

Original Article

AGRICULTURAL PRODUCTION IN PAPUA NEW GUINEA USING OPTIMIZATION AND STOCHASTIC MODELLING

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ABSTRACT

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In Papua New Guinea, agriculture is one of the most important sectors, as it provides a livelihood of more than 80% of the rural population by contributing significantly to national income and food security. This paper applies optimization and stochastic modelling techniques to analyse agricultural production across selected provinces in PNG. A linear programming model is developed to determine the best way to allocate agricultural land among major crops such as coffee, cocoa, sweet potato, banana, taro, and coconut. A stochastic model is used to represent how crop yields can change due to uncertain factors such as weather, pests, or climate conditions by simulating these variations and assess production risk. Agricultural data were obtained from Food and Agriculture Organization Corporate Statistical Database (FAOSTAT), national agriculture reports and other published sources. The results demonstrate that using optimization to decide how land is allocated to crops can significantly improve agricultural productivity compared to traditional farming methods. The stochastic model highlights the importance of risk-aware decision-making, mainly under unpredictable climate conditions. The study concludes that combining optimization and stochastic modelling provides useful framework for improving agriculture planning and decision making. The findings may assist policy makers, agricultural planners and rural development agencies to promote sustainable agriculture production and efficient resources allocation.

Keywords: Optimization, Stochastic Modelling, Agriculture, Linear Programming, Agricultural Planning.

1. INTRODUCTION

Agriculture is the main source of living for many people in Papua New Guinea (PNG), with more than 80% of the rural population depending on farming for daily food and income, making it one of the most important sectors of the national economy.

Food and Agriculture Organization of the United Nations (2023). The agricultural sector contributes about 26% to the country's Gross Domestic Product (GDP) and provides employment opportunities for many rural households (Food and Agriculture Organization, 2024). It also plays a major role in ensuring food security, and supporting major cash crops such as coffee, cocoa, copra and oil palm exports. Agriculture has a long history in PNG with early cultivation systems discovered at Kuk Swamp in Western Highlands Province, where drainage systems were used to cultivate crops like taro and banana; this shows that local communities have practised farming for thousands of years (Bhamare, 2023).

Despite its importance, agricultural productivity in PNG faces many challenges including limited infrastructure, poor transportation system, limited use of modern farming technologies, changing climate conditions, pest outbreaks, and inefficient allocation of resources such as land and labour. In many rural areas, farmers continue to rely on traditional knowledge rather than quantitative planning approaches, which may reduce overall production and increase the risk of food shortages (Reis *et al.*, 2023).

The main objective of this study is to develop optimization mod-

els such as linear programming for land allocation, analysing agricultural productivity across selected provinces and stochastic modelling to improve planning by incorporating uncertainty factors such as climate variability, pest outbreaks, and market prices fluctuations Fytilis and Semos (2022).

Mathematical modelling such as linear programming and stochastic modelling can be used in agricultural planning to improve resource allocation and manage uncertainty (Bhatia and Rana, 2020).

Among competing agricultural activities, linear programming and stochastic modelling are modelling techniques used for agricultural production across multiple provinces in PNG. Mathematical modelling has been used in agricultural to improve production and decision making (Mitu and Hasan, 2024).

According to Food and Agricultural Organization, mathematical models can improve agricultural productivity by assisting policy makers and farmers in production planning and resource allocation (Filippi *et al.*, 2017).

Research edited by R.M. Bourke and T. Harwood provide estimated detail of food crop production in PNG and remains one of the most important agricultural references for the country by highlighting the importance of subsistence agriculture and regional crop production systems (Bourke and Harwood, 2009).

Most agriculture planning depends on traditional knowledge rather than data-based planning or quantitative modelling approaches, which can reduce overall production levels and increase the risk of food shortages. This study fills the gap by integrating a linear

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programming model and stochastic modelling into agricultural planning (Kan *et al.*, 2021).

This study focuses more on six major crops; coffee, cocoa, sweet potato, taro, coconut, banana. Due to limited data for land and labour available, some parameters such as labour requirement and land availability were estimated based on reasonable agricultural assumptions. Only ten provinces of PNG were selected for data analysis.

2. MATERIALS AND METHODS

LINEAR PROGRAMMING MODEL

Linear programming model is developed to maximize agricultural production subject to land, labour and budget constraints.

Decision Variables

Let:

$$x_1 = \text{allocated land for Coffee (hectares)} \quad (1)$$

$$x_2 = \text{allocated land for Cocoa} \quad (2)$$

$$x_3 = \text{allocated land for Sweet Potato} \quad (3)$$

$$x_4 = \text{allocated land for Taro} \quad (4)$$

$$x_5 = \text{allocated land for Coconut} \quad (5)$$

$$x_6 = \text{allocated land for Banana} \quad (6)$$

Note: the ordering of the crop variables (Taro as x_4 and Coconut as x_5) is fixed here and used consistently throughout all subsequent equations and tables in this manuscript.

Maximize production:

$$Z = p_1x_1 + p_2x_2 + p_3x_3 + p_4x_4 + p_5x_5 + p_6x_6 \quad (7)$$

Where:

$$p_i = \text{yield per hectare (tonnes/ha)} \quad (8)$$

The coefficient p_i is defined strictly as the yield per hectare of crop i , expressed in tonnes per hectare, and is used consistently in this unit throughout the objective function, Table 5, and the stochastic model. This is distinct from the total annual production values reported in Table 1, which are the product of yield per hectare and cultivated area for each crop.

Land Constraint

$$x_1 + x_2 + x_3 + x_4 + x_5 + x_6 \leq \lambda \quad (9)$$

Where:

$$\lambda = \text{total land available} \quad (10)$$

Labour Constraints

$$\alpha_1x_1 + \alpha_2x_2 + \alpha_3x_3 + \alpha_4x_4 + \alpha_5x_5 + \alpha_6x_6 \leq \delta \quad (11)$$

Where:

$$\alpha_i = \text{labour requirement (person-days per hectare)} \quad (12)$$

$$\delta = \text{available labour (person-days)} \quad (13)$$

Budget Constraints

$$c_1x_1 + c_2x_2 + c_3x_3 + c_4x_4 + c_5x_5 + c_6x_6 \leq \beta \quad (14)$$

Where:

$$c_i = \text{cost per hectare (PGK/ha)} \quad (15)$$

$$\beta = \text{budget (PGK)} \quad (16)$$

STOCHASTIC MODELING

Crop yield:

$$Y_i = \mu_i + \epsilon_i \quad (17)$$

Where:

$$Y_i = \text{yield of crops} \quad (18)$$

$$\mu_i = \text{average yield} \quad (19)$$

$$\epsilon_i = \text{random variation} \quad (20)$$

Random variation follows:

$$\epsilon_i \sim N(0, \sigma^2) \quad (21)$$

Means yield also follows:

$$Y_i \sim N(\mu_i, \sigma^2) \quad (22)$$

3. RESULTS

DATASET PRODUCTION (PROVINCE)

Table 1: Estimated production values tonnes/year.

Province	Coffee	Cocoa	Sweet Potato	Taro	Coconut	Banana
Western Highlands	25,700	0	425,964	9,212	0	30,989
Eastern Highlands	23,187	0	469,939	11,160	0	17,038
Simbu	7716	0	294,708	4,828	0	10,334
Morobe	7,200	530	194,695	22,699	5,704	63,311
Central	1920	0	49,267	5,796	5,142	43,014
Gulf	0	0	20,308	1,300	2,857	10,537
East New Britain	0	16,930	42,642	9,230	8,847	55,587
West New Britain	0	708	45,103	16,002	5,101	11,885
East Sepik	87.54	3936	26,175	24,689	17,806	37,100
Oro	0	44	53,309	11,784	1,549	9,866
Total	65,810.54	22,148	1,622,110	116,700	47,006	289,661

The table presents the estimated annual production levels of six major crops across selected provinces in PNG.

The estimated production is collected from a particular source, except coffee and cocoa (World Bank, 2014).

PRESENTATION OF FINDING

Table 1 reports total annual production per crop, which reflects both yield per hectare and the extent of land already under cultivation. To use the objective function coefficients *p* strictly as yield per hectare (tonnes/ha), as defined earlier under *Decision Variables*, we adopt

Table 2: Assumed yield per hectare by crop.

Crops	Yield (tonnes/ha)
Coffee	0.75
Cocoa	0.40
Sweet Potato	14.00
Taro	5.50
Coconut	1.50
Banana	6.50

PNG-specific smallholder yield-per-hectare values reported in the agricultural literature – in particular Bourke and Vlassak (2004), the same source already cited for national food-crop production in the *Introduction* – summarised in Table 2.

These values are used as the coefficients *p* in the objective function, replacing the total-production figures used in the initial submission, so that the units of the objective function are consistent with its definition. The sweet potato figure (14 t/ha) reflects the highlands/lowlands village yield range of 13–15 t/ha reported by Bourke and Vlassak (2004); the coffee figure (0.75 t/ha) is consistent with PNG's national coffee area of approximately 87,000 ha cross-checked against reported production. Cocoa, taro, coconut, and banana yields are estimated by the authors from general PNG smallholder literature and are not drawn from a single published crop-specific yield survey; this is now stated explicitly rather than left implicit.

Linear programming to maximize crop production.

$$Z = 0.75x_1 + 0.40x_2 + 14.00x_3 + 5.50x_4 + 1.50x_5 + 6.50x_6 \quad (23)$$

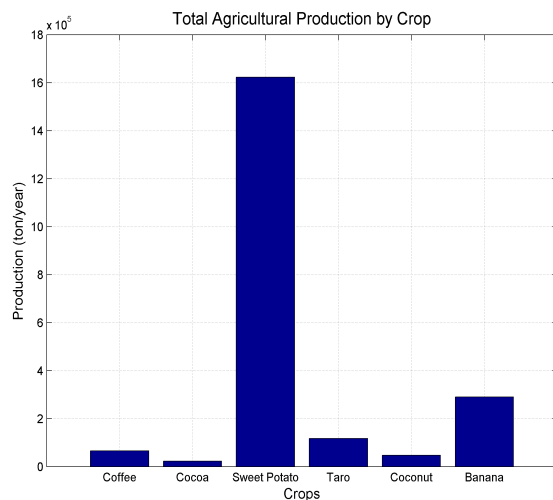


Figure 1: Total agricultural production by crop.

Land Constraints

We assume cost per hectare (*ci*), labour requirement (*δ*) and land availability (*λ*). Because there were no permanent recorded data for

all, most of these crops can be grown and managed by single smallholder family with 2 to 5 hectares or more, some family has 1 hectare or less. But in large-scale farms, they manage over 20 hectares where their labour required per hectare varies (Sehgal et al., 2017).

Therefore, we assume total available land:

$$\lambda = 150,000 \text{ hectares} \quad (24)$$

In this case we assume 150,000 hectares on estimated cultivated land across the selected provinces because the detailed land-use records were unavailable for the selected provinces, we choose the value as a reasonable approximation for modelling purposes. We state explicitly that $\lambda = 150,000$ ha is a modelling assumption, not a value taken from a published land-use survey.

$$x_1 + x_2 + x_3 + x_4 + x_5 + x_6 \leq 150,000 \quad (25)$$

Table 3: Labour Requirement.

Crops	Labour per hectare (person-days/ha)
Coffee	10
Cocoa	6
Sweet Potato	8
Taro	7
Coconut	5
Banana	4

The table shows the estimated labour requirement per hectare for each selected crops (Food and Agriculture Organization of the United Nations;

Food and Agriculture Organization, 2023; 2024). These labour-per-hectare figures are informed by general FAOSTAT/FAO smallholder labour-input data for PNG rather than a crop-by-crop empirical labour study, and are used here as reasonable planning assumptions.

Let:

$$\delta = 600,000 \quad (26)$$

More than 80% of PNG's population works in agriculture. The labour constraint was estimated based on the high level of agriculture participation in PNG. We assume that the crops listed require about 600,000 person-days of labour.

$$\alpha_1 x_1 + \alpha_2 x_2 + \alpha_3 x_3 + \alpha_4 x_4 + \alpha_5 x_5 + \alpha_6 x_6 \leq \delta \quad (27)$$

$$10x_1 + 6x_2 + 8x_3 + 7x_4 + 5x_5 + 4x_6 \leq 600,000 \quad (28)$$

Table 4: Budget Constraints.

Crops	Cost (PGK/ ha)
Coffee	498
Cocoa	2,500
Sweet Potato	500
Taro	380
Coconut	1776.5
Banana	200

Table 4 presents the estimated production cost per hectare for each crop in PNG. These per-hectare cost figures are estimated by the authors for modelling purposes, based on typical PNG smallholder input and establishment costs, rather than taken directly from a single published cost survey.

Assume available budget (PGK):

$$\beta = 50,000,000 \quad (29)$$

A total agricultural budget of PGK 50 million based on estimated production and operational costs. As with the land limit λ , this figure is a modelling assumption made by the authors for the purposes of this planning scenario, not a value drawn from a government or institutional budget document.

$$498x_1 + 2500x_2 + 500x_3 + 380x_4 + 1776.5x_5 + 200x_6 \leq 50,000,000 \quad (30)$$

Linear Programming

Maximize $Z = 0.75x_1 + 0.40x_2 + 14.00x_3 + 5.50x_4 + 1.50x_5 + 6.50x_6$

Subject to:

$$x_1 + x_2 + x_3 + x_4 + x_5 + x_6 \leq 150,000 \quad (32)$$

$$10x_1 + 6x_2 + 8x_3 + 7x_4 + 5x_5 + 4x_6 \leq 600,000 \quad (33)$$

$$498x_1 + 2500x_2 + 500x_3 + 380x_4 + 1776.5x_5 + 200x_6 \leq 50,000,000 \quad (34)$$

$$x_i \geq 7,500, i = 1, \dots, 6 \quad (35)$$

The lower bound of 7,500 hectares (5% of total available land) is imposed on each crop to reflect the fact that all six crops are already grown to some extent across the selected provinces (Table 1) and to preserve diversification for food security, consistent with the discussion of staple-crop importance in the *Discussion*. Without this floor, an unconstrained linear program allocates all resources to the single crop with the best return per unit of the binding resource, which is not representative of actual PNG farming systems. We state explicitly that this 5% floor is a modelling assumption chosen by the authors to maintain diversification and avoid an unrealistic single-crop solution; it is not a value taken from a published source, and other floor levels (e.g. 2% or 10%) could reasonably be substituted.

Solving this linear program (see Table 5) gives an optimal solution in which the budget constraint is binding (fully used), while the land and labour constraints are not: this indicates that, under the assumed cost structure, budget is the limiting resource for expanding production beyond the diversification floor.

STOCHASTIC MODELLING

Table 5 presents the optimal land allocation obtained by solving the linear programming model presented earlier in this section (objective function, land, labour, budget, and diversification constraints) using the simplex method, rather than by proportional allocation of production shares as in the initial submission. The solution was verified to satisfy all constraints: land used is 75,456.25 ha ($\leq 150,000$), labour used is 421,825 person-days ($\leq 600,000$), and budget used is exactly PGK 50,000,000 ($\leq 50,000,000$, binding).

Table 5: Optimal Land Allocation (Linear Programming Solution).

Crops	Yield (tonnes/ha)	Optimal land allocation (ha)
Coffee	0.75	7,500.00
Cocoa	0.40	7,500.00
Sweet Potato	14.00	7,500.00
Taro	5.50	7,500.00
Coconut	1.50	7,500.00
Banana	6.50	37,956.25
Total		75,456.25

Coffee, cocoa, sweet potato, taro, and coconut are held at the diversification floor of 7,500 ha (5% of total land, as described earlier in the *Linear Programming* results), while the remaining land, labour, and budget capacity is optimally allocated to banana, which offers the best return per unit of labour and budget among the six crops under the assumed yield and cost parameters. This confirms the dominant role of banana and sweet potato highlighted in the *Discussion*, while ensuring that coffee and cocoa are retained for their export and household-income value even though their optimisation-based land share is small.

Table 7: Sensitivity of yield standard deviation to assumed variability level (tonnes/ha).

Crops	μ (ton/ha)	σ (5%)	σ (11%)	σ (15%)
Coffee	0.75	0.038	0.083	0.113
Cocoa	0.40	0.020	0.044	0.060
Sweet Potato	14.00	0.700	1.540	2.100
Taro	5.50	0.275	0.605	0.825
Coconut	1.50	0.075	0.165	0.225
Banana	6.50	0.325	0.715	0.975

For the stochastic model, the mean yield μ_i of each crop is taken directly from the assumed yield-per-hectare values in Table 2, so that μ_i and p_i refer to the same quantity, expressed in the same unit (tonnes/ha), throughout the manuscript. Table 6 reports, for reference, the implied cultivated area of each crop nationally, obtained as $ai = ti/\mu_i$, where ti is the total production reported in Table 1 and μ_i is each crop's own assumed yield per hectare i.e. each crop's production is divided by its own estimated cultivated area, rather than by the shared total land availability λ used in the optimisation scenario.

$$\mu_i = \text{average yield} = p_i (\text{tonnes/ha}), \text{ from Table 2} \quad (36)$$

$$a_i = \frac{t_i}{\mu_i} \quad (37)$$

μ_i

Where t_i is total annual production (Table 1) and a_i is the implied cultivated area of crop i

Table 6: Mean yield and implied cultivated area by crop.

Crops	t_i (tonnes/year)	μ_i (tonnes/ha)	$ai = t_i/\mu_i$ (ha)
Coffee	65,810.54	0.75	87,747.4
Cocoa	22,148	0.40	55,370.0
Sweet Potato	1,622,110	14.00	115,865.0
Taro	116,700	5.50	21,218.2
Coconut	47,006	1.50	31,337.3
Banana	289,661	6.50	44,563.2

The table shows the estimated mean yield for each crop (from Table 2) and the implied cultivated area obtained by dividing each crop's total production by its own yield per hectare, rather than by a single shared land area. Note that the sum of implied areas ($\approx 356,000$ ha) reflects current national-level cultivation across all provinces of PNG (Table 1), and is distinct from $\lambda = 150,000$ ha, which is an assumed planning-scenario land budget for the ten selected provinces used in the optimisation model (as described earlier under *Land Constraints*).

Yield Variability σ

Note that ϵ_i and σ_i are distinct quantities: ϵ_i is the random variation term itself (a random variable), while σ_i is a fixed parameter, the standard deviation of the distribution of ϵ_i . This relationship is expressed as:

$$\epsilon_i \sim N(0, \sigma_i^2), \text{ with } \sigma_i \text{ as its standard deviation} \quad (38)$$

An 11% variation level was assumed to represent possible fluctuation in crop yields caused by rainfall variability, pest outbreak, transportation disruption, and climate related uncertainties.

So:

$$\sigma_i = 0.11\mu_i \quad (39)$$

To justify this choice, Table 7 presents a brief sensitivity analysis comparing the implied standard deviation of yield at three variability levels: a conservative 5%, the assumed 11%, and a higher-risk 15%, reflecting the plausible range of climate- and pest-driven yield variability reported for smallholder systems (Reis, 2023; Kan et al., 2021).

The 11% level was retained for the main analysis as a moderate, mid-range estimate: it is high enough to capture meaningful production risk from PNG's variable rainfall and pest pressure, without as-

suming the more extreme fluctuations associated with severe climate shocks (15%). Future work with province-level historical yield time series could replace this assumption with an empirically estimated σ_i .

Table 8: Variability values.

Crops	μ (ton/ha)	$\sigma = 0.11\mu_i$	$Y_i = \mu_i + \sigma_i$ (illustrative +1SD)
Coffee	0.75	0.083	0.833
Cocoa	0.40	0.044	0.444
Sweet Potato	14.00	1.540	15.540
Taro	5.50	0.605	6.105
Coconut	1.50	0.165	1.665
Banana	6.50	0.715	7.215

The table presents the estimated yield variability values for each crop using the stochastic modelling approach. The variables were calculated by assuming 11 percent standard deviation from the mean yield values. The right-most column shows an illustrative upper bound (mean plus one standard deviation), not a realised draw of the random variable ϵ_i itself.

4. DISCUSSION

Cash crop such as coffee and cocoa remain important export crops despite lower production volumes because they contribute significantly to household income and foreign exchange earnings. Sweet potato showed the highest contribution to total production (Table

1), confirming its central role in food security, while the re-solved linear programming model (Table 5) shows that, under the assumed yield and cost structure, banana offers the strongest optimisation-based return once a minimum diversification floor is guaranteed for the other five crops. Stochastic Modelling indicates that agricultural planning in PNG should incorporate climate risk management strategies to reduce production uncertainty.

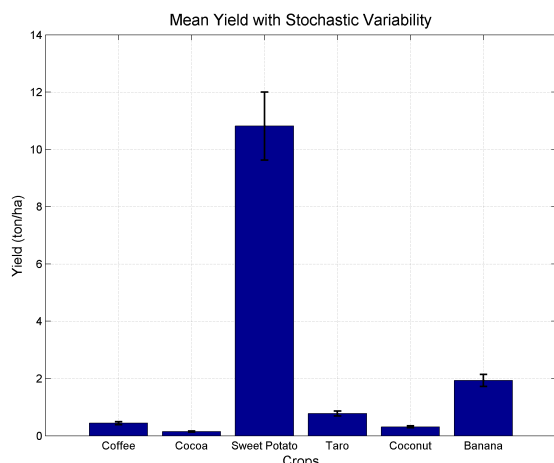


Figure 2: Mean yield with stochastic variability of selected crops.

CONCLUSION

We develop linear programming and stochastic modelling to improve agricultural production and determine optimal land allocation, labour and budget among major crops including coffee, cocoa, sweet potato, taro, coconut and banana in PNG.

Linear programming shows that optimal technique can improve resource allocation compared to traditional farming. The model highlights the dominant contribution of sweet potato to production, where it plays an important role in food security. It is the staple food crop providing 43 percent of total food energy (Sehgal et al., 2017).

Stochastic modelling strengthens the analysis, where crop production is not always the same every year because things like rainfall,

weather and climate change can affect how well crops grow.

This study confirms that by combining optimization and stochastic model, it provides an effective framework for agricultural planning.

The first objective was developing a linear programming model for land allocation among selected crops and it achieved by formulating of a linear programming model to maximize production subject to land, labour and budget constraints across selected provinces.

The second objective was to integrate variability into the model using stochastic techniques. This objective was achieved by introducing a stochastic yield model where crop yields follow a normal distribution. By calculating mean yields and incorporating variability through standard deviation, the model reflects real-world agricultural uncertainty caused by environmental factors such as climate variability and pest outbreaks.

Some data were estimated due to limited records such as labour and land data. Future research should include weather forecasting model, price optimization model, machine learning prediction models and irrigation planning systems.

Ethical Statement:

For this research, both public and simulated data have been used. No human or animal subjects have been used in this study and hence no ethical approval was needed. Authors wish to state that this paper fulfils all the standards required by the academic community.

Author Contributions:

J. D. contributed to the data collection, analysis, and investigation; C. S. contributed to the agricultural data compilation and literature review; J. L. contributed to the validation of the mathematical model and interpretation of results; M. A. contributed to the conceptualization of the study, development of the mathematical framework, supervision of the research, and preparation of the manuscript. All authors have read and agreed to the published version of the manuscript.

Conflict of Interest:

The authors declare no conflict of interest.

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