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A Robust Crop Rotation Optimization Model With Water Scarcity and Net Return Uncertainty Considerations

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ABSTRACT The tactical, technical, and economic considerations are critical factors in evaluating crop rotation decisions in any agricultural system. This system suffers from uncertainties that are amplified during the multi-period rotation planning. This study considers the crop rotation problem with water supply/demand and net return uncertainties, which vary within the allowable rotation cycle. Robust optimization is the most relevant tool for elaborating uncertainty in different parameters related to agricultural activities. It makes the formulated model numerically tractable, primarily when implemented in complex agricultural problems. The main objectives of this work include deciding the optimal cropping plans, achieving a reasonable income for the farmer, and taking water uncertainties into account on a tactical basis. All the mentioned goals are integrated while respecting the agronomic constraints and satisfying specific demand. A powerful feature of robust optimization is its robustness level adjustment for the solution against uncertainty sets. In this situation, the relationships between optimal values, the budget of uncertainty, and the perturbation values were outlined with insights towards tradeoff decisions. The proposed model compares the performance at each perturbation level with insights toward proper managerial decisions.

INDEX TERMS Crops, integer linear programming, mathematical programming, optimal scheduling, uncertainty.

NOMENCLATURE

i	Index of crops.
I	Set of all crops, $I = \{1, \ldots, I, I+1, \ldots, M, M+1\}$. Where $\{I+1, \ldots, M\}$ are the legumes, and M+1 is the fallow period.
F	Set of families, $F = \{1, \ldots, F\}$, where legumes belong to the last family.
j	Index of time periods.
J	Set of time periods, periods $J = \{1, \ldots, J\}$.
k	Index of plots.
K	Set of plots, $K = \{1, \ldots, K\}$.
t	Index of years in the rotation cycle.
T	Set of years in the rotation cycle, $T = \{1, \ldots, T\}$.
C_{ikt}	The net return for cultivating crop i in plot k at year t (EGP/fed.) (1 USD is approximately 15.7 EGP)
S_{it}	Planting date of crop i in year t, where $S_{it} \in J$
tp_i	Required maturity time for crop i in time periods.
E_{it}	Harvesting date of crop i in year t, where $E_{it} \in J$
N	Number of botanical families.
B_{it}	Minimum required number of plots from crop i in year t.
PS	Number of planting seasons in each year.
AP	Total number of cultivable plots.
W_i	The required amount of water for irrigating crop i per plot (m^3/fed.)
AW	Total yearly supplied water for irrigation (m^3/yr).
f_i	Planting frequency of crop i during the rotation cycle.
fm_i	Modification frequency factor for crop i.
T	The rotation cycle length in years (years).
F_i	The reciprocal of frequency of crop i.
TS	Available time periods per year.

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X_{ijk} Independent binary variable taking 1 if crop i is planted in period j in plot k; and 0, otherwise.
Y_{ikt} Dependent binary variable taking 1 if crop i is planted in plot k in year t; and 0, otherwise.
$\widetilde{W}_i$ Uncertain water needed for irrigating crop i.
$\widetilde{AW}$ Uncertain water supply.
$\widehat{W}_i$ Maximum deviation of water demand for crop i from the average needed value W_i.
$\widehat{AW}$ Maximum deviation of water supply from the average supplied value AW.
Z_t Random variable in the interval $[-1, 1]$ for water supply uncertainty.
Z_i^w Random variable in the interval $[-1, 1]$ for the uncertain needed water for each crop i
J_t Set of coefficients in row t, which is subjected to uncertainty.
Γ_t Conservatism degree for water supply and demand uncertainty.
λ_t Dual variable associated with dual transformation of constraint (28).
μ_{it} Dual variable associated with dual transformation of constraint (29).
μ_{to} Dual variable associated with dual transformation of constraint (30).
$\widetilde{C}_{ikt}$ Uncertain net return for cultivating crop i in plot$k$ at year t.

$\widehat{C}_{ikt}$ Maximum variation of the expected net return.
Z^o Random variable in the interval $[-1, 1]$ for net return uncertainty.
J_o Set of coefficients in the objective function, which is subjected to uncertainty.
Γ_o Robustness adjustment parameter for the objective function (conservatism degree).
λ_o Dual variable related to the objective function subproblem.
μ_{oikt} Dual variable related to the objective function that avoids non-linear formulation.

I. INTRODUCTION

Crop production is considered the central element in satisfying the global demand for food by supplying crops to various stockholders through agro-food supply chains. These crops can be transported directly to the customers as fresh crops or, after undergoing several processing stages, as processed products. Therefore, the agricultural decisions affect the whole agro-food supply chain, and proper planning should be considered for crop production. The planning of crop production starts with planting a particular crop according to the optimal cropping plans.

J. Dury *et al.* summarized several studies related to the cropping decisions, where different models were outlined to support the crop management options [1]. Figure 1 shows the main interacting factors affecting the cropping decisions, such as environmental considerations and uncertain conditions. The cropping decisions include the amount of cultivable area assigned to each crop, the proper planting, and harvesting dates, and the allocation of the production resources (e.g., water, labor, and machinery).

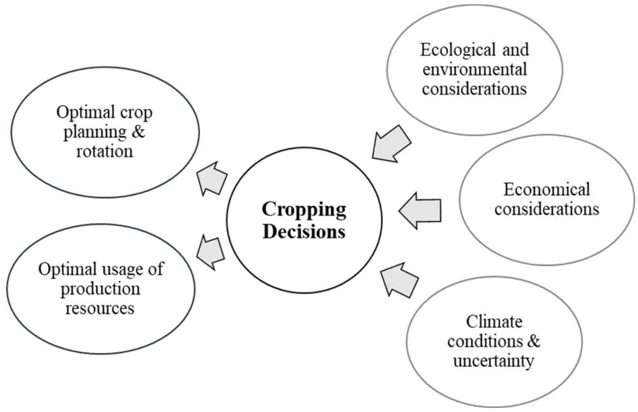

FIGURE 1. Schematic representation for the interacting factors and the expected outcomes from cropping planning problem.

The cropping problem is a complex planning problem that involves many decisions from many perspectives and integrates multiple considerations. One of these problems is the crop rotation planning problem, where a set of crops is allocated to a group of plots during a planning horizon while considering agronomical, economical, and environmental related issues [2]. Moreover, the crop rotation problem's main priority is to ensure optimum and sustainable usage of natural resources (e.g., water, soil).

Crop rotation is an agronomic practice defined by a specific rotation cycle to successively plant different crops in the same plot [3]. The cycle is determined according to the re-production of the main crop in the plot, and usually, the main crop is either the most profitable one or a strategic crop (e.g., wheat). For instance, the wheat is produced in a three-year cycle with yearly harvesting of two crops in Egypt [4]. Crop rotation improves the soil properties and the organic matter; hence, it increases the crop yields and maintains the soil fertility [5]. Also, it regulates the required water for irrigation, minimizes the usage of pesticides and synthetic fertilizers, and reduces agricultural pests and diseases.

The selection of optimum crop rotation schedules is considered one of the cornerstones in analyzing crop rotation decisions. These schedules determine the sequence of cultivating the competed crops in a limited cultivable area, consider the succession constraints, and allocate the available resources, to optimize a specific objective. Additionally, the optimum schedules consider planting each crop in its season and securing reasonable income for the farmer through satisfying the demand. It is necessary to introduce a fallow period in each plan and allow the growing of at least one legume crop to enhance soil fertility [6].

All the mentioned aspects make the crop rotation planning problem a complex combinatorial optimization problem involving many constraints and decision variables. These variables are usually related to selecting a crop among several crops and allocating a certain number of plots to plant this crop in the cultivable area [2]. Another aspect that increases the complexity of the problem is the uncertainties in the data.

The uncertainties associated with the input parameters affect the crop rotation problem, and if they are not considered, they may affect the decision process and lead to an ineffective solution. These uncertainties include crop yields, water availability, market prices, and climate conditions [7]. As an illustration, Ridier *et al.* [8] introduced a dynamic programming model investigating the risks associated with crop yield and price. The computational analysis showed that longer rotation cycles enhance crop diversification but have higher risks. Hence, a deeper insight into the crop rotation problem should be made due to the rising uncertainties in the input parameters such as water and net return. Therefore, the uncertainties in the amount of supplied water, required amount for irrigation, and the farmer's net return are considered in this work.

Stochastic programming and robust optimization are the two main methods that can be used to deal with data uncertainty. Both methods investigate the solution with uncertain data while considering different approaches [9]. The exact data distribution should be known in stochastic programming, and the investigated scenarios lead to a significant increase in the problem size. This reason limits the application of stochastic programming in agricultural applications [10]. Moreover, Robust Optimization is computationally tractable even with a greater number of scenarios [11]. It does not require the probability distribution of the uncertain parameter, which is the case in agricultural problems. The main objective is to find a solution and protect it from any perturbation in the defined uncertainty set [12].

Robust optimization is one of the most helpful tools to address uncertainties in the agricultural field [13]. In this work, an approach proposed by Bertsimas and Sim [14] is used to deal with data uncertainty. This approach has been selected due to its numerical tractability. One of the advantages of using such an approach is that the problem will remain of the same class (i.e., the linear programming model remains linear after coping with the uncertainties). Moreover, there is no need for a statistical distribution for each uncertain parameter in the proposed robust approach.

This article investigates the crop rotation problem by formulating a deterministic mathematical model and its robust counterparts for addressing different uncertainties. Three robust optimization models are developed to incorporate randomness in the amount of water and farmer's net return. The proposed models aid the farmer's decisions in obtaining optimal crop rotation schedules.

The rest of this article is organized as follows; in section II, the literature review for the problem is outlined. The formulation of the deterministic model is presented in section III, and robust models are presented in section IV. A case study for the crop rotation planning problem is explained in section V. The computational results are shown in section VI, and the article is concluded with future directions in section VII.

II. LITERATURE REVIEW

Many optimization models have been proposed to solve the crop rotation problem from the economical and/or agronomical points of view. An earlier network model described the crop rotation planning problem and explored its complexity [15]. Similarly, a transshipment network model was formulated to address the problem with risk constraints on the net income [3].

A binary programming optimization model was developed for vegetable farming considering adjacency constraints in multiple plots [16]. The model determines the crop rotation schedules using exact and approximate methods. Due to the problem's size and complexity, a heuristic based on column generation was used during the computational analysis. The results show that the column generation-based heuristic outperforms the branch and cut algorithm of CPLEX^{TM}. Each produced schedule included set aside periods (e.g., fallow periods) and legume crops to fully utilize the crop rotation concept. The same model was extended to involve more advanced agricultural features, such as the cultivable area's heterogeneity [2]. The extended model was solved using two additional heuristics referred to as plot elimination and plot minimization heuristics. The first heuristic aimed to eliminate tiny plot sizes, while the second heuristic guaranteed a minimum number of assigned plots to meet the demand.

Another binary mathematical model was formulated to minimize the planted area while covering the required demand during the planning horizon [17]. Later, two optimization models that used branch-price-and-cut algorithms to solve the crop rotation problem with restricted branching rules were introduced [18], [19].

In recent years, robust optimization gained more attention as a tool dealing with uncertainty. Robust optimization has been used in many fields due to its efficacy in solving complicated problems. Successful implementation of robust optimization can be found in procurement management [20], cellular manufacturing system with unreliable machines [21], selection of newsvendor problem [22], closed-loop supply chain with perishable products [23], and the production-inventory-routing problem [24].

Many studies addressed the uncertain nature of agricultural systems. For instance, crop yield uncertainty was handled through robust optimization to achieve similar revenue for a group of farmers [7]. The robust model considered the tradeoff between the optimal solution and the probability of constraint satisfaction to solve the crop production problem. One limitation in this study is revising the objective function by a penalty term to include yield uncertainty rather than transforming it into a robust objective function. Other interesting robust models covering agro-food supply chain problems are presented in [10], [13].

Many studies have focused on solving the crop rotation planning problem and analyzing the underlying model complexity. These studies have been conducted to solve the problem with tractable methods while considering different constraints [2], resulting in significant research output [18]. However, addressing different parameters' uncertainties still lags in this field. Therefore, this article presents a comprehensive model for the crop rotation problem with a conceptual robust optimization framework.

The proposed robust model considers the uncertainties in the net return and the amount of water required for irrigation while solving the crop rotation planning problem. The economical aspect is addressed by considering the net return of the farmer. During the rotation cycle, the net return is subject to changes due to the fluctuation in the expected selling price, the obtained crop yield, and the market demand. Moreover, water scarcity and uncertainty resulting from climate change and soil conditions are integrated into the formulated robust model. To the best of our knowledge, the proposed robust model is the first to consider the uncertainty in the amount of water required for irrigation as a critical resource parameter. Further, current challenges in sustaining natural resources force the grower to collaborate more effectively to optimize related cropping decisions. The model can generate different agriculture plans and estimate the required amount of water for irrigation under uncertainty.

This work attempts to answer the following research questions:

- How to obtain a fair net return from each plot during the crop rotation cycle while considering the previously mentioned constraints (e.g., crops succession, legumes presence, market demand).
- How to estimate the expected net return while managing disruptions due to the lack of water, fluctuation in the water required for irrigating different crops, and farmer's net return.
- How to consider different scenarios to deal with the raised uncertainties without considering only the worst-case scenario. At the same time, it is not likely to have the worst simultaneous values for all the induced uncertainties, where a less conservative solution may be obtained.

III. THE PROPOSED DETERMINISTIC CROP ROTATION MODEL

Crop rotation planning is the first step of crop production planning; it includes deciding on the crops that should be planted, hence, determining the crops' sequences. The proposed model determines the sequence of the crops to be produced and the area allocated for each crop during the rotation planning horizon. The model allows satisfying the required demand (e.g., micronational policies implementation) and considers advanced requirements in the agriculture system such as crop frequency and planting restrictions for the different botanical families. In this section, the deterministic crop rotation model is introduced, then the robust models are formulated (section IV) to incorporate the amount of water uncertainty and the net return uncertainty.

A. PROBLEM DESCRIPTION

A binary integer programming model is proposed to generate crop rotation schedules with the objective of maximizing the farmer's net return. The proposed model takes the environmental considerations into account through different agronomic constraints. The original deterministic model was proposed by Fikry *et al.* [25] to solve the crop rotation problem. An optimal solution should consider the following conditions:

- Each crop has specific planting and harvesting dates, the expected net return, amount of water for irrigation, and a deterministic demand.
- Each botanical family has a known number of crops. The crops' succession is controlled by preventing the same crop or two crops from the same family from being regrown consecutively.
- The same crop cannot be planted yearly in the same land to sustain soil fertility [5], and its repetition relies on crop frequency. The cropping frequency is defined as the time needed to return the same crop to a particular plot during the rotation cycle.
- Each rotation schedule must contain a minimum of one legume crop (e.g., Lentils and beans). Introducing a legume crop within the rotation positively impacts the soil content and, therefore, increases the next crop's productivity [6].
- At least one fallow period must be allowed to improve soil fertility and restore soil moisture content.
- The rotation cycle is described in years. Each agricultural year is divided into seasons, where the number of seasons limits the number of planted crops each year. However, each crop requires different planting and maturity times, so time periods are introduced to fully control the planting status.

Based on the requirements mentioned above, the optimal rotation schedules should involve agronomic constraints while achieving the highest net return to the farmer. The combinatorial nature of the suggested rotation plans makes the problem a challenging optimization task. The expected outcomes from the proposed model can be summarized as:

- Determine the optimal crops sequence during the rotation cycle for each plot.
- Estimate the area allocated for each crop.
- Describe the yearly cropping status for each plot.
- Facilitate obtaining the different operational plans through the optimal rotation schedules.

B. MATHEMATICAL FORMULATION

1) MODEL ASSUMPTIONS

The following assumptions are considered in the proposed model:

- All plots are homogenous with equal sizes.
- Crop water needs are depending on the present crop in the planted plot.

- The demand for each crop is a known deterministic value.
- The planting seasons are known before establishing the rotation schedules.

2) MATHEMATICAL MODEL

$$Max \sum_{i=1}^{I}\sum_{k=1}^{K}\sum_{t=1}^{T} C_{ikt}.Y_{ikt} \tag{1}$$

$$\sum_{i=1}^{M+1} X_{ijk} \leq 1 \quad \forall j \in J, \quad k \in K \tag{2}$$

$$\sum_{j=Sit}^{E_{it}X_{ijk}} = tp_i.X_{iSitk} \quad \forall i \in I,\ k \in K,\ t \in T \tag{3}$$

$$\sum_{j\in J/\{S_{it},..,E_{it}\}}\ \sum_{k=1}^{K} X_{ijk} = 0 \quad \forall i \in I,\ t \in T \tag{4}$$

$$X_{ijk}+\sum_{i\in F/\{I+1,..,M+1\}} X_{i(j+tp_i)k} \leq 1 \quad \forall i \in I,\ j=E_{it},\ k \in K \tag{5}$$

$$\sum_{j=1}^{F_i} X_{i(S_{it}+(j-1)TS)k} \leq 1 \quad \forall i \in I,\ k \in K \tag{6}$$

$$\sum_{t=1}^{T} X_{iS_{it}k} \leq T.f_i + fm_i \quad \forall i \in I,\ k \in K \tag{7}$$

$$Y_{ikt} - X_{is_{it}k} = 0 \quad \forall i \in I, \quad k \in K,\ t \in T \tag{8}$$

$$\sum_{i=1}^{I} Y_{ikt} \leq PS \quad \forall k \in K, t \in T \tag{9}$$

$$\sum_{i}^{I}\sum_{k=1}^{K} Y_{ikt} \leq PS.AP \quad \forall\, t \in T \tag{10}$$

$$\sum_{k=1}^{K} Y_{ikt} \geq B_{it} \quad \forall i \in I, t \in T \tag{11}$$

$$\sum_{I+1}^{M}\sum_{t=1}^{T} Y_{ikt} \geq 1\ k \in K \tag{12}$$

$$\sum_{t=1}^{T} Y_{(M+1)kt} \geq 1 \quad \forall\, k \in K \tag{13}$$

$$\sum_{i=1}^{I}\sum_{k=1}^{k} W_i.Y_{ikt} \leq AW \quad \forall\, t \in T \tag{14}$$

The objective function (1) maximizes the farmer's total net return during the rotation cycle from selling different crops. Constraint (2) allows growing at the most one crop per time period per plot, while constraint (3) ensures the planted crop's occupation of a specific plot during its maturation period. Constraint (4) prevents planting any crop outside the permissible planting dates, while constraint (5) controls the successive planting of two crops from the same botanical family.

Constraint (6) guarantees enough time before replanting the crops in the same plot, while constraint (7) defines the occurrence of each crop based on the crop's frequency. Constraint (7) adequately describes the crops' frequencies when the rotation cycle does not exceed the crops' frequency reciprocal [5]. Constraint (8) introduces the annual plot status (Y_{ikt}) and its interrelation with the binary decision variable X_{ijk}. Constraints (9) represents the number of different planting seasons, and constraint (10) is related to the total cultivable area each year.

Constraint (11) represents the minimum number of plots allocated to each crop to fulfill the seasonal demand within the rotation cycle. Constraints (12) and (13) assign at least one green manure crop (e.g., legume crop) and fallow period for each plot during the crop rotation cycle, respectively. Constraint (14) ensures that the total amount of water required for irrigation cannot exceed the total available water amount.

IV. METHODOLOGY AND ROBUST MODELS FORMULATION

A. ROBUST OPTIMIZATION METHODOLOGY

The proposed robust model relies on the robust optimization approach developed by Bertsimas and Sim [14] for solving discrete optimization problems under data uncertainty. There is a need for a tool that could capture different uncertainties related to agricultural activities, with insufficient available data to describe the probabilistic variation in each parameter. This tool is applied to deal with the uncertainty found in different coefficients. The robust optimization technique can guarantee that the robust solution will remain feasible in the given uncertainty set. The solution robustness is controlled through the conservation level (Γ), which guarantees more scenarios; from the nominal solution to the worst one. It is also referred to as a robustness adjustment parameter and budget of uncertainty. Figure 2 shows a brief outline to handle uncertainty with the detailed steps discussed in the following subsections.

To illustrate the used approach [14], let's consider the following linear optimization problem:

$$\begin{aligned} &Max \sum_j c_j x_j \\ &s.t.\ \sum_j a_{ij}\, x_j \leq b_i \quad \forall_i \\ &x_j \geq 0 \forall_j \end{aligned} \tag{15}$$

In this model, c_j, a_{ij}, b_i are the nominal values (i.e., deterministic values) for cost coefficient, column-wise, and row-wise parameters, respectively. These parameters are subjected to uncertainty, which can be defined using the associated random variables (Z_{jo}, Z_{ij}, Z_i) in the interval [-1,1] as follows:

$$Z_{jo} = (\tilde{c}_j - c_j)\big/\hat{c}_j \quad \forall j \in J_o \tag{16}$$

$$Z_{ij} = (\tilde{a}_{ij} - a_{ij})\big/\hat{a}_{ij} \quad \forall j \in J_i \tag{17}$$

$$Z_i = (\tilde{b}_i - b_i)\Big/\hat{b}_i \tag{18}$$

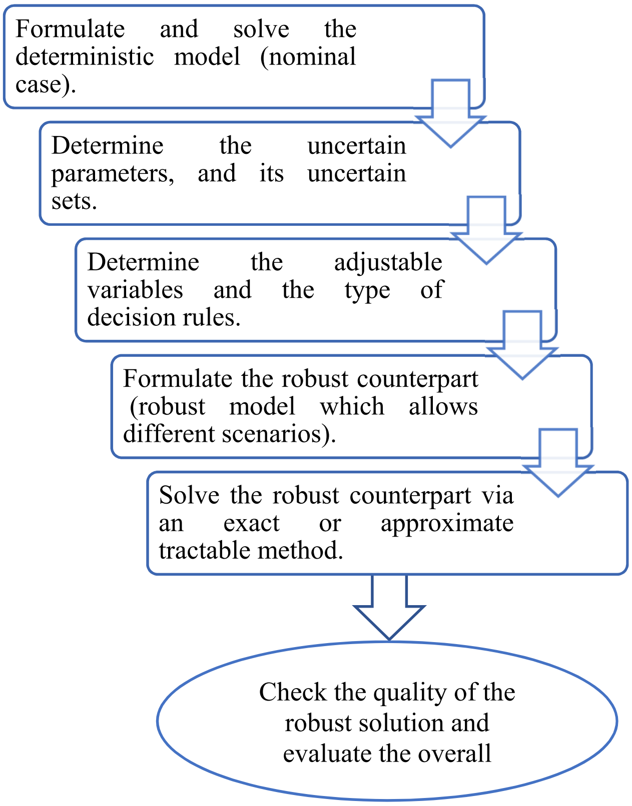

FIGURE 2. A general approach to model and solve robust optimization models.

where $\tilde{c}_j$, $\tilde{a}_{ij}$, $\tilde{b}_i$ represent the uncertain value for each parameter, and $\hat{c}_j$, $\hat{a}_{ij}$, $\hat{b}_i$ are the maximum variation from the deterministic value. In the i^{th} row, the number of uncertain coefficients is defined by (J_i), while the number of uncertain cost coefficients is measured by (J_o).

For the uncertainty found in the i^{th} constraint, the solution conservatism extends from the nominal to the worst-case solutions according to the given conservatism degree (Γ_i). This occurs through $\sum_J i\left|Z_j\right| \leq \Gamma_i$, where $\Gamma_i \in [0, |J_i|]$, and the same applies to cost uncertainty. The deterministic solution can be obtained when $\Gamma_i = 0$, meanwhile the maximum protection (i.e., worst-case scenario) happens when $\Gamma_i = |J_i|$. Other Γ_i values will result in changing the solution conservativeness with the level of protection. The robust linear counterpart for the above model (15) is formulated as:

$$
\begin{aligned}
&Max\ S \\
&s.t. \sum_j c_j x_j - \Gamma_o \lambda_o - \sum_{j \in J_o} \mu_{jo} \geq S \\
&\quad \lambda_o + \mu_{jo} \geq \hat{c}_j \left|x_j\right| \quad \forall j \in J_o \\
&\quad \sum_j a_{ij} x_j + \sum_{Ji} \mu_{ij} + \mu_{io} + \Gamma_i \lambda_i \leq b_i \quad \forall i \\
&\quad \lambda_i + \mu_{ij} \geq \hat{a}_{ij} \left|x_j\right| \quad \forall i, j \in J_i \\
&\quad \lambda_i + \mu_{io} \geq \hat{b}_i \quad \forall i \\
&\quad \mu_{jo}, \lambda_o, \lambda_i, \mu_{io}, \mu_{ij} \geq 0
\end{aligned} \tag{19}
$$

where μ_{jo}, λ_o, λ_i, μ_{io}, μ_{ij} are the dual variables added from the dual transformation that prevent the nonlinearity of the proposed model.

B. THE PROPOSED ROBUST MODELS

The objective of the robust model is to maximize the farmer's net return under water and net return uncertainties. For net return uncertainty, the selling prices fluctuate within a certain range each season depending on the market needs and the available amount of planted crops [26]. Even in the case of contract farming, the selling prices are linked to incentive schemes that fluctuate according to crop yield in each season [27].

On the other hand, climate conditions play an important role in changing the expected amount of water in both supply (i.e., the available water for irrigation) and demand (i.e., the estimated amount of water required for irrigation) [28]. As reported by FAO, the crop water demand will be increased due to the rising temperatures worldwide [29]. Furthermore, other climatic factors affect the needed water for irrigation. These factors include humidity, unpredicted rise in temperature, and rainfall [30]. Other general factors which affect the amount of water required by a crop are soil type and used irrigation system (e.g., Sprinkler irrigation and Manual irrigation).

In this study, a modification was made to decrease the uncertain coefficients found in the uncertain parameters' constraints. As can be seen, constraints (1) and (14) were modified in comparison to the originally formulated model [25]. In that case, dependent decision variables are added to describe the yearly status of the cropping decisions. The binary cropping variables (Y_{ikt}) were also utilized in an integrated production-logistics problem in the sugar beet supply chain with crop rotation as a main agricultural decision [31].

The robust model's core objective is to find a relatively good feasible solution that is robust against uncertainties in water and farmer's net return. In the developed robust models, the uncertain parameters are modeled with additional parameters and variables as follows:

1) UNCERTAINTY IN THE AMOUNT OF WATER

Uncertain information related to water supply and demand, which is represented by the nominal value AW and W_i respectively in the deterministic model, may lead to an ineffective solution to the problem. Therefore, the uncertainty in these parameters should be considered. These parameters are exposed to uncertainty defined by $\widetilde{AW}$ and $\widetilde{W}_i$. Each uncertain parameter is defined by a symmetric and bounded value in the interval $\widetilde{AW} = \left[AW - \widehat{AW}, AW + \widehat{AW}\right]$, and $\widetilde{W}_i = \left[W_i - \widehat{W}_i, W_i + \widehat{W}_i\right]$. Where $\widehat{AW}$ and $\widehat{W}_i$ represent the maximum deviation of water supply and demand, respectively. In this case, constraint (14) can be rewritten with the transformation of all uncertainties into the left-hand side as follows:

$$
-\widetilde{AW} + \sum_{i=1}^{I} \sum_{k=1}^{k} \widetilde{W}_i . Y_{ikt} \leq 0 \quad \forall t \in T \tag{20}
$$

Constraint (21) introduces the protection function for maximizing the deviation for each parameter. This protection function is applied to protect the model against infeasibility.

$$-AW+\sum_{i}\sum_{k}W_iY_{ikt}+max\{-Z_t\widehat{AW}+\sum_{i\in J_t,k}Z_i^w\widehat{W}_iY_{ikt}\}\leq 0 \quad \forall t\in T \tag{21}$$

where $Z_t, Z_i^w \in [-1,1]$ and J_t denotes the number of coefficients exposed to uncertainty on the column vectors (Y_{ikt}).

Various protection levels can be applied through the robustness adjustment parameter (Γ_t). This parameter controls the model robustness by varying the robustness parameter value in the interval of $[0,|J_t|]$. In particular, the deterministic model is obtained by setting $\Gamma_t=0$; meanwhile, the worst case is obtained when $\Gamma_t = J_t$ (i.e., all the coefficients are subject to data uncertainty). According to the conservation level of Γ_t, constraint (21) can be rewritten as:

$$-AW+\sum_{i}\sum_{k}W_iY_{ikt}+\beta_t(Y_{ikt}^*,\Gamma_t)\leq 0 \quad \forall t\in T \tag{22}$$

From constraints (21) and (22), the protection function β_t has the following linear primal subproblem for obtaining the optimal solution $\left(Y_{ikt}^*\right)$:

$$\beta_t\left(Y_{ikt}^*,\Gamma_t\right)=max\{-Z_t\widehat{AW}+\sum_{i\in J_t,k}Z_i^w\widehat{W}_iY_{ikt}\} \tag{23}$$

$$s.t. \sum_{i\in J_t}\left|Z_i^w\right|+|Z_t|\leq\Gamma_t \tag{24}$$

$$-1\leq Z_i^w\leq 1\forall i\in J_t \tag{25}$$

$$-1\leq Z_t\leq 1 \tag{26}$$

Since Z_t value will be negative or zero in an optimal solution. Meanwhile, Z_i^w will take a positive value or zero. The primal subproblem is equivalent to solving the following auxiliary model.

$$\beta_t\left(Y_{ikt}^*,\Gamma_t\right)=max\{Z_tA\hat{W}+\sum_{i\in J_t,k}Z_i^w\hat{W}_iY_{ikt}\} \tag{27}$$

$$s.t. \sum_{i\in J_t}Z_i^w+Z_t\leq\Gamma_t \tag{28}$$

$$0\leq Z_i^w\leq 1\forall i\in J_t \tag{29}$$

$$0\leq Z_t\leq 1 \tag{30}$$

For each year t, the dual problem associated with the primal subproblem (27-30) is as follows:

$$Min\ \Gamma_t\lambda_t+\sum_{i\in J_t}\mu_{it}+\mu_{to} \tag{31}$$

$$s.t.\ \lambda_t+\mu_{it}\geq\hat{W}_i\sum_{k}Y_{ikt}\forall i\in J_t,t\in T \tag{32}$$

$$\lambda_t+\mu_{to}\geq A\hat{W} \quad \forall t\in T \tag{33}$$

$$\lambda_t,\mu_{to}\geq 0 \quad \forall t\in T \tag{34}$$

$$\mu_{it}\geq 0 \quad \forall i\in J_t,\ t\in T \tag{35}$$

where λ_t, μ_{to} and μ_{it} are the dual auxiliary variables to protect the robust model against nonlinearity.

Inserting the objective function (31) from the dual problem in constraint (14), which was formulated in the deterministic model, and adding constraints (32-35) to the deterministic model.

$$\sum_{i=1}\sum_{k=1}W_i.Y_{ikt}+\Gamma_t\lambda_t+\sum_{i\in J_t}\mu_{it}+\mu_{to}\leq AW \quad \forall t\in T \tag{36}$$

$$\lambda_t+\mu_{it}\geq\hat{W}_i\sum_{k}Y_{ikt} \quad \forall i\in J_t,t\in T \tag{37}$$

$$\lambda_t+\mu_{to}\geq A\hat{W} \quad \forall t\in T \tag{38}$$

$$\lambda_t,\mu_{to}\geq 0 \quad \forall t\in T \tag{39}$$

$$\mu_{it}\geq 0 \quad \forall i\in J_t,\ t\in T \tag{40}$$

The robust model under water uncertainty has additional constraints and variables added from the dual sub-problem compared to the deterministic model. The additional number of constraints is calculated by $|\boldsymbol{I}|\,|\boldsymbol{T}|+|\boldsymbol{T}|$, and the newly added number of variables is $\mathbf{2}\,|\boldsymbol{T}|+|\boldsymbol{I}|\,|\boldsymbol{T}|$. The nominal and robust models are of the same class; that is, the robust version is formulated as a linear programming model.

2) NET RETURN UNCERTAINTY

The objective function (1) is revised to include the uncertainty induced due to the farmer's net return fluctuation during the rotation cycle. The robust counterpart allows more flexibility in determining the maximum net return under different demand scenarios. In such case, the farmer can predict the associated net return for each scenario and handle the related expenses.

The uncertain net return $\tilde{C}_{ikt}$ is defined in the interval $\left[C_{ikt}-\hat{C}_{ikt},C_{ikt}+\hat{C}_{ikt}\right]$, where $\hat{C}_{ikt}$ represents the maximum deviation of the farmer's return from its nominal value C_{ikt}. The symmetric uniform random variable $\tilde{C}_{ikt}$ plays a predominant role and directly affects the total net return found in the objective function. Therefore, the equivalent model to form the robust counterpart is as follows:

$$Max\ Z \tag{41}$$

$$s.t.\ \sum_{i=1}^{I}\sum_{k=1}^{K}\sum_{t=1}^{T}C_{ikt}.Y_{ikt}-max\{\sum_{i\in J_o,k,t}Z^o\hat{C}_{ikt}Y_{ikt}\}\geq Z \tag{42}$$

$$\beta_o\left(Y_{ikt}^*,\Gamma_o\right)=max\{\sum_{i\in J_o,k,t}Z^o\hat{C}_{ikt}Y_{ikt}\} \tag{43}$$

The symmetric and bounded variable Z^o is defined in the interval $[-1,1]$. The conservatism level of the solution is controlled through Γ_o, it is presented in an interval of $[0,|J_o|]$. Using the same approach discussed in section (4.2.1), the equivalent dual form for the net return uncertainty

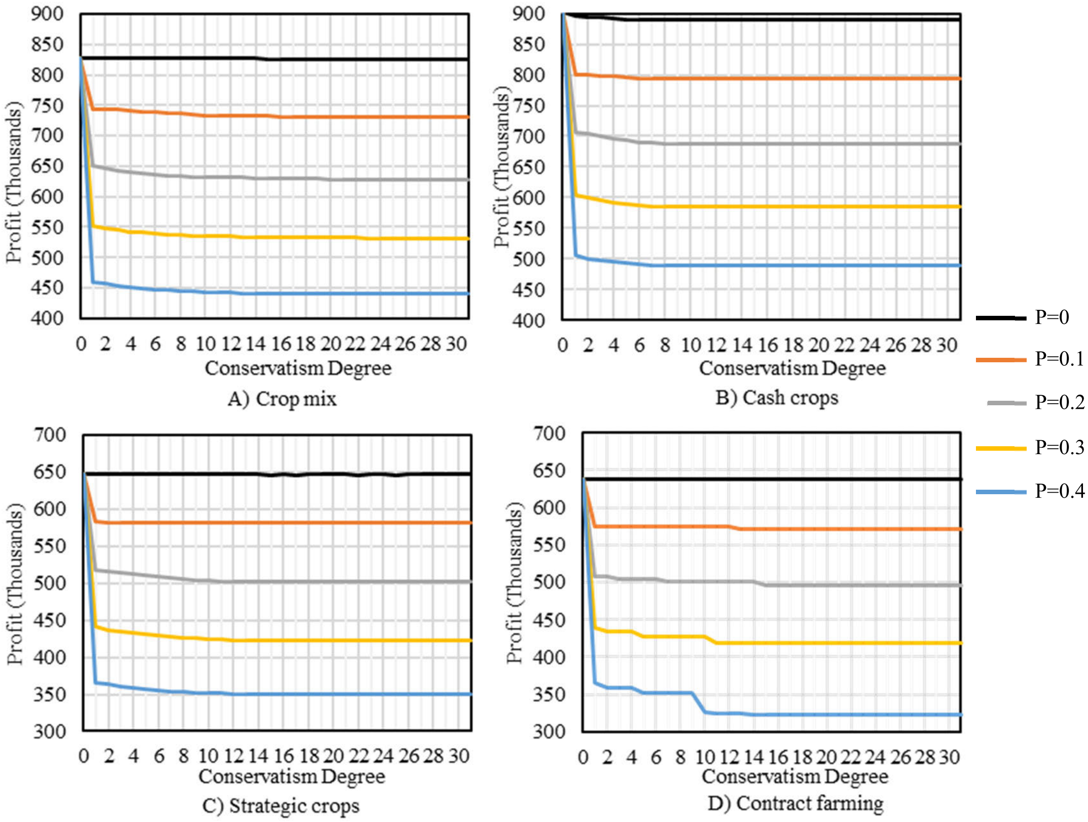

FIGURE 3. **Objective function values under water uncertainty for the different scenarios.**

can be obtained as:

$$\text{Min } \Gamma_o \lambda_o + \sum_{i \in J_o} \sum_{k} \sum_{t} \mu_{oikt} \quad (44)$$

$$\lambda_o + \mu_{oikt} \geq \hat{c}_i . Y_{ikt} \quad \forall i \in J_o,\ k \in K, t \in T \quad (45)$$

$$\lambda_o, \mu_{oikt} \geq 0 \quad (46)$$

where λ_o, μ_{oikt} are auxiliary robustness variables related to the dual problem. Substituting the obtained linear dual objective function of the protection function in (42), the robust model can be written as follows:

$$Max\ Z \quad (47)$$

$$s.t. \sum_{i=1}^{I} \sum_{k=1}^{K} \sum_{t=1}^{T} C_{ikt} . Y_{ikt} - \Gamma_o \lambda_o - \sum_{i \in J_o} \sum_{k} \sum_{t} \mu_{oikt} \geq Z \quad (48)$$

$$\lambda_o + \mu_{oikt} \geq \hat{c}_{ikt} . Y_{ikt} \quad \forall i \in J_o, k \in K, t \in T \quad (49)$$

$$\lambda_o, \mu_{oikt} \geq 0 \quad (50)$$

V. CASE DESCRIPTION

In order to elaborate the performance of the proposed models, a case study in Egypt will be presented. In Egypt, since 1987, farmers have been choosing the crops to cultivate and their allocated areas without any restrictions. Consequently, highly profitable crops (e.g., rice, maize, wheat) were usually selected to be planted by most farmers, regardless of the negative impacts of this decision. Excessive water usage due to the expansion of the annual rice area is an example of such consequent negative impacts. Other effects involve soil fertility deterioration due to mono-cropping (i.e., planting the same crop repeatedly in the same plot). This work's primary goal is to implement the crop rotation concepts and secure a reasonable net return for the farmer while considering the different agronomic constraints.

The case is based on data from the Delta region "old lands[1]" in Egypt's north region. Thirty-one crops divided into eleven families are chosen for this study due to the data availability of these crops. Table 1 illustrates the different production parameters for the selected crops (e.g., sowing and harvesting dates), Average Crop Water Requirement (ACWR), and Average Net Return (ANR). In Egypt, the rotation cycle is usually three years [4]; hence a planning horizon of the same length is used and divided into periods of two weeks to describe the considered periods. In addition to three planting seasons named Summer, Winter, and Nili seasons. This means that at most three crops can be planted per plot each year in Egypt. The total cultivable area of twelve feddans for a small farm (1 feddan $\simeq$ 0.42 hectares) is considered

[1] It is named for Delta and Nile Valley lands which are more fertile than the new lands. Historically, the new lands reclaimed after constructing the High Aswan Dam in 1970 outside the Delta and Nile Valley region.

TABLE 1. Data for different crops in Egypt[2].

No.	Crop Name	Crop Family	Planting Date	Harvest Date	f_i (#.yr-1)	ACWR (m3/fed.)	ANR (EGP/fed.)
1	Eggplant	Nightshade	15 Feb.	15 Apr.	1/2	2334	3556
2	Peppers	Nightshade	30 Jun.	30 Sep.	1/3	2856	2370
3	Potatoes	Nightshade	15 Sep.	15 Jan.	1/4	3024	3400
4	Tomatoes(W)	Nightshade	1 Oct.	1 Mar.	1/3	2058	21947
5	Tomatoes(S)	Nightshade	1 May	1 Sep.	1/3	3064	18951
6	Onions	Amaryllidaceae	15 Nov.	15 Apr.	1/3	2064	6100
7	Garlic	Amaryllidaceae	15 Sep.	15 Dec.	1/3	2510	3900
8	Broccoli	Brassicas	1 Feb.	1 Jun.	1/2	2334	2100
9	Cabbage	Brassicas	15 Sep.	30 Jan.	1/2	2334	2213
10	Cauliflower	Brassicas	15 Oct.	1 Feb.	1/3	2334	2600
11	Sugar Beets	Chenopodiaceae	15 Oct.	12 Apr.	1/4	2572	3838
12	Beans	Legumes	25 Oct.	25 Apr.	1/4	1308	2525
13	Cowpeas	Legumes	15 May	25 July	1/4	1319	2700
14	Soybeans	Legumes	15 May	25 Aug.	1/4	3250	3000
15	Lentils	Legumes	15 Nov.	1 Jan.	1/4	968	2746
16	Chickpeas	Legumes	30 Oct.	30 Feb.	1/4	2419	2650
17	Clover(short-cut)	Forage	15 Oct.	30 Dec.	1/3	1034	5620
18	Clover(long-cut)	Forage	15 Oct.	1 Apr.	1/3	3315	11924
19	Maize	Grass (Cereal)	15 May	1 Sep.	1/2	4104	2234
20	wheat	Grass (Cereal)	15 Nov.	18 Apr.	1/2	2309	3941
21	Rice	Grass (Cereal)	15 May	16 Sep.	1/3	5501	2948
22	Sorghum	Grass (Cereal)	15 May	1 Sep.	1/2	3864	1604
23	Barley	Grass (Cereal)	15 Nov.	15 May	1/2	1506	3645
24	Sunflower	Lettuce	15 May	15 Aug.	1/4	3318	4000
25	Lettuce	Lettuce	1 Apr.	1 July	1/2	3100	2000
26	Cucumbers	Cucurbitaceae	1 May	1 Aug.	1/2	3723	4939
27	Watermelon	Cucurbitaceae	15 Apr.	30 July	1/2	4700	6715
28	Zucchini	Cucurbitaceae	15 Feb.	30 May	1/3	3159	4402
29	Cotton	Malvaceae	15 Apr.	15 Aug.	1/3	4891	6350
30	Okra	Malvaceae	30 Nov.	30 Feb.	1/3	2505	3750
31	Sweet potato	Morning Glory	1 Sep.	1 Dec.	1/3	3723	2400

TABLE 2. Strategic crops and contract farming data.

Strategic Crops[3] (share per crop > 15%)	Contract farming (crop = required number of yearly planted plots)
Tomatoes(W), Potatoes, Tomatoes(S), Maize, Onions, Wheat, Cucumbers, Clover(short-cut), and Beans.	Tomatoes(W)=1, Potatoes=1, tomatoes(S)=1, Sugar beet=1, Clover=1, Maize=2, Wheat=2, Sweet potatoes=1, Cucumbers=1, Cowpeas=2, Beans=2, Soybeans=2, Sorghum=1, Barley=1

during the computational analysis. At least one legume crop and fallow period are adopted during each rotation cycle.

Three robust models are considered in the current study. Firstly, the crop rotation model considering the amount of water uncertainty is referred to as the 'Water Robust Model' (WRM). The associated robustness adjustment parameter (Γ_t) takes value in the interval [0,31]. Secondly, the crop rotation model involving net return uncertainty is called the 'Net Return Robust Model' (NRRM). The budget of uncertainty related to the objective function (Γ_o) varies from 0 to 31 according to the number of uncertain parameters. Thirdly, the simultaneous combination of both uncertainties is referred to as the 'Net Return and Water Robust Model' (NRWRM). The associated robustness of the NRWRM model (Γ_t, Γ_o) is controlled by an increase of one unit value until reaching $\Gamma_t = \Gamma_o = 31$. The proposed deterministic and robust models were implemented using Gurobi® solver v9.1, using a 3.47 GHz Intel Xeon® processor with 96 GBytes RAM computer.

Each uncertain parameter is allowed to deviate within ten percent from the average value reported in table 1, representing the nominal level (perturbation value $P = 0$). Four additional perturbation levels ($P = 10\%, 20\%, 30\%,$ and 40%) with the same deviation used for the nominal level are considered in the computational analysis.

Four different management scenarios are considered during the computational analysis to test the sensitivity of the model. The crops' demand controls the management scenarios; four possible scenarios can be regarded as crop mix, cash crops, strategic crops, and contract farming. The crop mix scenario ensures growing each crop at least once in any plot during the rotation cycle. In contrast, the cash crops

[2]Data have been collected from the Egyptian Central Agency for Public Mobilization and Statistics CAPMAS [32]. Production dates are listed in the Ministry of Agriculture and Land Reclamation, Egypt (MALR) database [33].

[3]Strategic crops were selected based on the data provided by MALR, Egypt [33].

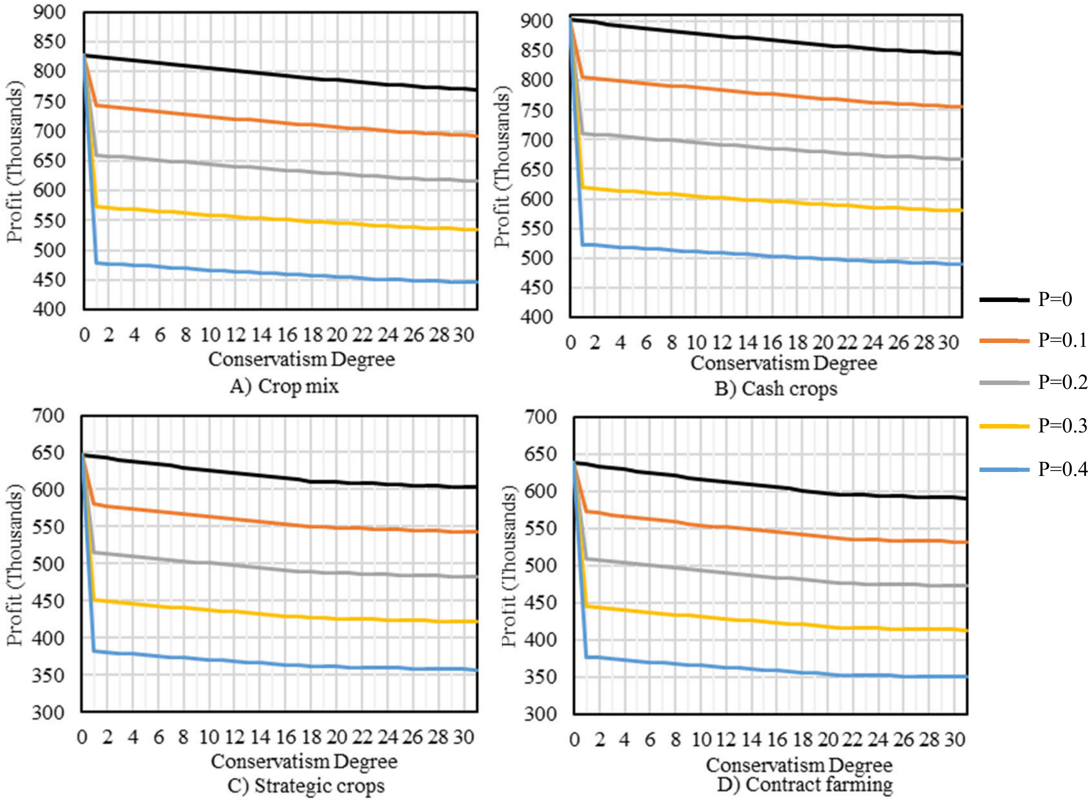

FIGURE 4. Objective function values under net return uncertainty for the different.

TABLE 3. Test problems' data.

No. of robust models	No. of perturbation levels	Conservatism degree (Γ_t, Γ_o)	No. of scenarios
3	5	31	4

scenario focuses on the most profitable crops that achieve the farmer's highest net return. The third scenario "strategic crops" and the fourth scenario "contract farming" guarantee cultivating the strategic crops every year and satisfying a particular demand, respectively. Table 2 provides the data for the third and fourth scenarios.

To sum up, table 3 demonstrates the values and the specifications of the different test problems. As can be seen, each model can generate 155 schedules as an expected number of schedules per scenario, with a total of 1860 schedules for all the considered instances.

VI. RESULTS AND COMPUTATIONAL ANALYSIS

In this section, the previously mentioned scenarios are considered to evaluate the performance of the proposed models. First, each of the models (e.g., WRM and NRRM) is addressed separately, and then further investigation was done through the NRWRM model.

A. WATER ROBUST MODEL (WRM)

The results for each scenario under water uncertainty and different perturbation levels are shown in Figure 3. In all scenarios at the nominal perturbation level (P = 0), there is no difference between the result of the deterministic ($\Gamma_t = 0$) and robust models. At this level, the same net return is achieved for each scenario, regardless of the conservatism degree's value. At the same time, the steady-state pattern was found in each scenario because of the sufficient amount of available water. This amount forms the ideal case (i.e., there is no shortage in the water supply) and exceeds the required water to irrigate different crops. The highest net return occurred at the "cash crops" scenario, followed by the "crop mix" scenario. On the other hand, the "contract farming" scenario has the lowest net return for the farmer. This is evident that satisfying the demand for specific crops (i.e., "contract farming" scenario) forces the farmer to plant these crops, in contrast, in the "cash crops" case, the farmer does not need to grow crops with low return values.

In the case when the perturbation level changes (P > 0), the objective function values decrease when increasing the robustness adjustment parameter until a point where no further deterioration in the objective value occurs. This point is $\Gamma_t = 13$ for the "crop mix" scenario and $\Gamma_t = 8$ for the "cash crops" case. The optimal values remain constant till reaching the worst case ($\Gamma_t = 31$).

This steady performance is triggered by the farmer's effort to compensate for any decline in the optimal solution by planting different crops with less amount of water to

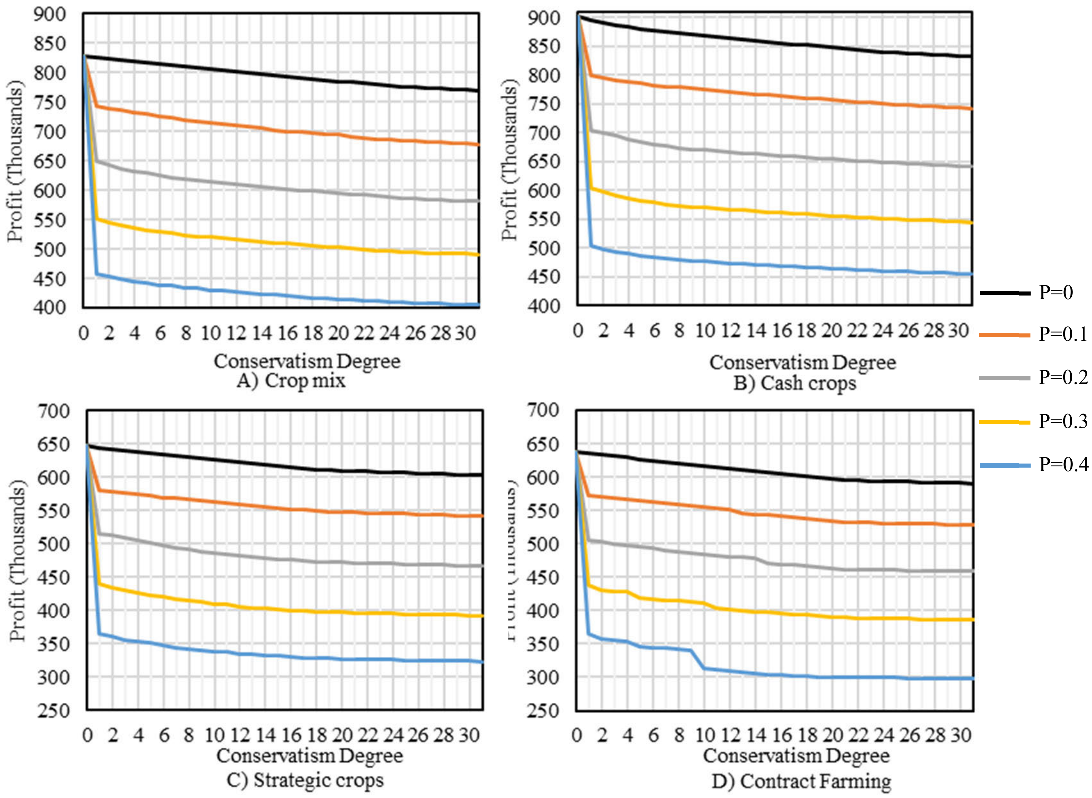

FIGURE 5. **Objective function values under water and net return uncertainties for the different.**

achieve a similar net return. This is because of the crop rotation model's combinatorial nature, which forms a knapsack problem [18].

As presented, dramatic changes in the optimal solutions are caused by the variation of demand among the different scenarios with water scarcity and uncertainty. The last perturbation level (P = 0.4) indicates that the minimum possible net return occurred in the contract farming case. More tight demand will force the farmer to reconsider contract farming as a favorable scenario. From this finding, a practical insight could be drawn to place on-demand data more accurately since it significantly influences the farmer's net return.

B. NET RETURN ROBUST MODEL (NRRM)

The solution conservativeness is being adjusted by varying the value of the uncertainty budget (Γ_o). The conservatism degree's impact on the optimal solution for the different scenarios is shown in Figure 4. It illustrates that the worst optimal value is determined at the highest value of the conservatism degree (Γ_o= 31) for all scenarios. In contrast to WRM, the optimal values' deterioration starts from the first perturbation level (P = 0). Additionally, an increase in the conservatism degree will eventually decrease the optimal value since the uncertain net return parameter directly affects the objective function.

All the cases have the same downward trend with variations in the total obtained net return. The third and fourth scenarios have slight differences in the obtained net return values in all perturbation levels.

The reason behind such performance is the similarity between the two scenarios in planting almost the same crops, according to table 2. In the worst case, the "cash crops" scenario has the highest obtained net return. A reflection on this analysis is to design a rotation cycle in a way that guarantees a reasonable net return by allocating enough area to the main cash crop.

Additional insights could be obtained by comparing the results of NRRM and WRM. The two models coincide when the conservatism degree equals zero (i.e., deterministic solution). In the WRM, the minimum possible solution is obtained when Γ_t is much less than 31 compared to Γ_o equals to 31 in the NRRM. This means that the water uncertainty will have a higher impact on the farmer's profitability even at low conservatism values, especially for high perturbation levels ($P > 0.2$). However, the decline rate is more intensive in NRRM at high conservatism values.

C. NET RETURN AND WATER ROBUST MODEL NRWRM

Net return and water parameters are considered important performance measures in any agricultural system, and unfavorable perturbations may cause a significant deterioration in

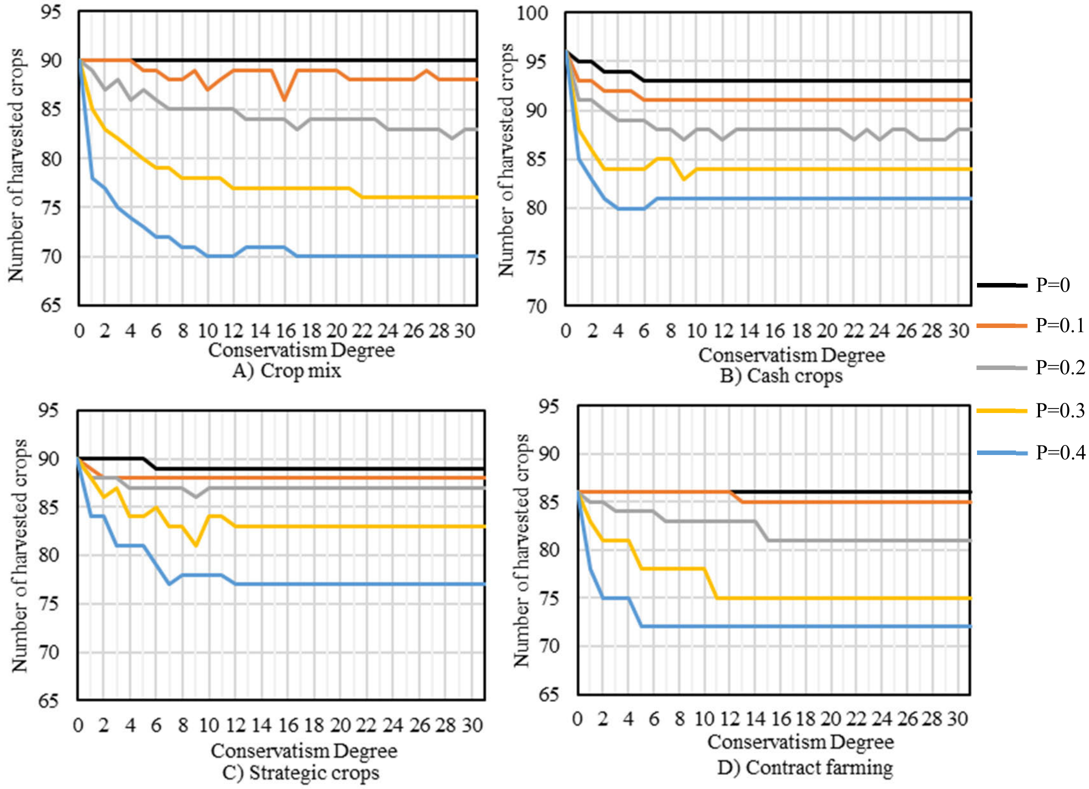

FIGURE 6. Total number of harvested crops during the rotation cycle.

the farmer's profitability. Figure 5 shows how the objective values are affected by both water and net return uncertainties. It is clear that the optimal solution is lower for any instance in the NRWRM compared to the obtained values in the other two models.

The number of planted crops in the available area during the rotation cycle is presented in Figure 6. As shown in the figure, the same behaviour was analyzed in WRM for the studied scenarios. As an example, for the "crop mix" scenario, the number of crops is unchanged at the nominal perturbation level ($P = 0$) regardless of the conservatism degree's value. At this level, there is an excessive amount of available water under any uncertain condition, which helps sustain the number of harvested crops.

At another perturbation level ($P = 0.4$), the number of considered crops deteriorates more intensively until reaching the minimum number of 70 crops. The initial explanation is now evident that water uncertainty is the leading source for the variation found in the number of harvested crops during the rotation cycle.

VII. CONCLUSION

This study's main objective is to develop a mathematical model that describes the crop rotation planning problem. It considers different uncertainties induced in the agricultural sector and solves the problem in a tractable manner with standard optimization packages.

The robust models are formulated to identify the optimal crop sequencing while maximizing the farmer's net return. Furthermore, the proposed robust models incorporate net return and water uncertainties to find the optimal rotation schedules from the farmer's point of view.

A robust approach was adopted to highlight the effect of changing the water amounts and the net return parameters on the objective value. This approach was used to analyze the solution by changing one of the important problem parameters, the conservatism degree, and providing the possibility of running what-if scenarios. Different demand scenarios have been tested during the computational analysis. Finally, various perturbation levels were investigated extensively as post optimality analysis for managing any disruption during the rotation cycle for multiple scenarios (e.g., contract farming). The results show that water uncertainty will have a higher impact on farmers' profitability even at low conservatism values. A comprehensive model that includes demand uncertainty, as well as the uncertainty in the amount of water and the net return, will be the future research direction. A stochastic programming version of the proposed model is another future direction to hedge against uncertain data.

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