit obtained under uncertain conditions when considering all possible scenarios simultaneously. Compared with the deterministic approach, the stochastic model provides a more realistic planning strategy by incorporating variability in yield, demand, and prices, allowing the farmer to make more robust decisions under uncertain agricultural environments.

Table 13: Second stage solution (selling amount)

Selling amount for different scenarios *i*			
Scenario *i*=1	Scenario *i*=2	Scenario *i*=3	Scenario *i*=4
$s_{1,i}$ = 22300	$s_{1,i}$ = 24530	$s_{1,i}$ = 20070	$s_{1,i}$ = 13380

$s_{2,i}$ = 6975	$s_{2,i}$ = 7672.5	$s_{2,i}$ = 6277.5	$s_{2,i}$ = 4185
$s_{3,i}$ = 0	$s_{3,i}$ = 0	$s_{3,i}$ = 0	$s_{3,i}$ = 0
$s_{4,i}$ = 0	$s_{4,i}$ = 0	$s_{4,i}$ = 0	$s_{4,i}$ = 0
$s_{5,i}$= 0	$s_{5,i}$= 0	$s_{5,i}$= 0	$s_{5,i}$= 0
$s_{6,i}$= 0	$s_{6,i}$= 0	$s_{6,i}$= 0	$s_{6,i}$= 0
$s_{7,i}$ = 0	$s_{7,i}$ = 0	$s_{7,i}$ = 0	$s_{7,i}$ = 0
$s_{8,i}$ = 635	$s_{8,i}$ = 698.5	$s_{8,i}$ = 571.5	$s_{8,i}$ = 381
$s_{9,i}$ = 1580	$s_{9,i}$ = 1738	$s_{9,i}$ = 1422	$s_{9,i}$ = 948
$s_{10,i}$ = 6390	$s_{10,i}$ = 7029	$s_{10,i}$ = 5751	$s_{10,i}$ = 3834
$s_{11,i}$ = 0	$s_{11,i}$ = 0	$s_{11,i}$ = 0	$s_{11,i}$ = 0
$s_{12,i}$ = 409.916	$s_{12,i}$ = 450.907	$s_{12,i}$ = 368.924	$s_{12,i}$ = 245.949
$s_{13,i}$ = 14845.2	$s_{13,i}$ = 16329.7	$s_{13,i}$ = 13360.7	$s_{13,i}$ = 8907.13

Table 14: Second stage solution (purchasing amount)

Purchasing amount for different scenario *i*			
Scenario *i*=1	Scenario *i*=2	Scenario *i*=3	Scenario *i*=4
$p_{1,i}$ = 0	$p_{1,i}$ = 0	$p_{1,i}$ = 0	$p_{1,i}$ = 0
$p_{2,i}$ = 0	$p_{2,i}$ = 0	$p_{2,i}$ = 0	$p_{2,i}$ = 0
$p_{3,i}$ = 30	$p_{3,i}$ = 33	$p_{3,i}$ = 27	$p_{3,i}$ = 18
$p_{4,i}$ = 20	$p_{4,i}$ = 22	$p_{4,i}$ = 18	$p_{4,i}$ = 12
$p_{5,i}$= 18	$p_{5,i}$= 19.8	$p_{5,i}$= 16.2	$p_{5,i}$= 10.8
$p_{6,i}$= 15	$p_{6,i}$= 16.5	$p_{6,i}$= 13.5	$p_{6,i}$= 9
$p_{7,i}$ = 0	$p_{7,i}$ = 0	$p_{7,i}$ = 0	$p_{7,i}$ = 0
$p_{8,i}$ = 0	$p_{8,i}$ = 0	$p_{8,i}$ = 0	$p_{8,i}$ = 0
$p_{9,i}$ = 0	$p_{9,i}$ = 0	$p_{9,i}$ = 0	$p_{9,i}$ = 0
$p_{10,i}$ = 0	$p_{10,i}$ = 0	$p_{10,i}$ = 0	$p_{10,i}$ = 0
$p_{11,i}$ = 15	$p_{11,i}$ = 16.5	$p_{11,i}$ = 13.5	$p_{11,i}$ = 9
$p_{12,i}$ = 0	$p_{12,i}$ = 0	$p_{12,i}$ = 0	$p_{12,i}$ = 0
$p_{13,i}$ = 0	$p_{13,i}$ = 0	$p_{13,i}$ = 0	$p_{13,i}$ = 0

3.5.2 Evaluation of decision quality measures

To evaluate the effectiveness of the stochastic programming model, several decision quality measures are analyzed, including the wait-and-see solution (WS), expected result of using the expected value solution (EEV), expected value of perfect information (EVPI), and the value of the stochastic solution (VSS). These measures help assess the benefit of considering uncertainty in the decision-making process.

The wait-and-see solution (WS) represents the ideal situation where the decision-maker has complete knowledge of all uncertain parameters before making decisions [10,11]. In other words, the land allocation and recourse actions are determined after observing the actual realization of yield, demand, and prices. Under this case, the obtained objective value is WS = 707,825.9. This value serves as a theoretical upper benchmark because such perfect information is not available in real agricultural planning.

The expected value of perfect information (EVPI) measures the potential benefit that could be achieved if the decision-maker had perfect knowledge of future uncertain events. It is calculated as the difference between the recourse solution (RS) and the wait-and-see solution (WS):

EVPI = RS−WS = 707,826−707,825.9 = 0.1

The EVPI value is extremely small, indicating that perfect information about future scenarios would provide almost no additional benefit in terms of profit improvement. This suggests that the stochastic model already performs very close to the theoretical best-case solution [10,11].

The expected result of using the expected value solution (EEV) represents the expected profit obtained when the deterministic solution, based on average parameter values, is applied to all stochastic scenarios [10,11]. In this study, the value of EEV = 350,090. The average parameter values used in this calculation are presented in Table 15, which are derived from the primary dataset shown in Table 3. The EEV value is significantly lower than the stochastic solution, indicating that decisions based solely on average values may lead to poor performance when uncertainty is present. This result highlights that relying only on deterministic average data cannot adequately capture the variability in agricultural production and market conditions. The value of the stochastic solution (VSS) quantifies the advantage of using the stochastic programming model instead of the deterministic expected-value model. It is computed as:

VSS = RS − EEV = 707,826 − 350,090 = 357,736

The large positive value of VSS clearly demonstrates that incorporating uncertainty into the crop planning model substantially improves the expected profit. This result highlights the importance of stochastic optimization in agricultural decision-making, as it provides a more reliable and robust cropping strategy compared to deterministic approaches.

Table 15: First stage value for EEV

Decimal of land allocation
x_1 = 200
x_2 = 25
x_3 = 50
x_4 = 25
x_5= 25
x_6 = 25
x_7 = 5
x_8= 25
x_9 = 75
x_{10} = 25
x_{11}= 12.5
x_{12}= 7.5
x_{13}= 200

3.5.3 Sensitivity analysis on scenario probabilities

To evaluate the impact of scenario probabilities on the stochastic optimization model, two additional probability distributions were considered while keeping all other model parameters unchanged. The scenario probability settings used in the sensitivity analysis are presented in Table 16.

Table 16. Scenario probability distributions used for sensitivity analysis

Scenario	Description	Case 1: Original probabilities	Case 2: Equal probabilities	Case 3: Reversed probabilities
1	Average yield	0.50	0.25	0.15
2	10% above average yield	0.10	0.25	0.25
3	10% below average yield	0.25	0.25	0.10
4	40% below average yield	0.15	0.25	0.50

The resulting objective function values are presented in Table 17.

Table 17. Effect of probability variations

Probability case	Objective value (z)	Change from original
Case 1: (Original probabilities)	707,826	–
Case 2: (Equal probabilities)	687,380	-20,446 (-2.89%)
Case 3: (Reversed probabilities)	642,398	-65,428 (-9.24%)

The results show that the objective value decreases as more weight is assigned to unfavorable yield scenarios. Under the equal-probability assumption (case 2), the objective value decreases by 2.89% compared with the original case. When the probability structure is reversed (case 3), giving the highest probability (0.50) to the worst-yield scenario, the objective value decreases by 9.24%.

This behavior is consistent with the principles of stochastic programming. Increasing the likelihood of adverse yield conditions leads the model to adopt a more conservative decision strategy, resulting in a lower expected objective value. Although the objective value changes across different probability distributions, the model remains stable and feasible, indicating that the proposed stochastic framework is reasonably robust to variations in scenario probabilities.

3.5.4 Comparison between deterministic and stochastic models

Based on these fixed parameters, the deterministic model produced an optimal profit of 739,956 Tk, while the profit increased to 1,017,700 Tk when secondary production and price data were applied.

To address the limitation of the deterministic model, the stochastic model incorporates multiple scenarios representing different realizations of uncertain parameters. The expected optimal profit obtained from the stochastic model is 707,826 Tk. The comparison is shown in Table 18.

Table 18. Comparison of deterministic and stochastic model results

Model type	Case description	Optimal Profit (Tk)
Deterministic	Based on primary data	739,956
Deterministic	With secondary production and price data	1,017,700
Stochastic	Expected value over multiple scenarios	707,826

Although the profit value of the stochastic model is lower than that of the deterministic solution, the stochastic approach is considered superior and more reliable. It accounts for uncertainty and provides a robust decision-making framework that performs reasonably well under different possible scenarios. In contrast, the deterministic model may overestimate profit since it assumes ideal conditions. Therefore, the stochastic model offers a more practical and risk-aware strategy for agricultural crop planning, enabling farmers to make better-informed decisions in uncertain and variable environments.

3.5.5 Computational time and scalability

The proposed stochastic optimization model was implemented in AMPL and solved using CPLEX 22.1.1.0. The computational performance was evaluated in terms of solver run time and number of iterations required to reach optimality. The model converged efficiently within approximately 100 simplex iterations, indicating good computational performance. This demonstrates that the proposed formulation is computationally tractable and suitable for practical agricultural planning problems.

Regarding scalability, the computational effort is expected to increase with the number of scenarios, constraints, and decision variables, as is typical in stochastic programming models. However, within the current problem size, the model remains efficiently solvable using a standard optimization solver.

4. Conclusion

This study develops an optimization framework for agricultural crop planning by integrating deterministic and stochastic programming approaches. The proposed models assist farmers in making systematic decisions regarding land allocation, crop production, purchasing, and selling activities while considering the limitations of land, labor, and budget resources. By formulating the crop planning problem as a mathematical programming model, the study provides a structured method to improve farm profitability through efficient resource utilization. The deterministic model offers an optimal production plan under fixed parameter values and provides a clear benchmark for profit maximization. However, agricultural production is strongly influenced by uncertain factors. To address this issue, the stochastic model incorporates multiple scenarios representing different possible realizations of the uncertain parameters. This approach allows the decision-making process to adapt to varying conditions and provides more realistic planning outcomes. The evaluation of the stochastic solution demonstrates its practical advantage. The EVPI indicates that perfect foresight would provide minimal additional benefit, confirming the efficiency of the stochastic solution. Meanwhile, the VSS highlights the substantial improvement in expected profit obtained by explicitly considering uncertainty, compared to decisions based solely on average parameter values. These metrics underline the robustness and reliability of stochastic crop planning under uncertain production and market conditions. The comparative analysis demonstrates that although the deterministic model may produce higher nominal profit values under ideal assumptions, the stochastic model provides more reliable and practical decisions by accounting for uncertainty. Such a framework helps farmers prepare for unfavorable situations, including significant reductions in crop yield caused by natural disasters or sudden market changes.

The developed models emphasize the importance of incorporating uncertainty into agricultural planning. The results indicate that optimization-based decision support systems can play a critical role in improving crop management strategies and supporting sustainable agricultural production. Future research may extend this framework by incorporating additional factors such as weather forecasting information and multi-season planning to further enhance its applicability in real-world agricultural decision-making.

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