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Allocation of Agricultural Land for Optimal Crop Pattern Using Hybrid Flower Pollination-Dragonfly Method

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Abstract

Allocation of agricultural land for optimal crop pattern is considered in this work. A mathematical model was constructed as a sensitizing tool in the agricultural sector to meet food demand and increase net production value of major crops grown in the country using data for known yield of crops, cost incurred during planting, total amount of land available and food production target. Two new classes of metaheuristic methods of optimization called Dragonfly Algorithm and Flower Pollination Algorithm are also presented in this work to solve the designed model. A new class of hybrid metaheuristic method combining the abilities of Flower Pollination Algorithm and Dragonfly Algorithm called Hybrid Flower Pollination-Dragonfly Method is also constructed and used in solving the designed model. A case study of the Nigerian agricultural sector was used to implement the model. A net production value of $31,934,937,026.00 was obtained using the designed model to allocate crops as against the initial net production value of $23,130,563,800.00 recorded by the agricultural sector in the year 2016. Results obtained also suggest that cost of planting, yield of crops, market price, food production target and land allocation are important factors to be considered for optimal profit before planting crops.

Keyword: Mathematical Model, Hybrid Algorithm, Land Allocation, Metaheuristic Methods.

1. Introduction

Land is one of the factors of production that has a lot to do with the growth of a nation. It is an asset that can yield profitable returns if properly managed. In agriculture, land plays a vital role for effective production of crops and rearing of animals. This role makes the agricultural sector a key driver in social and economic development of a country. The Agricultural sector plays a substantial role in achieving, among others, food security, economic diversification, poverty eradication, and human welfare. Every country has a demand for agricultural products, and where these demands are not met by the general agricultural activities in the

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country, importation of agricultural products like food and cash crops from other countries are used to meet these demands.

A number of factors could be responsible for not meeting a country's demand for agricultural products like food. For instance, low yield of crops, which is subject to weather conditions, pest/diseases, soil fertility, viability of seed, government policy on some cash crops, are possible factors responsible for low production. Allocation of land is considered as the most important of the factors, since crop allocated to small cultivation space can eventually turn out to be the most productive, yielding huge profit amidst other selected crops planted by a farmer or group of farmers (Aimin, 2010).

As long as a country's demand for food is not met by the internal production from its agricultural sector, there will be a high rate of food insecurity and the only way out is importation of food from countries that do not only meet their internal demand for food, but also have surplus to sell out to other countries. Although, countries earn revenue through international trade activities, international trade as a major factor of openness has made an increasingly significant impact on the economic growth of a country. For countries that import most of their products more than their exports, they run on economic deficit, while the converse creates a trade surplus, (Azeez, *et al*. 2014).

Countries blessed with favorable climatic conditions that aid agricultural activities can still apply optimal allocation of crops to improve on the production level to satisfy their demand for food and also enhance their economic development if the surplus agricultural outputs are exported to other countries which need them. Hence, commercialization of the agricultural system will boost the country's economy, as farmers will cultivate large portions of land with selected crops of interest to obtain maximum profit and meet certain production target. To achieve this, optimum crop pattern and allocation of land to selected crops will help in increasing crop production as against allocating crops based on intuition process. Optimal allocation of land between different crops is of crucial importance both for the purpose of improving the country's economy and also for ensuring adequate flow of different food and raw materials to meet some demands.

Different approaches have been employed to crop pattern by many researchers, depending on their geographical zones. (Raj, 1963; Campbell *et al*., 1992 and Wankhade and Lunge, 2012) used linear programing techniques for optimal crop planning. The models were solved using traditional methods of optimization. In recent years, stochastic algorithms have been gaining significance in producing fast, low cost and robust solutions to complex optimization problems compared to conventional deterministic approach because they do not require any gradient information and are simple and easy to implement. These stochastic methods of optimization termed modern methods, are the most trending methods used in solving optimization problems, and have been applied to virtually all fields of life including engineering, science and finance to mention but a few. A significant number of these methods are algorithms that are derived from studying biological and environmental factors, human and animal activities, as well as chemical processes. Differential Evolution Method by (Storn and Price (1997), Firefly Algorithm by (Yang, 2008), Wind Driven Optimization by (Bayraktar *et al*, 2010), Brain Storm Optimization by (Shi, 2011), Flower Pollination Algorithm by (Yang, 2012), Dragonfly Algorithm by (Mirjalili, 2015), Crow Search by (Askarzadeh, 2016), Rainfall Optimization by (Aghay *et al.*, 2017), Sea Lion Optimization Algorithm by (Masadeh *et al*., 2019) to mention but a few, are different types of stochastic methods developed in recent years.

However, there exist numerous optimization algorithms, and it is difficult to test and determine which algorithm is most suitable for solving a particular optimization problem because most of the algorithms work on generalized concept and do not have specific ability to solve every problem. In this situation, hybridization process gains importance as it combines the desirable properties of different approaches to mitigate their individual weaknesses. Improvement on solution accuracy, reduced computation time, enhancement of algorithm stability and the handling of search for convergence, can be considered as targets of hybridization and improvement processes.

This work considers problems faced by farmers in a country with a large land mass suitable for planting several types of crops at different seasons. They need to quantify their decision making process to meet the local demand for food, make huge net returns, thereby contributing to the country's economy. Land allocation and crop pattern are two of the major problems faced by farmers and they involve not only the selection of crops to be planted on a piece of land, but also the determination of the acreage assignment to each of the crops. This makes it possible to combine different types of crops on a given piece of land. In most cases, farmers use their intuition in selecting the crops of interest and this is a universal problem which has received attention from various investigators.

Researchers like (Wankhade and Lunge, 2012; Ahmed *et al*., 2012, and Majeke *et al*., 2013) have done a thorough investigation on the subject matter of the present study using different constraints that affect crops productivity. Angelo, (2013) also developed a model for crop rotation to address this problem. Hybrid metaheuristic method combining the search strength of Genetic Algorithm and Simulated Annealing was developed to solve the model. Ashutosh and Prakash (2018), recently developed an optimal water allocation model for crop planning and used three swarm intelligence techniques, namely, Genetic Algorithm, Cuckoo Search and Particle Swarm Optimization to solve the model. The designed model was used to maximize net returns of farmers using irrigation and water constraints.

In this research work, an agricultural model for crop pattern is designed using existing yield information from crops over a period of time, area of land harvested for individual crops, production quantity of crops over a period of time and the net profit obtained for each crop. The model was adopted from Ejieji and Akinsunmade (2020) and modified in this work for the allocation of agricultural land for optimal crop pattern. A hybrid metaheuristic algorithm is also constructed from the combination of Flower Pollination Algorithm by Yang (2012) and Dragonfly Algorithm by Mirjalili (2015) and used in solving the model.

2. Materials and Methods

Consider a country that desires to revisit its agricultural sector for a buoyant economy. The interest of the sector is to sensitize and also ensure that farmers maximize agricultural land to meet the country's food demand and have surplus to export to other countries for international trade. The sector is expected to maximize the land in such a way that maximum profit is obtained from all crops planted, while considering market price, history of average crop yield in the region, cost of planting and harvesting, with a set target of meeting local and international demand. The agricultural sector's decision is to see that there is optimal crop pattern for major crops grown in the country. Many works related to this have been discussed in the literature, but no proper attention was given to land allocation which is one of the major factors of production in this case. Studying the nature of the problem, the following notations are defined to develop a new model for allocation of agricultural land for optimal crop pattern.

Table 1: List of Model Parameters

Parameters	Descriptions
I	number of selectable crops
NP_i	net production of selected crops
P_i	crop market unit price
Y_i	crop yield per unit area
TY	total yield of all selected crops
PT_i	production target of selectable crops
C_i	variable cost of planting crop I per unit area
F_c^L	Fixed cost of cultivating the whole Land
A_i	area of land assigned to crop i
L	total amount of land available for cultivation

$$Maximize \sum_{i}^{I} NP_i = \left[\sum_{i=1}^{I} (P_i Y_i - C_i) A_i \right] - F_c^L \tag{1}$$

subject to

$$\sum_{i}^{I} A_i \leq L \, , \tag{2}$$

$$Y_i A_i \geq PT_i \, , \tag{3}$$

$$\sum_{i}^{I} A_i Y_i \geq TY \, , \tag{4}$$

$$A_i \geq 0 \, . \tag{5}$$

From the above model, the objective function equation (1) maximizes net production of all crops in the country considering market price of crops, yield of crops, cost of planting the crops, as well as total cost of cultivating the land. The constraint equations (2) to (5) are designed to meet the land requirement in such a way that all crops acreage must not be above the available land for cultivation, the crop acreage must be allocated in such a way that the country's production target is met, the allocation must satisfy yield information provided for every crop, crop acreage must be non-negative.

Before implementing the above model, the following assumptions are made:

1. Available land is country's selected land suitable for planting selected crops of interest.
2. Selected crops are known to be major crops planted in the country.
3. Cost for pesticides, herbicides, fertilizer and irrigation are accounted for under variable cost throughout the period of planting.
4. Factors that possibly cause low yield like weather condition, pests/diseases, herders' destruction of land, fire outbreak and flood are already addressed in the yield information of selected crops.

To solve this model, two classes of metaheuristic optimization methods, namely, Dragonfly Algorithm by Mirjalili (2015) and Flower Pollination Algorithm by Yang (2012) are presented and used. A hybrid of the two methods is proposed and also used in solving the model.

2.1 The Dragonfly Algorithm

Dragonfly Algorithm (DA) is a new class of meta-heuristic optimization technique. It 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 can be adopted in studying their foraging activities which can be modeled using mathematical formulae. Generally, swarm behaviors follow three principles;

1. Separation: the ability to avoid other individuals in a neighborhood during foraging activities.
2. Alignment: the velocity matching of an individual in a neighborhood.
3. Cohesion: the tendency of an individual towards the center of the mass of the neighborhood.

In any swarm community each individual strives to move towards the source of food while at the same time trying to escape from superior organisms during the process of foraging. These two processes (attraction to food and distraction from enemies) together with the three general swarm behaviors are modeled to form the DA.

$$S_i = -\sum_{j=1}^{N} x - x_j \ , \tag{6}$$

$$A_i = \frac{\sum_{j=1}^{N} v_j}{N} , \tag{7}$$

$$C_i = \frac{\sum_{j=1}^{N} x_j}{N} \ , \tag{8}$$

$$F_i = x^+ - x \ , \tag{9}$$

$$E_i = x^- + x \ , \tag{10}$$

where x is the position of the current dragonfly, x_j is the position of *jth* neighboring dragonfly, x^+ is the position of the food source, x^- is the position of the enemy, N is the number of neighboring N dragonflies, v_j is the velocity of the *jth* neighboring dragonfly, S_i is the separation from an individual, A_i is the alignment parameter, C_i is fly cohesion, F_i is the attraction to its prey, E_i is the distraction from enemy and i is the current dragonfly in the neighboring N dragonflies. In static swarm movement, dragonflies make small group and fly back and forth over a small area to hunt other flying insects.

This local movement and abrupt changes in the flying path are the characteristics of static swarm. However, in dynamic swarm, a massive number of dragonflies make up the swarm for migration in one direction over long distances. These two processes mimic the exploration and exploitation phases of optimization using meta-heuristic approach. Dragonflies create sub-swarms and fly over different areas in a static swarm, which is the main objective of the exploration phase, while in a dynamic swarm process, dragonflies fly in bigger swarms and along one direction, which is favorable in the exploitation phase. To update the search position of dragonflies and simulate their movement, a vector Δx defined in the region [0, 1] to mimic the movement of dragonflies during foraging and weight functions are assigned to the separation, alignment, cohesion, food attraction and enemy distraction behaviour of dragonflies during foraging. We thus have the step vector as:

$$\Delta x_{t+1} = (sS_i + aA_i + cC_i + fF_i + eE_i) + w\Delta x, \tag{11}$$

where s, a, c, f, e and w are weight functions assigned to separation S_i, alignment A_i, cohesion C_i , food attraction F_i, enemy distraction E_i and vector Δx respectively, t is current iteration. We then calculate the position vector as

$$x_{t+1} = x_t + \Delta x_{t+1}. \tag{12}$$

With separation, alignment, cohesion, food, and enemy factors (s, a, c, f, e), different exploratory and exploitative behaviors can be achieved during optimization while the weight functions are randomized in the region of [0, 1] at every stage and iteration. To improve the randomness, stochastic behavior, and exploration of the dragonflies, they are required to fly around the search space when there is no neighboring solutions, this is mimicked using *Lévy* flight. In this case, the position of dragonflies is updated using the following equation:

$$x_{t+1} = x_t + L(d) \times x_{t+1}, \tag{13}$$

where L = *Lévy* flight and d is the dimension of the position vectors. *Lévy* flight is calculated as

$$Le'vy(x) = 0.01 \times \frac{r_1 \times \sigma}{|r_2|^{\frac{1}{\beta}}}, \tag{14}$$

where r_1 , r_2 are random numbers in [0,1], β is a constant and σ is calculated as

$$\sigma = \left(\frac{\Gamma(1+\beta) \times \sin(\frac{\pi\beta}{2})}{\Gamma(\frac{1+\beta}{2}) \times \beta \times 2^{(\frac{\beta-1}{2})}} \right)^{1/\beta}, \tag{15}$$

where $\Gamma(x) = (x-1)!$. The algorithm is presented below.

Dragonfly Algorithm

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

Initialize the dragonflies population x_i $(i = 1,2, \dots, n)$

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

while the end condition is not satisfied

Calculate the objective values 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 velocity vector using Equation (11)

Update position vector using Equation (12)

else

Update velocity vector using Equation (13)

end if

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

end while

2.2 The Flower Pollination Algorithm

Flower Pollination Algorithm (FPA) has the ability of solving different types of optimization problems, but has not been applied to solve land allocation models. The algorithm is based on the principle of flower 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 like insects, birds, bats and other animals tend 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 involves this process. There are over 2000 varieties of pollinators, and they tend to behave by moving randomly based on this characteristic of flower pollination. For simplicity the following rules are used:

1. biotic and cross pollination can be considered as a process of global pollination process, and pollen-carrying pollinators move in a random direction which obeys *Lévy* flight.
2. self-pollination and abiotic factors are used to generalize local pollination
3. pollinators such as insects can develop flower constancy which is equivalent to reproduction probability that is proportional to the similarity of two flowers involved
4. the interaction of switching of local pollination and global pollination can be controlled by a switch probability $p \in [0,1]$, with a slight bias toward local pollination.

From implementation point of view, a set of updating formulae are needed to convert the rules into updating equations. In global pollination, flower pollen gametes are carried by pollinators such as insects and pollen can travel over a long distance because insects can often fly and move in a much longer range. Rule 1 and flower constancy can be represented as:

$$x_i^{t+1} = x_i^t + L(\lambda)(g^* - x_i^t), \tag{16}$$

where x_i^t is the pollen or solution vector x_i at iteration t and g^* is the current best solution found among all solutions at the current generation/iteration. $L(\lambda)$ is the parameter that corresponds to the strength of the pollinators which is essentially the step size. Since insects may move over a long distance, *Lévy* flight is designed to mimic this characteristics efficiently. L > 0 is drawn from a *Lévy* distribution.

Rule 2 and Rule 3 can be represented as

$$x_i^{t+1} = x_i^t + e(x_j^t - x_k^t), \tag{17}$$

where x_j^t and x_k^t are pollen from different flowers of the same plant specie. This essentially mimics the flower constancy in a limited neighborhood. Mathematically, if x_j^t and x_k^t come from the same flower type or selected from the same population, this equivalently becomes a local random walk if we draw e from a uniform distribution in [0, 1]. Though flower pollination activities can occur at all scales, both local and global, adjacent flower patches or flowers in not so far away neighborhood are more likely to be pollinated locally. In order to mimic this, we can effectively use a switch probability (Rule 4) or proximity probability p to switch between common global pollination to intensive local pollination.

Flower Pollination Algorithm

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

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

Find the best solution *g** in the initial population

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 Lévy 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

2.3 Hybrid Flower Pollination-Dragonfly Method (HFPDM)

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. DA and FPA both operate on randomly generalized initial starting population of search and pollen agents, and both algorithms explore search regions using Lévy flight.

Meanwhile, 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 DA has no memory of keeping track on previously obtained solution as in most metaheuristic optimization methods like FPA. While search is conducted, DA discards all fitness values and does not look for possible set of solutions which has the potential to converge to global optimum. This weakens the exploitation ability of DA tending to converge very slowly and sometimes trapped at local optima. To overcome this, a hybrid algorithm based on FPA and DA is proposed. New characteristics were added to DA to improve its performance. A stored location to keep track on possible solution that has the potential to converge to global optimum with an iterative level of hybridization with FPA which run on the stored solution is added. This will also boost the search ability of FPA, and instead of having a randomly guessed initial solution, DA stored solution is accessed and this replaces the randomly guessed initial solution. The concept behind this hybridization is, if the solution obtained from the stored location of DA does not have the potential of converging to an optimum solution compared to the initial randomly guessed solution, FPA discards the stored solution and updates it with the initial solution before exploration and exploitation are conducted. The algorithm for the proposed (HFPDM) is presented below:

HFPDM Algorithm

Minimize $f(x), \ x = (x_1, x_2, \ldots, x_n)$

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 velocity vector using Equation (11)

Update position vector using Equation (12)

else

Update position vector using Equation (13)

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 Lévy 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

3. Result and Discussion

To implement the model, Nigeria agricultural sector was used as a case study. Nigeria is a West African country having about 77.74 percent of its land area suitable for planting different kinds of food and cash crops. Twelve major food crops (Cassava, Cowpea, Groundnut, Maize, Millet, Rice, Sorghum, Soybean, Potatoes, Cocoyam, Wheat and Yam) grown in Nigeria are used for this study. Data for net production, average yield, production quantity and harvested area of land for each of the twelve selected crops, were harvested from www.fao.org, 2016, a dedicated data website for Food and Agriculture Organization of the United Nations (FAO). A total net production of 23,130,563,800.00 USD was recorded as annual income from planting the selected twelve major crops in Nigeria for the year 2016, and a total of 42,059,876 hectares of land was recorded as area of harvested land for the twelve major crops in the same year. The records for the selected major crops as reported in (FAO, 2016) are presented in Tables 1 and 2 below:

Table 1: Data from FAO (2016) showing input-output coefficients in Nigeria

Crops	**Average Yield (hg/ha)**	**Harvested Land Area (Hectares)**	**Production Quantity (Tonnes)**	**Net Production (USD)(1000)**
Cassava	96846	6150574	59565916	5968438.97
Cowpea	8505	3586579	3050342	829537.02
Groundnut	13365	2680000	3581800	1278838.82
Maize	17495	6600865	11547980	995937.04
Millet	8497	1827104	1552576	249344.97
Rice	20233	5607643	11346076	1648558.91
Sorghum	11361	6651076	7556076	964890.94
Soybean	9576	641823	614632	125772.88
Potatoes	25215	1558399	3929517	295819.51
Cocoyam	38801	833435	3233857	673554.72
Wheat	10000	60000	60000	5759.043
Yam	84239	5862378	49384352	10102083.97
Total	344133	42059876	155423124	23130563.80

Table 2: Average production per hectare for the 12 crops from FAO, (2016)

Crops	Net Production (USD)(1000) per hectare
Cassava	0.970387312
Cowpea	0.008747741851
Groundnut	0.477178664
Maize	0.150879776
Millet	0.136470049
Rice	0.293984283
Sorghum	0.14236658
Soybean	0.211542568
Potatoes	0.189822697
Cocoyam	0.808167068
Wheat	0.09598405
Yam	1.7232058384

LINGO optimization software along with DA, FPA and the proposed HFPDA were used to solve the model. The results obtained for the optimal crop allocation are presented in Table 3. When the values in Table 2 were applied to the optimal crop allocation shown in Table 3, the net production for each of the selected crops were obtained and this is shown in Table 4.

Table 3: Optimized crop pattern obtained by implementing the model and solving with LINGO and the three algorithms presented

Crops	Base Year crop allocation (ha)	LINGO (ha)	DA (ha)	FPA (ha)	HFPDM (ha)
Cassava	6150574	6087721	3079475.918	6815063.251	7556797.537
Cowpea	3586579	3586528	5502064.459	2794921.84	1134691.654
Groundnut	2680000	2679985	1503719.507	2164338.858	2866738.192
Maize	6600865	6600732	1007881.428	1838164.053	1339398.358
Millet	1827104	1827205	5228684.245	1037250.035	1518598.52
Rice	5607643	5607708	5126036.929	1571009.679	4949222.399
Sorghum	6651076	650890	3158013.102	920583.0761	1348793.761
Soybean	641823	641846.3	6946458.641	4796828.423	2772997.499
Potatoes	1558399	1558405	1109438.967	2726105.509	1853062.302
Cocoyam	833435	833444.2	1395209.695	6328132.953	6473116.709
Wheat	60000	60000	1977332.801	1798546.944	1634731.488
Yam	5862378	5925412	6025559.602	9268887.217	8611686.866
Total (ha)	42059876.00	42059876.50	42059875.29	42059831.84	42059835.28

Table 4: Optimal production of the selected crops obtained by using the four algorithms

Crops	Base Year (USD)	LINGO (USD)	DA (USD)	FPA (USD)	HFPDM (USD)
Cassava	5968438975	5911177091	2990171116	6617426417	7337650408
Cowpea	829537019.7	31202793.6	47867960.79	24315820.01	9871817.388
Groundnut	127883821	1278352845	717274204.7	1032389635	1367434117
Maize	995937037.8	996710532	152190095.6	277562772	202249152.1
Millet	249344972.9	248499880	711101057.4	141066004.8	206529398.7
Rice	1648558909	1648666152	1507054857	461876845.6	1455071385
Sorghum	964890943.2	951077270	451595873.5	131643379.9	192877507.9
Soybean	125772886	136071415.6	1472649232	1016927626	587875469.9
Potatoes	295819502	294538545	209683964.8	515233941.1	350228775
Cocoyam	673554720.5	673422913.6	1127329433	5113131426	5230278301
Wheat	5759048	5760000	189823948.9	172660506.6	156934222.8
Yam	10102083970	10209484876	10382039194	15970292675	14837936470
Total	23,130,563,800	22,384,964,314	19,958,780,939	31,474,527,049	31,934,937,026

Table 5: A comparison of CPU time

Methods	CPU Time (seconds)
DA	5.926836
FPA	5.629687
HFPDM	5.723334

Table 3 shows the allocation of crops for optimal profit using LINGO optimization software, Dragonfly Algorithm, Flower Pollination Algorithm and Hybrid Flower Pollination-Dragonfly Algorithm to solve the model equations. From the table it can be observed that the constraint equations in the model are satisfied. The optimal production values obtained by using the four algorithms are shown in Table 4. Flower Pollination Algorithm and Hybrid Flower Pollination-Dragonfly Algorithm optimized the crop allocation pattern with a total net production of \$31,474,527,049.00 and \$31,934,937,026.00 respectively compared to the base-year net production value of $23,130,563,800. Meanwhile, results from LINGO optimization software $22,384,964,314.00 and Dragonfly Algorithm $19,958,780,939.00, show a decrease in the net production value compared with that of base-year cropping, Flower Pollination Algorithm and Hybrid Flower Pollination-Dragonfly Algorithm.

Therefore the Hybrid Flower Pollination-Dragonfly Algorithm proposed in this work performs better than all the other methods in allocating crops for optimal profit. Yam, Cassava, Cocoyam and Rice are competing crops that must be well allocated to meet food and profit demand of the country. It is therefore recommended that in order to boost the nation's economy and at the same time meet the country's demand for food, the developed crop pattern model and the Hybrid Flower Pollination-Dragonfly Method be applied for optimum production.

Graphical representation of the information in Tables 3 and 4 are shown in Figures 1 and 2 respectively.

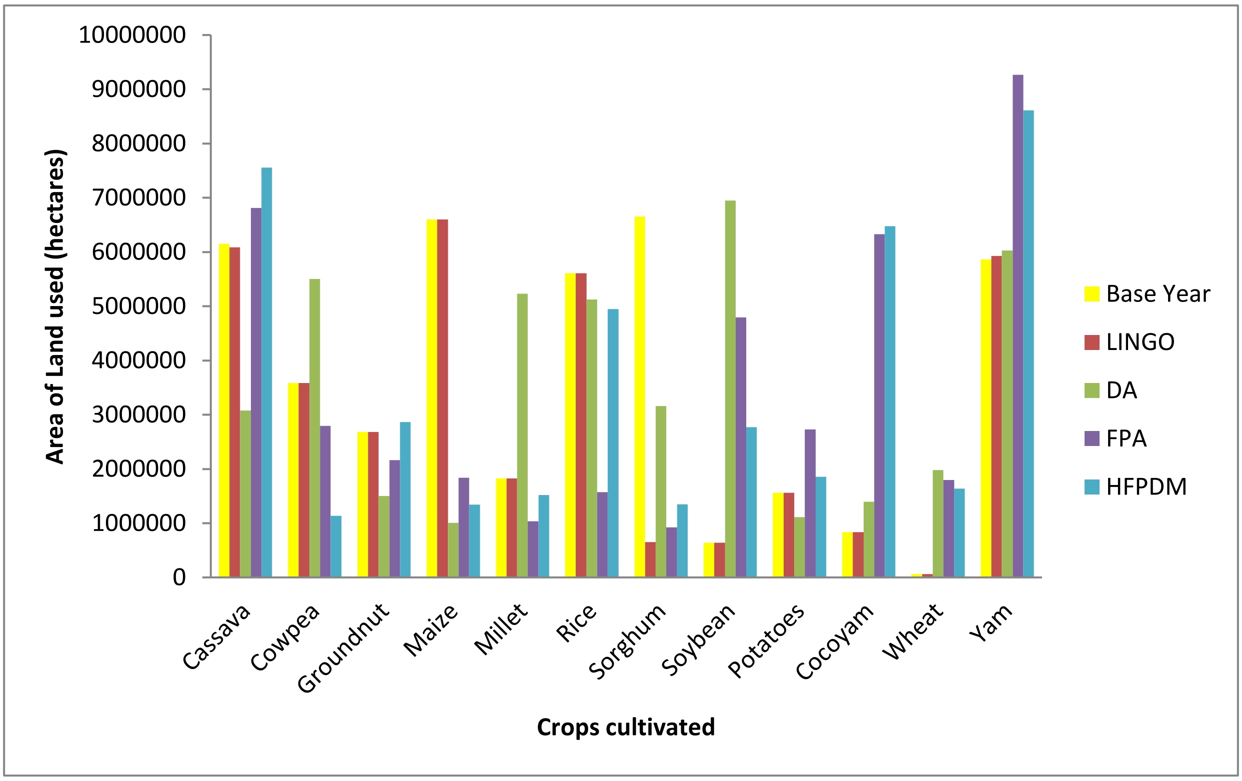

Fig 1: Comparison of land allocated to different crops

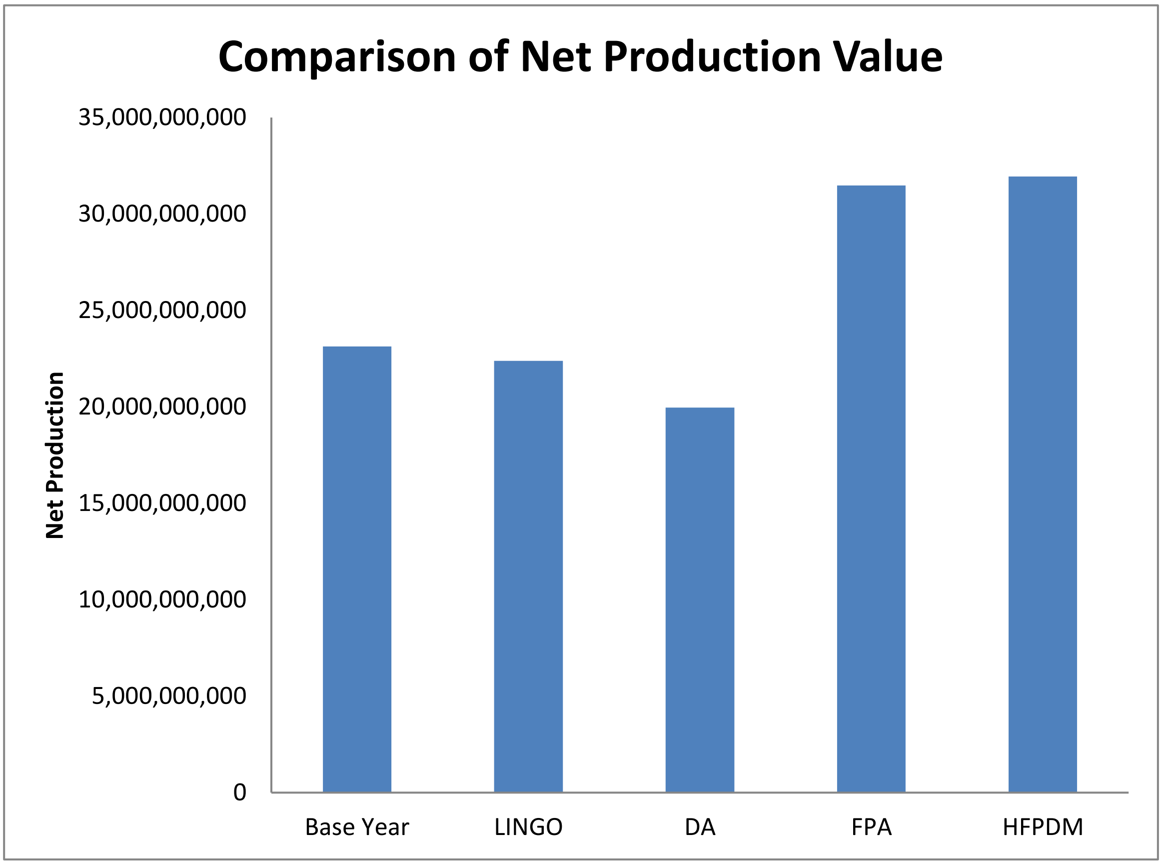

Fig 2: Comparison of net production value

4. Conclusion

A model for the allocation of agricultural land for optimal crop pattern is presented in this work. The developed model was solved using LINGO optimizer, Dragonfly Algorithm and Flower Pollination Algorithm. A hybrid algorithm combining the strengths of Flower Pollination and Dragonfly Algorithms was done and also used to solve the model. Results from Tables 3 and 4 produce an answer to agricultural sector decision in sensitizing farmers on how best to assign crops for cultivation, thereby meeting the nation's food demand. The Proposed Hybrid Flower Pollination-Dragonfly Method has a result relatively close to the solution obtained with Flower Pollination Algorithm, and produces more profit from the assigned crop acreage. It is worthwhile to note that hybridization of metaheuristic methods of optimization will help in overcoming the disadvantages of metaheuristic methods. Furthermore, from this study, we can deduce from the result that metaheuristic methods of optimization have the ability of solving the problem having to do with crop pattern with respect to allocation of agricultural land.

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