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Original article

An Integrated Risk Sensitive Crop Allocation Model with Pollination Intelligence Algorithm

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Abstract

A risk sensitive model for allocation of crops is considered in this work. The constructed model was designed to help farmers decision making process, thereby maximizing the use of agricultural land. Market price, cost of cultivation, yield of crops and climatic conditions were factors considered in the models. The theory of chance constraint programing was used to handle uncertainties that arise in crop planing. Data of known yield of crops were harvested and analyzed with the help of statistical tools. A class of Pollination Intelligence Algorithm was adopted to solve the model.

Keywords: Metaheuristic Algorithm, Agricultural Model, Risk Analysis.

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INTRODUCTION

Cropping plan decisions are the main land-use decisions in farming systems. It involves the choice of crops to be grown and the acreage to be allocated to each crop on a particular farmland. Decision making is indeed a crucial step in crop production which can have effect on the yearly and long-term productivity and profitability of farms. Crop allocation process can be referred to as management of acreage occupied by different types of crops and spatial distribution within a farming land. The problem of resource allocation for maximization of profit is generally faced by farmers, who mostly depend on historical and traditional ways of decision making that are often based on intuition,(Ashourloo et al., 2008). However, only a proper understanding of the planning environment and use of precise input-output data alongside realistic constraints and sophisticated modeling techniques can give better results (Bamiro et al., 2012). The large spectrum of consequences involved in farm decision making at higher levels, motivates the use of models in the design of cropping plans. Cropping plan selection models are mostly used to support farmers, policy makers and other stakeholders in knowing strategies for the allocation of scarce and competing resources more efficiently, (Lowe and Preckel, 2004). Agriculture is one of the fields where mathematical models of operations research were first used and also where they have been most widely applied. The number of mathematical models in agriculture has rapidly grown in the last decades due to the impressive development of personal computers and software programs (Ahmed et al., 2012; Chowdhury and Chukrabarty. 2015; Mellaku et al., 2018). Metaheuristic approach based on algorithm development has also been employed to help farmers decision making process, (Angelo, 2013; Ashutosh and Prakash, 2018, Ejieji and Akinsunmade, 2020). Economic benefit approach has been extensively integrated with climatic factors and soil factors using geographic information system to mark out soil suitability to strengthen acreage decisions of agricultural lands. This approach have been reported to produce a robust crop decision making models (Patel et.al. 2017; Akinsunmade and Ejieji, 2021). It is a point to note that decision making in agriculture involves uncertainty. The importance of uncertainties has been less considered by authors in the development of land and crop allocation models. There are different possible sources and types of uncertainties in farming process, which vary based on geographical location. According to McConnel and Dillon (1997), uncertainties in agricultural management has to do with environmental and market factors due to the high dependency of agricultural production on agro-ecological conditions. In view of the above, a model for agricultural land management and crop planning that will bridge the gap is of necessity. In this work, a new decision model for allocation of crops is developed considering climatic and economic factors with possible uncertainties that may arise during cultivation.

Model Formulation

The Table 1 presents definition of parameters used to formulate the model. The model is formulated to assist the farmer decision making process by allocating the total resources available on the farm over a period of time so as to achieve the required goal.

Table 1. Definition of Parameters for the Model

Parameters	Description
I	Number of Selectable Crops
N	Net Production Benefit of Selected Crops
P_i	Price of Crop i
Y_i	Yield of Crop i
D_i	Market Demand of Selectable Crops
C_i	Variable Cost of Planting Crop i per hectare
A_i	Area of Land Assigned to Crop i
L	Total Area of Land Available for Cultivation
F_l	Fixed Cost of Land Used
Ω_i	Percentage area of Land allocated to crop i
Q_i	Quality of Seed Planted

In formulating the model, farm decision is made by allocating the total resources available on the farm over a period of time. The intention of the farmer is to allocate crops to the land available for cultivation such that the process follows a pattern that guarantees maximum profit. The objective function is formulated as follows

$$N = \sum_{i=1}^{I} (P_i Y_i - C_i) A_i - F_l. \quad (1)$$

The model can then be formulated as,

$$Maximize \sum_{i=1}^{I} (P_i Y_i - C_i) A_i - F_l, \quad (2)$$

subject to

$$\sum_{i}^{I} A_i \leq L, \quad (3)$$

$$Q_i A_i \geq 0, \quad (4)$$

where $Q_i \in [0,1]$ is the percentage quality of crop seedling planted.

$$Q_i Y_i A_i \geq D_i, \quad (5)$$

and

$$A_i \geq 0. \quad (6)$$

From the above model, the objective function stated in equation (2) which represent the profit from all crops is maximized subject to the constraint equation (3) to (6).

Considering the variables involved in the objective function equation (2) stated as,

$$Maximize = \sum_{i=1}^{I} (P_i Y_i - C_i) A_i - F_l,$$

it is important to note that practically there are lots of uncertainties regarding their values. For example previous information known on market price, yield of crop and cost of planting crop i may not be the same at certain stages of production since they rely on other factors. Deterministic approach may not guarantee optimal profit under this condition of uncertainty. The yield of crop in particular, depends on environmental factors such as rainfall and temperature, which are events characterized by random occurrence. Other factors like pest and diseases, natural disaster can also result in low production of crop which are uncertain events. Putting into consideration constraint equation (5),

$$Q_i Y_i A_i \geq D_i,$$

agricultural practices although can be embarked upon by picturing certain production target, realistically, production targets can only be achieved if all the variables projected by the decision maker are exact. Hence, uncertainty of the occurrence of events which may affect production target should be well addressed. To address this, constraint equation (5) is reformulated since production level is not independent of some uncertain events. The Chance Constrained Programing (CPP) by Charnes and Cooper (1959), is adapted to handle uncertainties in farmers' decision making process by considering the feasibility of resource requirement in probabilistic term. Following chance constraint (Charnes and Cooper (1959)), equation (5) is reformulated to handle uncertainty term in the form

$$Pr[Q_i Y_i A_i \geq D_i] \geq \alpha, \tag{7}$$

where Pr is the probability, α is a specified probability. Inequality (7) indicates that the constraint equation (5) has to be satisfied with a probability α where $0 \leq \alpha \leq 1$. For simplicity, the decision variables A_i are deterministic while Y_i are farm variables distribution with known mean and standard deviation. The objective function (2) is also transformed to include the uncertainty state variable based on the assumption that Y_i's are farm variables with known mean and standard deviation, this becomes

$$Maximize = \sum_{i=1}^{I} (P_i Y(\xi)_i - C_i) A_i - F_l, \tag{8}$$

$$Y(\xi)_i = r_1 \overline{Y}_i + r_2 \sqrt{Var(Y_i)}, \tag{9}$$

where $\overline{Y}_i$ is the mean of Y_i and $Var(Y_i)$ is the variance of Y_i given as

$$Var(Y) = (PA)^T V(PA), \tag{10}$$

where

V is the covariance matrix of Y_i defined as

$$V = \begin{bmatrix} Var(Y_1) & Cov(Y_1, Y_2) & \dots & Cov(Y_1, Y_I) \\ Cov(Y_2, Y_1) & Var(Y_2) & \dots & Cov(Y_2, Y_I) \\ \vdots & & & \\ Cov(Y_I, Y_1) & Cov(Y_I, Y_1) & \dots & Var(Y_I) \end{bmatrix}. \tag{11}$$

with $Var(Y_i)$ and $Cov(Y_k, Y_i)$ denoting the variance of Y_i and covariance between Y_k and Y_i respectively. Here r_1 and r_2 are non-negative constants that indicate the relative importance of the mean and standard deviation of Y_i. In this model equation, r_1 and r_2 are set to be equal to 1, to indicate that there is an equal importance given to the operation of the mean as well as the standard deviation. Constraint equation (7) is reconstructed to separate variable Y_i from the deterministic variables as

$$Pr[D_i(QA_i)^{-1} \leq Y_i] \geq \alpha \tag{12}$$

if the expected mean $\overline{Y}_i$ is subtracted from both sides of the inequality in equation (12) and in turn both sides are divided by the standard deviation σY_i, equation (12) becomes

$$Pr\left[\frac{D_i(QA_i)^{-1} - \overline{Y}_i}{\sigma Y_i} \leq \frac{(Y_i - \overline{Y}_i)}{\sigma Y_i}\right] \geq \alpha. \tag{13}$$

The term $\frac{(Y_i - \overline{Y}_i)}{\sigma Y_i}$, gives the standard error term that Y_i is away from the expected mean. If we denote this error term as w, we have

$$w = \frac{(Y_i - \overline{Y}_i)}{\sigma Y_i}. \tag{14}$$

Using a chosen probability level α in equation (13), an appropriate level of w can be written as w_α in equation (14). The constraint equation (13) then becomes

$$Pr\left[\frac{D_i(QA_i)^{-1} - \overline{Y}_i}{\sigma Y_i} \leq w\right] \geq \alpha. \tag{15}$$

If w denotes the value of the standard normal variable at which

$$\phi(w) = \alpha, \tag{16}$$

then

$$\phi\left(\frac{D_i(QA_i)^{-1} - \overline{Y}_i}{\sigma Y_i}\right) \geq \phi(w), \tag{17}$$

satisfying

$$-\frac{D_i(QA_i)^{-1} - \overline{Y}_i}{\sigma Y_i} \geq w_\alpha. \tag{18}$$

Multiplying both sides of equation (18) by $-\sigma Y_i$ with further simplification the stochastic equation (14) is converted into deterministic constraint as

$$D_i(QA_i)^{-1} \leq \overline{Y}_i - w_\alpha \sigma Y_i, \tag{19}$$

where, w_α is an error term under a confidence level of α derived using probability of exceedance from known distribution of Y_i, (McCarl and Spreen, 1997). The crop planning model under uncertainty therefore maximizes the objective equation (8) subject to the constraint equations (3), (4), (6) and (19).

Pollination Intelligence Algorithm

The hybrid flower pollination dragonfly method Ejieji and Akinsunmade (2020), combines the search ability of Dragonfly Algorithm by Mirjalili (2015), and Flower Pollination Algorithm by Yang (2012). The Dragonfly Algorithm (DA) is a novel swarm intelligence technique modeled by studying the static and dynamic swarming behaviors of dragonflies in relationship to their foraging(searching for food and avoidance of enemies). Dragonflies belong to a class of fancy insects with over 3000 different species around the world. They are considered as small predators that hunt small sized insects and fishes. Since Dragonflies are known for their foraging behaviors, a general phenomenon known to swarms was adopted in studying their foraging activities. These behaviors was modeled into mathematical formulae, using swarm behavioral activities to avoid other individuals in a neighborhood during foraging activities(separation), the velocity matching of an individual in a neighborhood(alignment) and the tendency of an individual towards the centre of the mass of the neighborhood(cohesion). The major objective of any swarm is survival, all individuals will be attracted towards food source and also create a possible means of escaping from being a prey to superior organisms. These two processes(attraction to food and distraction from enemies) together with the three general swarm behaviors are modeled to form Dragonfly Algorithm (DA).

However, Flower Pollination Algorithm (FPA), is based on the principle of pollination, the transfer of pollen grains from the anther of a flower to the stigma of the same flower or another flower of the same type. The primary purpose of flower is ultimately reproduction. Pollen agents such as insects, birds, bats and other animals tends to visit flowering plants having been attracted by its nature(bright colour, scent). Apart from this, abiotic factor can also be responsible for transfer of pollen grain in flowering plants, and ten percent of pollination process involves this process. There are over 2000 varieties of pollinators, and they tend to behave by moving randomly. Biotic and cross pollination was considered as a process of global pollination process, and pollen-carrying pollinators move in a random direction which obeys Le'vy flight, self-pollination and abiotic factors were used to generalized local pollination, the interaction of switching between local pollination and global pollination was controlled by a switch probability $p \in [0,1]$, with a slight bias toward local pollination.

To achieve a global optimum using any optimization algorithm, there must be an accurate balance between exploration and exploitation. Exploration also known as diversification has to do with searching global region in the entire search region, while exploitation which is also known as intensification involves searching through local region to get possible solution. Dragonfly Algorithm and Flower Pollination Algorithm both operates on randomly generalized initial population of search and pollen agents, and both algorithm explore search regions using Levy flight. Meanwhile, Dragonfly Algorithm (DA) has few parameters to adjust and adaptive tuning of these parameters helps in balancing local and global search abilities. However, the tuning of these parameters can affect the search strength as Dragonfly Algorithm have no memory of keeping track on previously obtained solution as in most metaheuristic optimization methods like Flower Pollination Algorithm (FPA). While search is conducted, Dragonfly Algorithm (DA) discards all fitness values and does not look for possible set of solution which has the potential to converge to global optimum. This weakens the exploitation ability of Dragonfly Algorithm (DA) tending to converge very slowly and sometimes tracked at local optima. To overcome this, an hybrid algorithm based on Flower Pollination Algorithm and Dragonfly Algorithm is proposed. New features were added to Dragonfly Algorithm (DA) to improve its performance. A stored location to keep track on possible solution that have the potential to converge to global optimum with an iterative level of hybridization with Flower Pollination Algorithm (FPA) which run on the stored solution is added. This will also boost the search ability of Flower Pollination Algorithm (FPA), and instead of having a randomly guessed initial solution, Dragonfly Algorithm (DA) stored solution is accessed and replaces the randomly guessed initial solution. The concept behind this hybridization is, if the solution obtained from the stored location of Dragonfly Algorithm (DA) does not have the potential of converging to an optimum solution compared to the initial randomly guessed solution, Flower Pollination Algorithm (FPA) discards the stored solution and update it with the initial solution before exploration and exploitation is conducted. The HFPDM Algorithm is presented below:

HFPDM Algorithm

Minimize $f(x)$, $x = (x_1, x_2, \dots, x_d)$

Initialize a population of n flowers/pollen gametes with random solutions

Initialize the dragonflies population= population of n flowers

Find the best solution g^* in the initial population

Starts Dragonfly Algorithm

Initialize step vectors Δx_i (i = 1, 2, ..., n)

while the end condition is not satisfied

Calculate the objective values f(x) of all dragonflies

Update the food source and enemy

Update w, s, a, c, f, and e

Calculate S, A, C, F, and E

Update neighboring radius

if a dragonfly has at least one neighboring dragonfly

Update dragonfly elements

else

Update position vector using $x_{t+1} = x_t + L(d) \times x_t$

end if

Check and correct the new positions based on the boundaries of variables

end while

if objective values f(x) of all dragonflies < objective values f(x) of the initial random solution

g^*= new position

else

discard Dragonfly search result

end if

Start Flower Pollination Algorithm Define a switch probability $p \in [0,1]$

Define a stopping criterion

while $(t < MaxGeneration)$

for $i = 1{:}n$ (*all n flowers in the population*)

if $rand < p$,

Draw a (d-dimensional) step vector L which obeys a Le′vy distribution

Global pollination via $x_i^{t+1} = x_i^t + L(\lambda)(g^* - x_i^t)$

else

Draw e from a uniform distribution in $[0,1]$

Do local pollination via $x_i^{t+1} = x_i^t + e(x_j^t - x_k^t)$

end if

Evaluate new solutions

If new solutions are better, update them in the population

end for

Find the current best solution g^*

end while

Output the best solution found

MODEL IMPLEMENTATION

A population size parameter of 20 pollen agents/flies was used, with the algorithm set to perform 1000 iterations. This means a total number of 20,000 evaluations will be performed by the algorithm to obtain best solution. Unlike deterministic models, stochastic models require the interpretation of stochastic variables before implementation. Data for cassava, rice and yam in Benue state Nigeria as shown in table 2 were used. The yield of crops is considered as the only uncertain variable in the model equation. The data for the average yield in Nigeria for the 3 selected crops between 1980 and 2016 were obtained from FAO. The mean, standard deviation and variance of the data were calculated using SPSS 20. It is important to determine how reliable the data are as well as the risk level involved in using the yield information as the farmers' projected production level. To achieve this the data were ranked from 1 to n, where n is the total number of observed data. The probability of exeedance was calculated for the obtained data by using the formula from Sevruk and Geiger (1981).

$$p_x = \frac{r}{n+1},$$

where p_x is the exceedance probability, r is the rank of the data and n is the total number of sample. The results are presented in the Tables below.

Table 2. 2016 Calculated data for the study area based on FAO input-output coefficient in Nigeria

Crops	Land Area used (ha)	Yield (tonnes/ha)	Price (USD/tonnes)	Planting Cost (USD/ha)	Net Profit (USD/ha)
Cassava	528,994	9.66	159.79	575.53	967.76
Rice	27,8142	2.02	375.71	318.64	440.19
Yam	418,357	8.53	459.38	2,173.81	1,745.19

Table 3. Selected crop yield from 1980-2016

Rice Yield (kg/hectare)	Cassava Yield (kg/hectare)	Yam Yield (kg/hectare)
19.818	70.323	105.382
20.683	79.585	56.285
20.833	87.217	56.328
20.317	90.455	56.284
20	91.667	56.373
21.343	92.727	56.405
20.233	93.6	56.374
23.893	93.725	65.06
19.99	95.833	97.668
19.994	95.998	104.332
20.695	96.012	106.771
19.528	96.584	103.453
19.591	97	113.488
19.597	99.013	113.494
14.160	101.936	113.998
16.258	104.023	107.734
17.498	105.928	106.819
15.957	105.931	110.476
16.023	105.935	94.354
14.957	106.136	99.016
14.998	106.646	98.984
13.000	106.671	97.990
13.400	107.461	99.896
14.100	107.733	105.011
14.199	109.902	112.006
14.302	110.011	114.981
14.833	112.026	120.988
12.999	112.108	99.699
17.544	112.465	114.998
19.306	113.132	104.797
18.386	114.618	130.109
20.325	116.533	74.037
18.971	117.679	72.013
16.454	118.004	70.001
19.478	118.818	84.651
20.042	120.003	84.748
20.197	122.155	85.306

Table 4. Analysis of crop yield from 1980-2016

Selected Crop Yield	Rice	Cassava	Yam
Number of Examined Data	37	37	37
Mean	17.943	103.665	93.252
Std. Deviation	2.849	11.645	21.684
Variance	8.116	135.614	470.202

Table 5. Confidence level of rice yield

yield(Y)	rank	w_α	$\bar{Y} - w_\alpha \sigma Y$	probability	risk
12.999	1	-1.735345735	22.887	0.03	0.97
13	2	-1.734994735	22.886	0.05	0.95
13.4	3	-1.594594595	22.486	0.08	0.92
14.1	4	-1.348894349	21.786	0.11	0.89
14.16	5	-1.327834328	21.726	0.13	0.87
14.199	6	-1.314145314	21.687	0.16	0.84
14.302	7	-1.277992278	21.584	0.18	0.82
14.833	8	-1.091611092	21.053	0.21	0.79
14.957	9	-1.048087048	20.929	0.24	0.76
14.998	10	-1.033696034	20.888	0.26	0.74
15.957	11	-0.697086697	19.929	0.29	0.71
16.023	12	-0.673920674	19.863	0.32	0.68
16.258	13	-0.591435591	19.628	0.34	0.66
16.454	14	-0.522639523	19.432	0.37	0.63
17.498	15	-0.156195156	18.388	0.39	0.61
17.544	16	-0.14004914	18.342	0.42	0.58
18.386	17	0.155493155	17.5	0.45	0.55
18.971	18	0.360828361	16.915	0.47	0.53
19.306	19	0.478413478	16.58	0.50	0.50
19.478	20	0.538785539	16.408	0.53	0.47
19.528	21	0.556335556	16.358	0.55	0.45
19.591	22	0.578448578	16.295	0.58	0.42
19.597	23	0.580554581	16.289	0.61	0.39
19.818	24	0.658125658	16.068	0.63	0.37
19.99	25	0.718497718	15.896	0.66	0.34
19.994	26	0.71990172	15.892	0.68	0.32
20	27	0.722007722	15.886	0.71	0.29
20.042	28	0.736749737	15.844	0.74	0.26
20.197	29	0.791154791	15.689	0.76	0.24
20.233	30	0.803790804	15.653	0.79	0.21
20.317	31	0.833274833	15.569	0.82	0.18
20.325	32	0.836082836	15.561	0.84	0.16
20.683	33	0.961740962	15.203	0.87	0.13
20.695	34	0.965952966	15.191	0.89	0.11
20.833	35	1.014391014	15.053	0.92	0.08
21.343	36	1.193401193	14.543	0.95	0.05
23.893	37	2.088452088	11.993	0.97	0.03

Table 6. Confidence level of cassava yield

yield(Y)	rank	w_α	$\bar{Y} - w_\alpha \sigma Y$	probability	risk
70.323	1	-2.863203091	137.007	0.03	0.97
79.585	2	-2.067840275	127.745	0.05	0.95
87.217	3	-1.412451696	120.113	0.08	0.92
90.455	4	-1.134392443	116.875	0.11	0.89
91.667	5	-1.030313439	115.663	0.13	0.87
92.727	6	-0.939287248	114.603	0.16	0.84
93.6	7	-0.86431945	113.73	0.18	0.82
93.725	8	-0.85358523	113.605	0.21	0.79
95.833	9	-0.672563332	111.497	0.24	0.76
95.998	10	-0.658394161	111.332	0.26	0.74
96.012	11	-0.657191928	111.318	0.29	0.71
96.584	12	-0.608072134	110.746	0.32	0.68
97	13	-0.572348647	110.33	0.34	0.66
99.013	14	-0.399484757	108.317	0.37	0.63
101.936	15	-0.148475741	105.394	0.39	0.61
104.023	16	0.030742808	103.307	0.42	0.58
105.928	17	0.194332331	101.402	0.45	0.55
105.931	18	0.194589953	101.399	0.47	0.53
105.935	19	0.194933448	101.395	0.50	0.50
106.136	20	0.212194075	101.194	0.53	0.47
106.646	21	0.255989695	100.684	0.55	0.45
106.671	22	0.258136539	100.659	0.58	0.42
107.461	23	0.325976814	99.869	0.61	0.39
107.733	24	0.349334478	99.597	0.63	0.37
109.902	25	0.535594676	97.428	0.66	0.34
110.011	26	0.544954916	97.319	0.68	0.32
112.026	27	0.717990554	95.304	0.71	0.29
112.108	28	0.725032203	95.222	0.74	0.26
112.465	29	0.755689137	94.865	0.76	0.24
113.132	30	0.812966939	94.198	0.79	0.21
114.618	31	0.940575354	92.712	0.82	0.18
116.533	32	1.105023615	90.797	0.84	0.16
117.679	33	1.203434951	89.651	0.87	0.13
118.004	34	1.231343924	89.326	0.89	0.11
118.818	35	1.30124517	88.512	0.92	0.08
120.003	36	1.403005582	87.327	0.95	0.05
122.155	37	1.587805925	85.175	0.97	0.03

Table 7. Confidence level of yam yield

yield(Y)	rank	w_α	$\bar{Y} - w_\alpha \sigma Y$	probability	risk
56.284	1	-1.704851503	130.22	0.03	0.97
56.285	2	-1.704805386	130.219	0.05	0.95
56.328	3	-1.702822357	130.176	0.08	0.92
56.373	4	-1.700747095	130.131	0.11	0.89
56.374	5	-1.700700978	130.13	0.13	0.87
56.405	6	-1.699271352	130.099	0.16	0.84
65.06	7	-1.300129127	121.444	0.18	0.82
70.001	8	-1.072265265	116.503	0.21	0.79
72.013	9	-0.979477956	114.491	0.24	0.76
74.037	10	-0.886137244	112.467	0.26	0.74
84.651	11	-0.396651909	101.853	0.29	0.71
84.748	12	-0.392178565	101.756	0.32	0.68
85.306	13	-0.366445305	101.198	0.34	0.66
94.354	14	0.050820882	92.15	0.37	0.63
97.668	15	0.203652463	88.836	0.39	0.61
97.99	16	0.218502121	88.514	0.42	0.58
98.984	17	0.264342372	87.52	0.45	0.55
99.016	18	0.265818115	87.488	0.47	0.53
99.699	19	0.297315993	86.805	0.50	0.50
99.896	20	0.306401033	86.608	0.53	0.47
103.453	21	0.470439033	83.051	0.55	0.45
104.332	22	0.510975835	82.172	0.58	0.42
104.797	23	0.532420218	81.707	0.61	0.39
105.011	24	0.542289246	81.493	0.63	0.37
105.382	25	0.559398635	81.122	0.66	0.34
106.771	26	0.623455082	79.733	0.68	0.32
106.819	27	0.625668696	79.685	0.71	0.29
107.734	28	0.667865707	78.77	0.74	0.26
110.476	29	0.794318391	76.028	0.76	0.24
112.006	30	0.864877329	74.498	0.79	0.21
113.488	31	0.933222653	73.016	0.82	0.18
113.494	32	0.933499354	73.01	0.84	0.16
113.998	33	0.956742298	72.506	0.87	0.13
114.981	34	1.002075263	71.523	0.89	0.11
114.998	35	1.002859251	71.506	0.92	0.08
120.988	36	1.279099797	65.516	0.95	0.05
130.109	37	1.699732522	56.395	0.97	0.03

Using the data presented in tables 2, 4, 5, 6 and 7, the model was solved using different probability level of 89, 79 and 21 percents using Hybrid Flower Pollination Dragonfly Algorithm. Optimized crop acreage and profit obtained from the model for the three selected crops were compared with the production output in Benue State, Nigeria. The results obtained from the model using the algorithm are presented in tables 8 and 9.

Table 8. Comparison of acreage allocation using the uncertainty model at different risk levels

Crops	Base-year (Hectare)	Model (21% prob.) (Hectare)	Model (79% prob.)(Hectare)	Model (89% prob.) (Hectare)
Cassava	528994	118797.24	182163.23	177710.89
Rice	278142	122337.15	149193.52	208440.33
Yam	418357	984358.28	894135.70	839341.63
Total	1225493	1225492.67	1225492.46	1225492.85

Table 9. Comparison of net profit obtained from uncertainty model at different risk levels

Crop	Base-year (USD)	21% prob.(USD)	79% prob.(USD)	89% prob.(USD)
Cassava	512,090,000.00	2,338,997,490.83	3,586,609,738.50	3,498,947,667.50
Rice	122,460,000.00	1,352,942,279.93	1,649,950,330.70	2,305,168,424.31
Yam	729,910,000.00	100,131,463,325.82	90,953,789,765.30	85,379,995,627.38
Total	1,364,460,000.00	103,823,403,096.58	96,190,349,834.51	91,184,111,719.19

DISCUSSION OF RESULTS

The desired goal of every farmer is to have good returns. The combination of different farm resources to achieve this goal, comes with different level of risk due to the uncertainties of some events before, during and after cultivation. The combination of socioeconomic and environmental factors to design stochastic model is important in farm management as the model predicts production output at different risk and confidence level. The result presented in Table 3 and Table 4 show the mean, standard deviation and variance of the observed yield data for rice, cassava and yam in the study area. A mean yield value of 17.943, 103.665 and 93.252, standard deviation of 2.849, 11.645, 21.684 and variance of 8.116, 135.614, 470.202 was obtained for rice, cassava and yam respectively. Table 5, Table 6 and Table 7 show the confidence level of each crop yield obtained for different probability and confidence level. The result presented in Table 8 shows the comparison of acreage allocation at 21, 79 and 89 percent probability level. A total land area of 1,225,492.67, 1,225,492.46 and 1,225,492.85 hectares was reallocated for optimal production at 21, 79 and 89 percent probability compared to 1,225,493 used in the study area. Although, base year acreage allocation in the study area has cassava to be occupying about 43 percent of the total land area. Meanwhile, from the three confidence scenario used in solving the model, new acreage allocation was achieved for the three selected crops, with yam observed to cover about 80, 73 and 68 percent of the total land area obtained at 21, 79 and 89 percent confidence level. Result from Table 9 show an increase in the net-production output of the three crops at different risk level. A total optimized net-production value of $103,823,403,096.58, $ 96,190,349,834.51 and $ 91,184,111,719.19 was observed using 21, 79 and 89 percent confidence level, as against the initial production value of $ 1,364,460,000.00 recorded in the study area.

Conclusion

Agriculture plays a significant role in human life. Generally, agriculture is practiced mainly to meet the demand for food and make provisions for necessary raw materials for industrial use. In agriculture, land plays a vital role for effective production and farmers are always faced with the problem of decision making when it comes to choosing crops to be planted for a particular period and the area of land needed for cultivation. In this study, mathematical programing techniques were employed to optimize farm benefits. Decision making process in agriculture becomes more difficult when there are uncertainties. The constructed model was designed to handle these uncertainties that arise in crop planing, using chance constraint approach. Data of known yield of crops were harvested and analyzed with the help of statistical tools.

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