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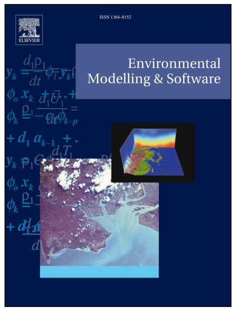

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Land Use Optimization for Nutrient Reduction Under Stochastic Precipitation Rates

Görkem Emirhüseyinoğlu* and Sarah M. Ryan†

Department of Industrial and Manufacturing Systems Engineering, Iowa State University, Ames, IA, 50011, USA

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Abstract

A nutrient reduction strategy for Iowa identifies land use and conservation alternatives to reduce nutrient loss from agriculture and the resulting Gulf of Mexico hypoxia. From the viewpoint of a policy maker concerned with regional costs and benefits, we develop a land use optimization model to maximize profit while satisfying nutrient reduction constraints. Because uncertain precipitation levels affect both yields and nutrient loss, we formulate two variants of a multistage stochastic mixed-integer program with probabilistic scenarios for annual precipitation generated from a Markov chain model. Numerical sensitivity analyses on the recourse variant reveal complicated interactions among the nutrient reduction and labor availability constraints as well as crop prices. The chance-constrained variant provides needed flexibility in meeting nutrient reduction goals by neglecting low-probability precipitation outcomes. Case study results indicate that, although significant financial incentives might be required for landowners to implement optimal strategies, substantial reductions in nutrient loss can be achieved.

Keywords: land use optimization; stochastic programming; nutrient reduction

1. Introduction

Nitrogen (N) and phosphorus (P) are necessary agricultural nutrients but, when lost from the environment through runoff or leaching, may also negatively affect aquatic life by reducing the level of dissolved oxygen. Nitrogen (N) can be found in water bodies naturally in dissolved form and it primarily moves

*gorkem@iastate.edu
†smryan@iastate.edu

as nitrate-N in the water. Excess nitrate is discharged to streams through agricultural drainage systems. Phosphorus (P), on the other hand, is fixed to soil and naturally uncommon in surface water. It reaches waterways mostly on soil particles as erosion transports sediments (Minnesota Pollution Control Agency, 2008). Excess delivery of these nutrients to waterways enhance growth of plants and algae. This eutrophication causes hypoxia and presents a serious ecological threat (EPA, 2008). Hypoxia causes both economic and ecological problems. During hypoxic incidents, mobile aquatic animals are forced to change their habitat and move to waters with more oxygen while less mobile ones die. This alteration in aquatic life results in serious economic impacts. Both the fishing and tourism sectors suffer, though it is difficult to quantify the exact impact (Rabotyagov et al., 2014). In the US, the Gulf of Mexico provides more than 1.3 billion pounds of fish each year which is equivalent to more than $20 billion (Karnauskas et al., 2013). The tourism sector, which generates $20 billion each year (Karnauskas et al., 2013), also is affected negatively as unsightly algal blooms cause disturbing odors (Rabotyagov et al., 2014).

Nutrients lost from watersheds within the Mississippi River Basin move downstream and create the Gulf of Mexico dead zone, one of the largest in the world at nearly 9,000 square miles (EPA, 2017). The 2008 Gulf Hypoxia Action Plan (Mississippi River/Gulf of Mexico Watershed Nutrient Task Force, 2008) calls on the twelve states that border the Mississippi River for action to reduce the nutrient load in the Gulf. The plan aims to decrease the area of the Gulf with dissolved oxygen less than 2 mg/l to 1930 square miles. To reach that goal, the original plan set a target to reduce nutrients by about 30% but over the years subsequent studies revealed that a 45% reduction is necessary (Iowa State University et al., 2017). Several studies investigate Iowa's share of nutrients reaching the Gulf of Mexico (Goolsby et al., 2000; Jones et al., 2018; Libra et al., 2004; Turner and Rabalais, 2004). Although estimates differ, the studies all agree that Iowa contributes a considerable amount (20-40%) of the nutrients in the Gulf compared to the eleven other states along the Mississippi. A major statewide study established a strategy for reducing N loss by 41% and P loss by 29% (Iowa State University et al., 2017). This Iowa Nutrient Reduction Strategy (INRS) summarizes ways to decrease nutrient concentrations in surface water originating from both point and non-point sources. Because 93% of the total nitrate-N load and 79% of total P load come from non-point sources in Iowa, particularly corn and soybean production, the strategy emphasizes land use and management practices to reduce nutrient loss from agriculture.

Nutrient reduction practices have long been studied empirically and independently (Schnepf and Cox, 2007). Aggregating different land use options for a region results in making several interrelated decisions. These include crop choices and rotations; in-field conservation practices such as reduced tillage or cover crops; edge-of-field practices such as filter strips, riparian buffers, or bioreactors; or wetland construction. To apply the results of these studies requires thousands of decisions even for a small watershed area. Moreover, the nutrient movement process is inherently stochastic. Precipitation is the major uncertain factor because it dictates hydrological processes that affect nutrient movement. The combinatorial nature of this problem renders it practically impossible to test all possible combinations of land use alternatives and best management practices. Therefore, an optimization model that accounts for uncertainty is necessary for achieving nutrient reduction goals economically.

Optimization methods have a long history of application in managing the use of land for crop production, which accounted for 10% of the earth's land surface at the end of the last century (Delcourt and Delcourt, 1988; Ramankutty and Foley, 1999). Traditionally, the goal was to maximize overall income but spatial criteria such as compactness were soon added. In recent years, social and governmental influences have motivated the consideration of additional cultural and ecological criteria (Memmah et al., 2015; Williams and ReVelle, 1998). As a result, a great variety of land use optimization studies have been proposed for various purposes. Nutrient reduction criteria are less commonly included but have drawn more interest recently. We briefly review land use optimization studies concerned with water quality and models with similar types of decision making structure as ours.

To the best of our knowledge, all the previous land use optimization models considering water quality impacts used a multi-objective approach and almost all of them combined metaheuristic search techniques with agricultural simulation tools to evaluate solution quality. Kaim et al. (2018) provided an exhaustive review of multi-criteria land use optimization studies while Memmah et al. (2015) surveyed the related metaheuristic procedures. Groot et al. (2007) and Groot et al. (2012) considered minimizing nitrogen loss from the soil as one component of a multi-objective function to increase the quality of agricultural operations. Groot et al. (2007) pursued agricultural income, landscape quality such as diversification of land uses, and reduction in nutrient loss. To find the optimal land use decisions for the multi-objective function, an iterative heuristic strategy was coupled with an evolutionary algorithm to explore Pareto optimality and rank candidate solutions. Groot et al. (2012) applied a similar approach to investigate potential farming operations with the goals of maximizing farming income and minimizing nitrogen loss in the soil. More recently, Whittaker et al. (2017) formulated a model predicated on the existence of a higher authority concerned with nutrient reduction in a similar way as in this paper. The study examined the relationship between the governmental authority and farmers by adopting a game theoretic approach. The governmental authority was responsible for setting a tax rate with two objectives: maximizing the profit and reducing nutrient load to streams. In their turn, farmers responded to the tax rate with land management decisions such as the use of labor and fertilizer to maximize their own profit. As a result, a bilevel structure with government decision on the upper level and farmer decisions on the lower level was formulated. To explore and evaluate solutions, Whittaker et al. (2017) and several other authors (Ahmadi et al., 2013; Panagopoulos et al., 2012, 2013; Rabotyagov et al., 2010) used a genetic algorithm to explore different land use practices while employing the Soil and Water Assessment Tool (SWAT), a detailed river basin simulation model, to evaluate fitness.

Although Stewart et al. (2004) considered neither nutrient reduction nor uncertainty, their study identified a similar decision making and data structure as defined in this paper, where a watershed is divided into cells and land use assignment decisions are made for each cell. A single objective was formulated to include multiple criteria, including total cost and spatial attributes, by assigning weights to each. A genetic algorithm was employed to solve the problem. Unlike most other published studies, Sadeghi et al. (2009) found an exact solution to a land use optimization problem incorporating environmental criteria. A watershed in Iran was designed to maximize net income and minimize gross erosion. A linear programming model was proposed to apportion the area among orchard, rangeland, irrigated farming and dry farming. The decisions to allocate cells to those four land use categories were made using a multi-objective mathematical programming software package called ADBASE (Steuer, 1992).

We have found only two studies that incorporate uncertainty explicitly in their models. Altinakar and Qi (2008) combined a multi-objective function that incorporates agricultural income and nutrient concentration levels with an agriculture simulation tool (AnnAGNPS) that evaluated nutrient transportation and nutrient loading to streams for each candidate solution. A tabu search framework with a fuzzy objective was adopted to solve the problem with uncertain parameter values. Klein et al. (2013) developed a procedure to find an optimal set of decisions among land use alternatives, soil management and fertilization options under changing climate conditions. Hundreds of solutions were generated by considering all possible combinations of decisions for two possible climate futures. A multi-criteria procedure was used with the CropSyst agricultural simulation tool to identify, for each climate future, a solution that would balance critical indicators such as yield, erosion and nitrate loss. Kaim et al. (2018) identified the integration of uncertainty into optimization models as a future research direction.

In this study, we focus our efforts on non-point sources and approach the land use optimization problem from the viewpoint of a policy maker concerned with regional costs and benefits. This policy maker has two goals: first, to maximize agricultural profit and second, to meet the nutrient reduction targets imposed by the Gulf Hypoxia Action Plan. Given that nutrient reduction targets have been established, we treat them as constraints and formulate the problem with a single objective to facilitate optimization under uncertainty. Whereas deterministic optimization models are formulated assuming all parameter values are known at the time of decision making, real world decisions have uncertain effects.

Stochastic programming models explicitly include the uncertainty in parameter values by specifying a set of probabilistic scenarios for the uncertain parameter values as they unfold over time. By solving a deterministic equivalent with ordinary mathematical programming solvers, a solution that is feasible for all possible outcomes while optimizing the expected value of the objective function is identified. Stochastic programming models are commonly defined by stages where, at each stage, decisions are made based on data available at that time. After a decision is taken in a stage using the available information, the decisions in the following stages can take recourse to additional information as it is revealed. For introductorial tutorials of stochastic programming, we refer the reader to Higle (2005) and Shapiro and Philpott (2007).

Our land use optimization model accounts for spatial features of the land and the effects of uncertain precipitation levels over multiple years. Specifically, we build a multi-stage stochastic mixed-integer program for land use decisions to maximize the agricultural profits of a watershed while meeting target reductions in nitrate-N and P levels under uncertain precipitation rates. We formulate the problem at a watershed scale because individual watersheds can be combined easily to represent an entire river basin, and each watershed model can be solved separately since watershed decisions are mutually independent. We consider the whole watershed area as a single entity by prioritizing the total prosperity instead of individual benefits for farmers. This viewpoint aligns with the INRS where it is assumed that all Iowans work together to achieve the nutrient reduction goals (Iowa State University et al., 2017). Formulating the model from this perspective can inform policy decisions on state investments in supporting infrastructure, watershed prioritization, and the structure of landowner incentives.

While other studies relied on metaheuristics to solve their multi-objective models (Memmah et al., 2015), we demonstrate the ability of a commercial mixed-integer solver to obtain solutions in a reasonable amount of time. The results demonstrate the value of developing and solving the stochastic formulation. From traditional sensitivity studies, we find that labor availability and crop prices, which are both hard to estimate, have major impacts on land use decisions and profitability. We analyze and compare two constraint relaxation strategies for their effects on the expected profit. First, the results of simply relaxing the nutrient reduction targets reveal complicated interactions between the constraints and uncertain precipitation levels. Second, a chance-constrained formulation allows the decision-maker to specify a probability with which nutrient reduction targets are met in each year, granting the solver freedom to choose which low-probability outcomes will be ignored. Numerical results show that the chance-constrained formulation finds a more profitable way to achieve the same nutrient reduction amounts than the solution to a deterministic formulation based on expected precipitation rates. Hence, the chance-constrained formulation appears to be a promising way to incorporate flexibility in meeting the nutrient reduction targets. Finally, we illustrate how the model can be used to identify financial incentives for landowners to implement optimal strategies. Numerical results show that, although the financial burden to ensure such cooperation is significant, optimal strategies generate substantial reduction in nutrient loss.

The rest of the paper is organized as follows. In Section 2, we provide a detailed problem description and a multi-stage stochastic mixed-integer mathematical model for the problem. In Section 3 we specify the parameters for a watershed-scale computational study and in Section 4, we discuss the results of computational studies conducted to evaluate the performance of the proposed model. Finally, concluding remarks are provided in Section 5.

2. Model Definition

In this section, we provide a formal definition of the problem and the notation used in our model. We present both a deterministic mixed-integer programming model and two variations of stochastic programming for addressing N and P targets. The mathematical models for yield and nutrient reduction are constructed in part according to their formulations in an open source web platform called People in Ecosystems Watershed Integration (PEWI). PEWI is an interactive decision-making tool that helps its users to analyze land use alternatives and their ecological consequences (Chennault et al., 2016). The tool incorporates detailed information about several land use options and mathematical expressions that approximate total yield, total P delivery to streams and the nitrate-N contributions resulting from each land use alternative. The nomenclature of the model is provided in Table 2. For a detailed guide to parameters generated through PEWI and to understand how they are calculated, we refer the reader to Chennault (2014). It is important to underline that PEWI allows its users to conduct "what-if" analyses by presenting quantitative performance measures of proposed land use combinations. Our deterministic optimization model described in Section 2.2 adds the conversion of yield to profit and allows the use of commercial solvers that implicitly enumerate all land use combinations. We further enhance the model to explicitly incorporate uncertain precipitation levels over multiple years in the stochastic programming formulations given in Section 2.3.

2.1 Assumptions and Formulations Based on PEWI

Here, we summarize assumptions we have in common with PEWI. As that tool allows a user to select a land use alternative for each portion of a simulated watershed, we formulate an optimization problem from the viewpoint of a single decision maker who is responsible from making all land use decisions in a region. The watershed is divided into subwatersheds, which in turn are divided into smaller cells and we try to select best land use option for each cell among different alternatives to maximize overall profit without exceeding N and P loss standards. Land use alternatives considered in this paper are given in Table 1. Cells (sometimes called locations in the remainder of the paper) are assumed to be large enough to accommodate any land use alternative assigned.

Multiple physiographic features, such as water holding capacity of the soil or slope of the land, affect the actual impact of a wetland (Chennault et al., 2016). It is technically possible to highlight some locations in a region as better candidates to install a wetland for maximum impact. To simplify our model, in each subwatershed we assume some cells, more favorable to install a wetland, are separated from the rest. We call those cells the "strategic wetland locations" and we allow construction of a wetland only on those strategic cells. A wetland and its associated buffer are assumed to occupy one whole cell. According to Christianson et al. (2013), a wetland can treat a region up to hundred times its size. PEWI assumes that constructing a wetland in one cell of a subwatershed is adequate to treat that whole subwatershed, and having more than one wetland in a subwatershed does not provide any additional benefit beyond not having its land planted in row crop.

Nitrogen naturally exists in water bodies in dissolved form as a result of the nitrogen cycle. Therefore, without human interference and agricultural production, nitrate-N concentration naturally will not drop below a minimum level. Based on Randall et al. (1997), the minimum nitrate contribution of a subwatershed is 2 mg/L.

It is important to note that we assume nutrient loss from each cell is proportional to its area and total loss in the watershed is the sum of individual cell losses. Therefore, our model ignores the upstream-downstream relationship when calculating the nutrient loss by isolating each cell. Incorporating such dependency require an extremely data-intensive modeling approach and result in a highly nonlinear model.

2.2 Deterministic Model

Tillage and crop rotations have a critical impact on yield, and numerous studies in the literature over the past couple of decades analyzed that impact under different conditions. The general perception, with a few exceptions, agrees that tillage and rotation increase the crop yield (Lund et al., 1993; Meyer-Aurich et al., 2006; Al-Kaisi et al., 2015). Our model approximately captures the impact of tillage and other best management practices, as in PEWI, by including "conservation corn" and "conservation soybean" along with their conventional counterparts. Unlike PEWI, our model also incorporates the effect of rotation by introducing a yield loss multiplier as a penalty for not rotating crops. To maintain linearity,

Table 1: Land use alternatives

Land use strategy	**Description**
Conventional Corn	Corn grain grown using conventional tillage
Conservation Corn	Corn grain grown using conservation practices including no-till, cover crops, buffers, grassed waterways and contouring
Conventional Soybean	Soybean grown using conventional tillage
Conservation Soybean	Soybean grown using conservation practices including no-till, cover crops, buffers, grassed waterways and contouring
Alfalfa	Perennial legume mainly used for grazing, hay or silage
Permanent Pasture	Practice of continuously grazing forage with few or no shifts between pastures
Rotational Grazing	Practice of frequent shifting cattle between pastures to improve forage
Switchgrass	Biomass crop harvested for producing biofuel or biopower
Fruits and Vegetables	A mixed land use including grapes, strawberries, green beans and winter squash
Wetland	Constructed wetlands designed to capture and contain nutrients

however, we model this effect only for pairs of successive periods; i.e., we neglect the compounding yield reduction that may result from planting the same crop for more than two years.

Another added constraint, motivated by shortages experienced in Iowa, is a restriction on the ability of labor (Hertz and Zahniser, 2013).

It is important to note that yield, P loss and nitrate-N concentration are parameters that depend on the precipitation level (ω_t) of each period t. The deterministic formulation relies on an assumption that realizations of the precipitation random variable are known (i.e., can be forecast accurately) for each year in the study. Given these realizations, one can build a multi-period deterministic mixed integer programming (MIP) model using the decision variables:

Table 2: Nomenclature for the model

Sets	
$\mathcal{I}$	Set of subwatersheds ($\{1,\ldots,I\}$) – indexed by i
$\mathcal{J}_i$	Set of cells located in each subwatershed i ($\{1,\ldots,J_i\}$) – indexed by j
$\mathcal{K}$	Set of land use alternatives ($\{1,\ldots,K\}$) – indexed by k or l
$\mathcal{T}$	Set of decision stages ($\{1,\ldots,T\}$) – indexed by t
$\mathcal{T}'$	Set of decision stages ($\{2,\ldots,T\}$) – indexed by t
$\mathcal{U}$	Specific set of (i,j) which indicates strategic locations which are more beneficial to install wetlands
Parameters	
$Y_{ijk}(\omega_t)$	Yield of subwatershed i, cell j for land use k in period t (units of yield)
$N_{ijk}(\omega_{[t]})$	Nitrate-N contribution of subwatershed i, cell j for land use k in period t if there is no wetland in subwatershed i (mg/L)
$N^w_{ijk}(\omega_{[t]})$	Nitrate-N contribution of subwatershed i, cell j for land use k in period t if there is wetland in subwatershed i scenario s (mg/L)
$P_{ijlk}(\omega_t)$	Phosphorus loss of subwatershed i, cell j for consecutive selection of land use alternatives l and k respectively for periods $t-1$ and t (Mg/yr)
$P^w_{ij}(\omega_t)$	Phosphorus loss of subwatershed i, cell j if there is a wetland in period t (Mg/yr)
r_k	Base profit for land use k (\$/unit of yield)
μ_k	Yield loss of not using rotation in consecutive periods for land use k (%)
F_{ij}	Fixed cost of installing a wetland in subwatershed i, cell j (\$)
η	Target nitrate-N concentration (mg/L)
ρ	Target phosphorus loss (Mg/yr)
A_{ij}	Area of cell j in subwatershed i (acres)
n_k	Annual labor required for land use alternative k (hrs)
N	Total available labor force in the watershed in terms of hours per year (hrs)
b_t	Number of potential precipitation outcomes of ω_t in period t
H	Length of study horizon (years)
c_t	Cyclical multiplier
R_t	Expected profit in decision stage t
M	A sufficiently large number
Random Variables	
ω_t	Uncertain precipitation level in period t
$\omega_{[t]}$	History of precipitation levels up to period t: $\omega_{[t]} = (\omega_0, \omega_1, .., \omega_t)$ where ω_0 represents precipitation in the period before $t = 1$

$$x^1_{ijkt} = \begin{cases} 1, & \text{if land use } k \text{ is assigned to subwatershed } i\text{, cell } j \text{ given that there is a wetland} \\ & \text{in subwatershed } i \text{ in period } t \\ 0, & \text{otherwise} \end{cases}$$

$$x^2_{ijkt} = \begin{cases} 1, & \text{if land use } k \text{ is assigned to subwatershed } i\text{, cell } j \text{ given that there is no wetland} \\ & \text{in subwatershed } i \text{ in period } t \\ 0, & \text{otherwise} \end{cases}$$

$$z_{ijlkt} = \begin{cases} 1, & \text{if land use alternatives } l \text{ and } k \text{ are assigned to subwatershed } i\text{, cell } j \\ & \text{for periods } t-1 \text{ and } t \text{ respectively} \\ 0, & \text{otherwise} \end{cases}$$

u^1_{it} = cumulative nitrate-N contribution of subwatershed i in period t if there is a wetland in subwatershed i

u^2_{it} = cumulative nitrate-N contribution of subwatershed i in period t if there is no wetland in subwatershed i

$$y_{ijt} = \begin{cases} 1, & \text{if a wetland is newly constructed in subwatershed } i\text{, cell } j \text{ in period } t \\ 0, & \text{otherwise} \end{cases}$$

Note that the wetland land use option is distinguished from the rest of the land use alternatives and defined as a distinct decision variable because it plays a unique role by reducing nutrient loss without providing any profit. Also, to reflect subwatershed nitrate contribution successfully and to prevent a non-linear structure, we create two groups of decision variables. The first group, denoted as (x^1_{ijkt}, u^1_{it}), represents the condition of having at least one wetland in subwatershed i and the second group, denoted as (x^2_{ijkt}, u^2_{it}) represents the opposite case. This implementation is necessary to maintain a linear structure because installing a wetland in one of the cells of a subwatershed impacts the nitrate discharge of the entire subwatershed.

Using these decision variables, we develop the following mixed-integer linear programming model:

$$\text{Max} \quad \sum_{i\in\mathcal{I}}\sum_{j\in\mathcal{J}_i}\sum_{k\in\mathcal{K}}\sum_{t\in\mathcal{T}} r_k Y_{ijkt}(\omega_t)\Big(x^1_{ijkt}+x^2_{ijkt}-\sum_{l\in\mathcal{K}}\mu_k z_{ijlkt}\Big) \tag{1}$$
$$-\sum_{i\in\mathcal{I}}\sum_{j\in\mathcal{J}_i}\sum_{t\in\mathcal{T}} F_{ij}y_{ijt}-\epsilon\sum_{i\in\mathcal{I}}\sum_{t\in\mathcal{T}}\Big(u^1_{it}+u^2_{it}\Big)$$

s.t.

$$\sum_{i\in\mathcal{I}}\Big(u^1_{it}+u^2_{it}\Big)\frac{\sum_{j\in\mathcal{J}_i}A_{ij}}{\sum_{i\in\mathcal{I}}\sum_{j\in\mathcal{J}_i}A_{ij}}-2\le\eta \qquad \forall t\in\mathcal{T} \tag{2}$$
$$u^1_{it}\ge 2 \qquad \forall i\in\mathcal{I},t\in\mathcal{T} \tag{3}$$
$$u^1_{it}\ge\sum_{j\in\mathcal{J}_i}\sum_{k\in\mathcal{K}}N^w_{ijkt}(\omega_{[t]})x^1_{ijkt} \qquad \forall i\in\mathcal{I},t\in\mathcal{T} \tag{4}$$
$$u^2_{it}\ge 2 \qquad \forall i\in\mathcal{I},t\in\mathcal{T} \tag{5}$$
$$u^2_{it}\ge\sum_{j\in\mathcal{J}_i}\sum_{k\in\mathcal{K}}N_{ijkt}(\omega_{[t]})x^2_{ijkt} \qquad \forall i\in\mathcal{I},t\in\mathcal{T} \tag{6}$$
$$\sum_{i\in\mathcal{I}}\sum_{j\in\mathcal{J}_i}\sum_{l\in\mathcal{K}}\sum_{k\in\mathcal{K}}\sum_{t\in\mathcal{T}}P_{ijlkt}(\omega_t)z_{ijlkt}+\sum_{i\in\mathcal{I}}\sum_{j\in\mathcal{J}_i}\sum_{\delta=1}^{t}P^w_{ijt}(\omega_t)y_{ij\delta}\le\rho \qquad \forall t\in\mathcal{T} \tag{7}$$
$$\sum_{k\in\mathcal{K}}x^1_{ijkt}+\sum_{k\in\mathcal{K}}x^2_{ijkt}+\sum_{\delta=1}^{t}y_{ij\delta}\le 1 \qquad \forall i\in\mathcal{I},j\in\mathcal{J}_i,t\in\mathcal{T} \tag{8}$$
$$\sum_{j\in\mathcal{J}_i}\sum_{k\in\mathcal{K}}x^1_{ijkt}\le M\sum_{j\in\mathcal{J}_i}\sum_{\delta=1}^{t}y_{ij\delta} \qquad \forall i\in\mathcal{I},t\in\mathcal{T} \tag{9}$$
$$\sum_{j\in\mathcal{J}_i}\sum_{k\in\mathcal{K}}x^2_{ijkt}\le M\Big(1-\sum_{j\in\mathcal{J}_i}\sum_{\delta=1}^{t}y_{ij\delta}\Big) \qquad \forall i\in\mathcal{I},t\in\mathcal{T} \tag{10}$$
$$x^1_{ijkt}+x^2_{ijkt}+x^1_{ijl(t-1)}+x^2_{ijl(t-1)}-z_{ijlkt}-1\le 0 \qquad \forall i\in\mathcal{I},j\in\mathcal{J}_i,\forall l,k\in\mathcal{K},t\in\mathcal{T}' \tag{11}$$
$$\sum_{l\in\mathcal{K}}\sum_{k\in\mathcal{K}}z_{ijlkt}\le 1 \qquad \forall i\in\mathcal{I},j\in\mathcal{J}_i,t\in\mathcal{T} \tag{12}$$
$$x^1_{ijk1}+x^2_{ijk1}=z_{ijkk1} \qquad \forall i\in\mathcal{I},j\in\mathcal{J}_i,\forall k\in\mathcal{K} \tag{13}$$
$$\sum_{i\in\mathcal{I}}\sum_{j\in\mathcal{J}_i}\sum_{k\in\mathcal{K}}n_k\Big(x^1_{ijkt}+x^2_{ijkt}\Big)\le N \qquad \forall t\in\mathcal{T} \tag{14}$$
$$y_{ijt}=0 \qquad \forall (i,j)\notin\mathcal{U} \tag{15}$$
$$y_{ijt}\in\{0,1\} \qquad \forall i\in\mathcal{I},j\in\mathcal{J}_i,t\in\mathcal{T} \tag{16}$$
$$x^1_{ijkt},x^2_{ijkt}\in\{0,1\} \qquad \forall i\in\mathcal{I},j\in\mathcal{J}_i,\forall k\in\mathcal{K},t\in\mathcal{T} \tag{17}$$
$$z_{ijlkt}\in\{0,1\} \qquad \forall i\in\mathcal{I},j\in\mathcal{J}_i,t\in\mathcal{T} \tag{18}$$
$$u^1_{it},u^2_{it}\ge 0 \qquad \forall i\in\mathcal{I},t\in\mathcal{T} \tag{19}$$

Our objective function (1) includes three terms. The first term is the profit generated annually from crop production and calculated based on per unit profit of each crop alternative. It involves a potential yield loss ratio (μ_k) determined according to land use decisions in consecutive years. This ratio reflects a more realistic environment where not using rotation in successive periods may reduce the yield for some types of crops. The second term is a fixed wetland construction cost. The third term is a modeling construct with negligible magnitude that is added to obtain an accurate nitrate concentration, utilizing the maximization nature of our objective, in case Constraint (2) is not binding. Constraint (2) ensures that the target nitrate concentration is not exceeded. Constraints (3-4) represent the case of having at least one wetland in a subwatershed while Constraints (5-6) represent the case of not having any wetland in the subwatershed. Those constraints also ensure that nitrate-N concentration of a subwatershed cannot realistically drop below 2 mg/L. Constraint (7) guarantees that the target phosphorus loss is not exceeded. Constraint (8) assigns only a single land use alternative to each location. Constraints (9-10) employ a large number, M, to ensure that the correct group of decision variables is selected for each subwatershed where x^1_{ijkt} may take positive values if a wetland exists in subwatershed i and x^2_{ijkt} may take positive values otherwise. Constraint (11) investigates which land use alternatives are assigned to a specific location in consecutive periods. Constraint (12) allows the selection of a single land use combination for consecutive periods. In Constraint (13), we assume our model is initialized without any land use rotation from the previous period. Constraint (14) restricts the availability of labor. Constraint (15) allows wetland construction only on strategic locations. Finally, the remaining constraints enforce sign and binary restrictions.

2.3 Stochastic Programming

Stochastic programs are mathematical models to optimize under uncertainty where random variables may be incorporated into the objective function or constraints. Precipitation is the uncertain element in our model, and it is incorporated both into the objective and in some of the constraints, as yields and nutrient losses depend on stochastic precipitation levels. Therefore, the general structure of the problem can be considered as a variant of a stochastic assignment problem where we assign a land use alternative to each cell to maximize overall profit with nutrient reduction constraints and by taking the random precipitation variables into consideration. Our multi-period stochastic land use optimization model can be structured with $T+1$ stages as shown in Figure 1, where each stage consists of one period.

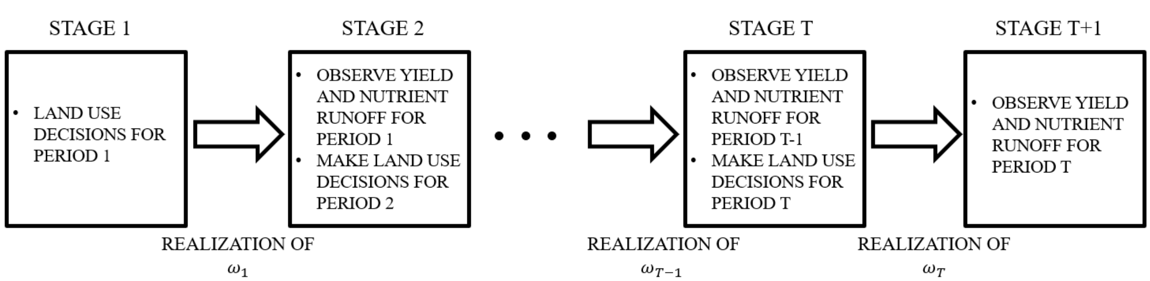

Figure 1: Stage representation

Assuming we have a finite number, b_t, of realizations for the random precipitation level ω_t in period t, the scenario set $\mathcal{S} = \{1, ..., S\}$ consists of scenario paths s, each of which represents a sequence of precipitation levels in periods $t \in \mathcal{T}$. We denote the precipitation in period t for scenario s as ω_t^s. Scenario s occurs with probability $p(s)$. Panel (a) of Figure 2 illustrates a scenario tree representation of an instance with $T = 2$ periods and $b_t = 3$ precipitation outcomes for each t: High, Medium, Low. In the scenario representation depicted in panel (b), we create a copy of each decision variable for each scenario path. The dashed ovals in panel (b) represent non-anticipativity, corresponding to the nodes of the scenario tree in panel (a), and imply that it is not possible to anticipate the future. Therefore decisions taken at each stage for nodes which belong to the same dashed oval should be identical for all scenarios.

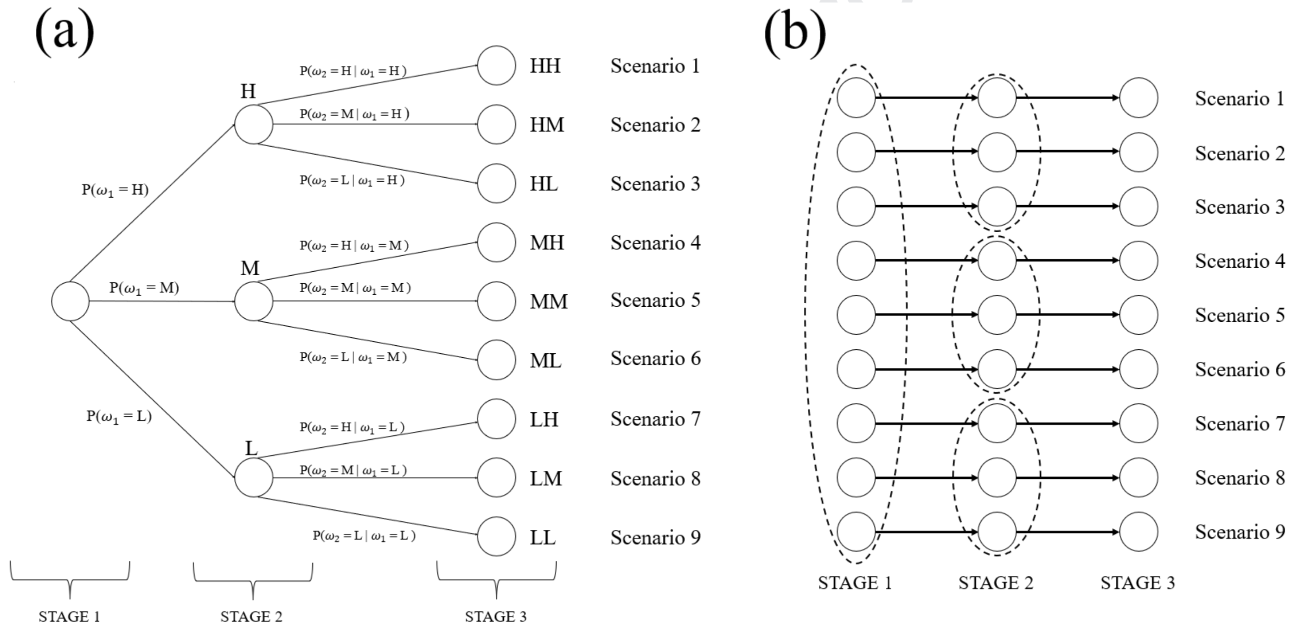

Figure 2: (a) Scenario tree representation; (b) Scenario formulation assuming 3 precipitation levels in each of 2 periods

Let $\theta_{ijkt}(s) = \left(x^1_{ijkt}(s), x^2_{ijkt}(s), y_{ijt}(s)\right)$ represent the whole group of decision variables for scenario s. This notation makes it appear that decisions can depend on scenario data, including future realizations of the uncertain precipitation. To force each decision to depend only on information available when the decision is made, we include non-anticipativity constraints (34) in the formulation below, which correspond to agreement of decisions within the dashed ovals of Figure 2(b).

2.3.1 Recourse Formulation

The scenario representation of a multi-stage recourse stochastic program can be formulated as follows:

$$\text{Max} \quad \sum_{s\in\mathcal{S}}\sum_{t\in\mathcal{T}} p(s)\Bigg[\sum_{i\in\mathcal{I}}\sum_{j\in\mathcal{J}_i}\sum_{k\in\mathcal{K}} r_k Y_{ijk}(\omega_t^s)\Big(x_{ijkt}^1(s)+x_{ijkt}^2(s)-\sum_{l\in\mathcal{K}}\mu_k z_{ijlkt}(s)\Big) - \sum_{i\in\mathcal{I}}\sum_{j\in\mathcal{J}_i} F_{ij}y_{ijt}(s) - \epsilon\sum_{i\in\mathcal{I}}\Big(u_{it}^1(s)+u_{it}^2(s)\Big)\Bigg] \tag{20}$$

s.t.

$$\sum_{i\in\mathcal{I}}\Big(u_{it}^1(s)+u_{it}^2(s)\Big)\frac{\sum_{j\in\mathcal{J}_i}A_{ij}}{\sum_{i\in\mathcal{I}}\sum_{j\in\mathcal{J}_i}A_{ij}} - 2 \le \eta \qquad \forall t\in\mathcal{T}, s\in\mathcal{S} \tag{21}$$

$$u_{it}^1(s) \ge 2 \qquad \forall i\in\mathcal{I}, t\in\mathcal{T}, s\in\mathcal{S} \tag{22}$$

$$u_{it}^1(s) \ge \sum_{j\in\mathcal{J}_i}\sum_{k\in\mathcal{K}} N_{ijk}^w(\omega_{[t]}^s)x_{ijkt}^1(s) \qquad \forall i\in\mathcal{I}, t\in\mathcal{T}, s\in\mathcal{S} \tag{23}$$

$$u_{it}^2(s) \ge 2 \qquad \forall i\in\mathcal{I}, t\in\mathcal{T}, s\in\mathcal{S} \tag{24}$$

$$u_{it}^2(s) \ge \sum_{j\in\mathcal{J}_i}\sum_{k\in\mathcal{K}} N_{ijk}(\omega_{[t]}^s)x_{ijkt}^2(s) \qquad \forall i\in\mathcal{I}, t\in\mathcal{T}, s\in\mathcal{S} \tag{25}$$

$$\sum_{i\in\mathcal{I}}\sum_{j\in\mathcal{J}_i}\sum_{l\in\mathcal{K}}\sum_{k\in\mathcal{K}} P_{ijlk}(\omega_t^s)z_{ijlkt}(s) + \sum_{i\in\mathcal{I}}\sum_{j\in\mathcal{J}_i}\sum_{\delta=1}^{t} P_{ij}^w(\omega_t^s)y_{ij\delta}(s) \le \rho \qquad \forall t\in\mathcal{T}, s\in\mathcal{S} \tag{26}$$

$$\sum_{k\in\mathcal{K}} x_{ijkt}^1(s) + \sum_{k\in\mathcal{K}} x_{ijkt}^2(s) + \sum_{\delta=1}^{t} y_{ij\delta}(s) \le 1 \qquad \forall i\in\mathcal{I}, j\in\mathcal{J}_i, t\in\mathcal{T}, s\in\mathcal{S} \tag{27}$$

$$\sum_{j\in\mathcal{J}_i}\sum_{k\in\mathcal{K}} x_{ijkt}^1(s) \le M\sum_{j\in\mathcal{J}_i}\sum_{\delta=1}^{t} y_{ij\delta}(s) \qquad \forall i\in\mathcal{I}, t\in\mathcal{T}, s\in\mathcal{S} \tag{28}$$

$$\sum_{j\in\mathcal{J}_i}\sum_{k\in\mathcal{K}} x_{ijkt}^2(s) \le M\Big(1-\sum_{j\in\mathcal{J}_i}\sum_{\delta=1}^{t} y_{ij\delta}(s)\Big) \qquad \forall i\in\mathcal{I}, t\in\mathcal{T}, s\in\mathcal{S} \tag{29}$$

$$x_{ijkt}^1(s)+x_{ijkt}^2(s)+x_{ijlt}^1(s)+x_{ijlt}^2(s)-z_{ijlkt}(s)-1 \le 0 \qquad \forall i\in\mathcal{I}, j\in\mathcal{J}_i, \forall l,k\in\mathcal{K}, t\in\mathcal{T}', s\in\mathcal{S} \tag{30}$$

$$\sum_{l\in\mathcal{K}}\sum_{k\in\mathcal{K}} z_{ijlkt}(s) \le 1 \qquad \forall i\in\mathcal{I}, j\in\mathcal{J}_i, t\in\mathcal{T}, s\in\mathcal{S} \tag{31}$$

$$x_{ijk1}^1(s)+x_{ijk1}^2(s) = z_{ijkk1}(s) \qquad \forall i\in\mathcal{I}, j\in\mathcal{J}_i, \forall k\in\mathcal{K}, s\in\mathcal{S} \tag{32}$$

$$\sum_{i\in\mathcal{I}}\sum_{j\in\mathcal{J}_i}\sum_{k\in\mathcal{K}} n_k\Big(x_{ijkt}^1(s)+x_{ijkt}^2(s)\Big) \le N \qquad \forall t\in\mathcal{T}, s\in\mathcal{S} \tag{33}$$

$$\theta_{ijkt}(s)-\theta_{ijkt}(s') = 0 \qquad \forall i\in\mathcal{I}, k\in\mathcal{K}, j\in\mathcal{J}_i \; t,s,s' \text{ for which } \omega_{[t-1]}^s = \omega_{[t-1]}^{s'} \tag{34}$$

$$y_{ijt}(s) = 0 \qquad \forall (i,j) \notin \mathcal{U}, s \in \mathcal{S} \tag{35}$$

$$y_{ijt}(s) \in \{0,1\} \qquad \forall i \in \mathcal{I}, j \in \mathcal{J}_i, t \in \mathcal{T}, s \in \mathcal{S} \tag{36}$$

$$x^1_{ijkt}(s), x^2_{ijkt}(s) \in \{0,1\} \qquad \forall i \in \mathcal{I}, j \in \mathcal{J}_i, \forall k \in \mathcal{K}, t \in \mathcal{T}, s \in \mathcal{S} \tag{37}$$

$$z_{ijlkt}(s) \in \{0,1\} \qquad \forall i \in \mathcal{I}, j \in \mathcal{J}_i, t \in \mathcal{T}, s \in \mathcal{S} \tag{38}$$

$$u^1_{it}(s), u^2_{it}(s) \geq 0 \qquad \forall i \in \mathcal{I}, t \in \mathcal{T}, s \in \mathcal{S} \tag{39}$$

Constraint (34) is the only new constraint added to the deterministic model introduced in Section 2.2. This constraint enforces non-anticipativity and ensures that decisions in one period do not depend on unknown outcomes in later periods.

2.3.2 Cyclical Recourse Formulation

Recal that we use mathematical expressions defined in PEWI (Chennault et al., 2016) to estimate nutrient loss and yield of each land use alternative. Those expressions hypothesize that nutrient loss for a given year depends on the precipitation levels of the most recent pair of consecutive years. That is, the nutrient loss of the current year is calculated based on the current year's annual precipitation, which is not known when the land use decision is made, and the observed precipitation in the previous year. We model annual precipitation as a Markov chain, where one year's precipitation level depends only on the precipitation in the previous year. Moreover, we incorporate the effect of rotating crops in our model only for pairs of successive years. These three model assumptions produce a cyclical pattern of land use decisions after the first stage. Specifically, we observe similar land use decisions in all even numbered years (2,4,6,..) and all odd-numbered years (3,5,7,..) excluding the first year. We illustrate this cyclical decision pattern surfacing in our numerical results in Section 4.

Wetland construction is generally a long term decision. In the literature, studies investigating wetland installation decisions commonly consider planning horizons of 50 years. However, extending a scenario tree over a long time horizon results in an enormous number of scenarios and renders the stochastic program intractable to solve. On the other hand, solving the model for shorter planning horizons does not allow the benefit of a wetland to outweigh its large land acquisition and installation cost. Therefore, we suggest an alternative recourse formulation that takes advantage of the land use cyclical pattern to investigate a longer planning horizon.

To do so, we introduce new decision variables, R_t, which represent the expected profit in each decision stage $t = 1, 2, 3$. The cyclical recourse objective (40) is formed by modifying Equation (20) to include the land use decisions of only three stages, where the second stage represents all even years and the third stage represents all odd years after the first year. That is, R_1 is the expected profit in the first year based on the the initial precipitation level and first-stage decisions, R_2 is the expected profit of an even year, based on second stage decisions, and R_3 is the expected profit of an odd year, based on third stage decisions.

$$\text{Max} \quad \sum_{s\in\mathcal{S}}\sum_{t\in\mathcal{T}} p(s)\Big[-\sum_{i\in\mathcal{I}}\sum_{j\in\mathcal{J}_i} F_{ij}y_{ijt}(s) - \epsilon\sum_{i\in\mathcal{I}}\Big(u^1_{it}(s)+u^2_{it}(s)\Big)\Big] + R_1 + c_2R_2 + c_3R_3 \tag{40}$$

Also, an additional constraint (41) is included to calculate the expected profit in each decision stage t, where we define cyclical multipliers, c_t, for even and odd years as follows:

$$c_2 = \begin{cases} \frac{H-1}{2}, & \text{if planning horizon } H \text{ is an odd number} \\ \frac{H}{2}, & \text{otherwise} \end{cases}$$
$$c_3 = \begin{cases} \frac{H-1}{2}, & \text{if planning horizon } H \text{ is an odd number} \\ \frac{H}{2}-1, & \text{otherwise} \end{cases}$$

$$\sum_{s\in\mathcal{S}} p(s)\Big[\sum_{i\in\mathcal{I}}\sum_{j\in\mathcal{J}_i}\sum_{k\in\mathcal{K}} r_kY_{ijk}(\omega^s_t)\Big(x^1_{ijkt}(s)+x^2_{ijkt}(s)-\sum_{l\in\mathcal{K}}\mu_kz_{ijlkt}(s)\Big)\Big] = R_t \quad \forall t=1,2,3 \tag{41}$$

In the cyclical recourse model, Equation (40) replaces (20) and (41) is appended to the constraints in Section 2.3.1 with $\mathcal{T} = \{1, 2, 3\}$.

2.3.3 Chance-constrained Formulation

The recourse formulations in Sections 2.3.1 and 2.3.2 ensure that nutrient restrictions are met for all scenarios. In this section, we provide a different approach to our problem by making sure that the probability of meeting nutrient restrictions at each period is above some minimum level. Therefore, those constraints now hold each year with some specified probability. In our model, we consider nitrate-N and P loss restrictions separately, and ensure that those restrictions are met with some predefined probabilities α_t and γ_t, respectively, for all t. Therefore, we update Constraint (21) and Constraint (26) accordingly:

$$P\left(s \in \mathcal{S} : \sum_{i \in \mathcal{I}} \left(u^1_{it}(s) + u^2_{it}(s)\right) \frac{\sum_{j \in \mathcal{J}_i} A_{ij}}{\sum_{i \in \mathcal{I}} \sum_{j \in \mathcal{J}_i} A_{ij}} - 2 \leq \eta \right) \geq \alpha_t \qquad \forall t \in \mathcal{T} \tag{42}$$

$$P\left(s \in \mathcal{S} : \sum_{i \in \mathcal{I}} \sum_{j \in \mathcal{J}_i} \sum_{l \in \mathcal{K}} \sum_{k \in \mathcal{K}} P_{ijlk}(\omega^s_t) z_{ijlkt}(s) + \sum_{i \in \mathcal{I}} \sum_{j \in \mathcal{J}_i} \sum_{\delta=1}^{t} P^w_{ij}(\omega^s_t) y_{ij\delta}(s) \leq \rho \right) \geq \gamma_t \quad \forall t \in \mathcal{T} \tag{43}$$

Those constraints can be reformulated as linear mixed-integer by introducing new binary variables β^s_t and ν^s_t and a big number M as follows:

$$\sum_{i \in \mathcal{I}} \left(u^1_{it}(s) + u^2_{it}(s)\right) \frac{\sum_{j \in \mathcal{J}_i} A_{ij}}{\sum_{i \in \mathcal{I}} \sum_{j \in \mathcal{J}_i} A_{ij}} - 2 \leq \eta + M(1 - \beta^s_t) \qquad \forall t \in \mathcal{T}, s \in \mathcal{S} \tag{44}$$

$$\sum_{i \in \mathcal{I}} \sum_{j \in \mathcal{J}_i} \sum_{l \in \mathcal{K}} \sum_{k \in \mathcal{K}} P_{ijlk}(\omega^s_t) z_{ijlkt}(s) + \sum_{i \in \mathcal{I}} \sum_{j \in \mathcal{J}_i} \sum_{\delta=1}^{t} P^w_{ij}(\omega^s_t) y_{ij\delta}(s) \leq \rho + M(1 - \nu^s_t) \quad \forall t \in \mathcal{T}, s \in \mathcal{S} \tag{45}$$

$$\sum_{s \in \mathcal{S}} p_s \beta^s_t \geq \alpha_t \qquad \forall t \in \mathcal{T} \tag{46}$$

$$\sum_{s \in \mathcal{S}} p_s \nu^s_t \geq \gamma_t \qquad \forall t \in \mathcal{T} \tag{47}$$

We simply replace Constraints (21) and (26) with Constraints (44-47) to create our chance-constrained model. Likewise, we obtain a cyclical chance-constrained formulation by applying the same changes and by additionally making the same modifications as in Section 2.3.2.

3. Computational Study

Computational experiments are performed on watershed instance generated by Chennault et al. (2016) for PEWI. The virtual watershed instance implemented in that tool is shaped according to typical landscape and soil properties of Iowa. It consists of 21 subwatersheds and 593 cells where the area of each cell is roughly equal to 10 acres. Parameters including yield $Y_{ijk}(\omega_t)$, nitrate concentration $N_{ijk}(\omega_{[t]})$ and phosphorus loss $P_{ijlk}(\omega_t)$ are obtained directly from PEWI.

To our knowledge, limited quantitative data on the number of available agricultural workers exists. A significant portion of agricultural workers in Iowa are migrants who work seasonally. Therefore, labor surveys may not always be accurate (Kandel, 2015). Thus, it is difficult to estimate a realistic numerical value for the total labor availability (N), especially at a watershed level. The latest USDA farm labor report (USDA, 2018) divides the United States into regions according to agricultural laborshed and provides exhaustive information about agricultural workers in each identified region. Because our watershed instance is based on Iowa, we use the Cornbelt 2 region (which includes Iowa and Missouri) to estimate the value of N. According to the study, the weekly average number of hours worked in agriculture in the US in 2018 was 40.4 hours, and there were only 21,000 hired workers in Cornbelt 2. However, this report may not include seasonal workers, and to reflect a practical restriction, it is critical to focus on busy seasons. Edwards and Plastina (2016) estimates that the average number of full-time laborer equivalents in Iowa is 4.4 workers per harvesting operation. Also, the watershed instance generated by PEWI approximately contains 18 farms considering the average size of each farm in Iowa (Thessen et al., 2018). Assuming there are 4.4 full-time equivalent workers available per farm, and a full-time laborer works 40.4 hours per week, we estimate the weekly available labor force as 3200 hours. Therefore N is set to 166,400 hours per year. Acknowledging the crudeness of this approximation, in Section 4, we conduct sensitivity analyses on this parameter value.

To estimate profit (r_k) and required labor hours (n_k) of each land use alternative, we utilize several different sources. Table 3 summarizes those parameters and the sources of the information. Fruit and vegetable crops are considered to be grapes, green beans, strawberries and winter squash for consistency with PEWI. Estimates of annual averages for for r_k and n_k are given in Table 3.

Table 3: Profit and labor hours estimates

Land use Type	Profit (r_k)	Labor Hours (n_k)	Sources
Corn	\$1.2/bushel	2.8 hrs/acre	(Johanns, 2018; Plastina, 2018)
Soybean	\$4.2/bushel	2.2 hrs/acre	(Johanns, 2018; Plastina, 2018)
Alfalfa	\$50/ton	2.5 hrs/acre	(Biensen, 2018; Plastina, 2018)
Pasture-Grazing	\$60/head	6 hrs/acre	(Ellis and Schulz, 2018; University of Minnesota, 2010) (Holmgren and Feuz, 2015; Paine and Gildersleeve, 2011)
Switchgrass	\$30/ton	4.2 hrs/acre	(Duffy, 2018; Jacobs et al., 2016; Quals, 2009)
Fruits and Veggies	\$0.82/pound	132 hrs/acre	(Center for Crop Diversification, 2017; Chase, 2018) (Nordquist et al., 2011; Yeh et al., 2014)

Drinking water is considered safe for human consumption if the nitrate level is less than 10 mg/L (Tang et al., 2018). EPA (2013) on the other hand, suggests that the nitrate level in surface water should be between 2 mg/L and 6 mg/L for a healthy environment. Data gathered between 2000-2002 shows that the nitrate concentration of individual watersheds in Iowa varies between 3.5-15.4 ppm while their average is 8.78 ppm (Libra et al., 2004). Likewise, phosphorus load to streams ranges from 0.18 to 3.4 pounds/acre with an average of 0.75 pounds/acre. For a relative comparison, the watershed instance used in this study is around 5930 acres and total phosphorus load may range from 0.13 to 11 Mg/year. According to Iowa State University et al. (2017), Iowa must achieve reductions of 41% for nitrogen and 29% for phosphorus. If we consider average nitrate concentration and phosphorus load along with the size of our watershed, the target nitrate concentration should be approximately 5 ppm and that for phosphorus load should be 2 Mg/yr. Along with these baseline values, in Section 4, we investigate how different nitrate concentration (η) and phosphorus load (ρ) target values impact the total profit.

The yield loss due to not rotating corn or soybean crops in successive years is assumed to be 10 percent for each (Iowa State University et al., 2017; Meyer-Aurich et al., 2006).

Conservation land use alternatives for both corn and soybean involve combined implementation of no-till, cover crops, buffers, grassed waterways and contouring, which may decrease crop yield. Here, an 8% yield reduction is estimated to occur as a result of selecting the conservation alternatives (Iowa State University et al., 2017; Meyer-Aurich et al., 2006).

To estimate wetland construction cost, we use the information provided from Tyndall and Bowman (2016). Because we expect a wetland to treat an entire subwatershed, measuring 282 acres on average, the cost of constructing a wetland to treat this area is approximately $15,000. Also, we include land acquisition cost by using per acre state average in 2018 in state of Iowa (Zhang, 2018) which is approximately equal to $7,200 per acre. Therefore, for a ten-acre cell, we approximate a $87,000 wetland construction cost in total.

From analysis of historical annual precipitation data in Iowa from 1893 to 2018, we find a small correlation in successive years with negligible correlations across longer time lags. Therefore, we assume the annual precipitation level is Markovian. To explore an effective discretization, we consider two Markov chain models for precipitation. The first has $b_t = 3$ precipitation levels for each t as shown in Table 4. The second model has the $b_t = 7$ states for all t, taken directly from PEWI, shown in Table 5. To estimate transition probabilities, we applied k-nearest neighbor clustering on the historical data and the frequency of transitions among these states. The resulting transition probability matrices are also provided in Tables 4 and 5. We use the smaller Markov chain with $b_t = 3 \ \forall t \in \{1, 2, 3\}$ as our baseline case.

Table 4: State space and precipitation transition probabilities for Markov chain model 1

State Space		Transition Probabilities			
Precipitation (cm/yr)	Type		71.6	81.7	92.6
71.6	Dry	71.6	0.2500	0.6250	0.1250
81.7	Normal	81.7	0.1899	0.6329	0.1772
92.6	Wet	92.6	0.0909	0.6364	0.2727

Table 5: State space and precipitation transition probabilities for Markov chain model 2

State Space		Transition Probabilities							
Precipitation (cm/yr)	Type		62.4	71.6	77.2	81.7	87.2	92.6	114.6
62.4	Very Dry	62.4	0.3000	0.1000	0.0000	0.2000	0.2000	0.1000	0.1000
71.6	Dry	71.6	0.0714	0.0714	0.1429	0.2857	0.3571	0.0714	0.0000
77.2	Dry-Normal	77.2	0.0400	0.1600	0.2000	0.2700	0.2000	0.1100	0.0200
81.7	Normal	81.7	0.0800	0.1600	0.2400	0.1300	0.1600	0.2100	0.0200
87.2	Normal-Wet	87.2	0.0769	0.0769	0.3077	0.1154	0.1923	0.1538	0.0769
92.6	Wet	92.6	0.0526	0.0526	0.1579	0.2105	0.2105	0.1053	0.2105
114.6	Very Wet	114.6	0.0000	0.0000	0.1667	0.3333	0.1667	0.3333	0.0000

4. Results and Discussion

In this section, we describe computational tests performed to answer questions under six main categories: (i) How do parameters that are hard to estimate affect the solution? (ii) What is the economic benefit of relaxing nutrient reduction targets? (iii) What is the value of granting flexibility to policy makers to meet nutrient reduction goals with probabilities (α_t, γ_t) less than one? (iv) How does precipitation uncertainty affect optimal land use assignments and to what extent does multistage stochastic programming improve the decision making? (v) How does employing a finer discretization of annual precipitation levels impact the results? (vi) How could landowners be encouraged to cooperate with optimal strategies and what is the financial burden of such cooperation? We use IBM ILOG CPLEX as the optimization engine and perform the experiments on a machine with Intel Core i7-7700HQ @ 2.80 GHz processor and 16 GB RAM.

4.1 Cyclical Land Use Decisions

First we demonstrate the cyclical land use decision pattern by comparing the results of the original recourse formulation with $T = 5$ and the cyclical recourse formulation with $T = 3$, $H = 5$, using the three-state Markov chain. Table 6 summarizes the expected land use decisions at each stage. In the original recourse formulation, similar expected land use decisions are observed in years 2 and 4 as well as in years 3 and 5. The second stage decisions from the cyclical formulation approximately match the even-year decisions while the third stage decisions from cyclical formulation echo the odd-year results of the original recourse model. Here, as in all the following tables, the percentages represent probability-weighted average proportions of the land devoted to each land use alternative. Similar results, not shown, are found for the seven-state Markov chain.

Wetland construction decisions are not short term decisions. When the study horizon is longer, the benefits of installing a wetland accrue over additional periods, allowing more time to absorb their costs. For the remainder of the paper, we continue to use the cyclical formulations so that we can consider

Table 6: Expected land use assignments in odd and even years for the original recourse model with $T = 5$ vs. the cyclical recourse model with $T = 3$, $H = 5$ for Markov chain model 1

Land Use Alternative	Original Recourse				Cyclical Recourse	
	Stage 2	Stage 3	Stage 4	Stage 5	Stage 2	Stage 3
Wetland	0.51%	0.51%	0.51%	0.51%	0.51%	0.51%
Conventional Corn	8.17%	0.90%	8.02%	0.78%	8.22%	0.85%
Conservation Corn	4.88%	0.00%	4.90%	0.00%	4.77%	0.00%
Conventional Soybean	18.18%	27.41%	18.24%	27.23%	18.34%	27.59%
Conservation Soybean	7.85%	10.04%	7.67%	10.20%	7.64%	10.76%
Alfalfa	58.56%	59.29%	58.80%	59.43%	58.67%	58.44%
Permanent Pasture	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
Rotational Grazing	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
Switchgrass	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
Fruits and Veggies	1.85%	1.85%	1.85%	1.85%	1.85%	1.85%

a planning horizon of 50 years. This approach provides a more accurate economic analysis without excessively increasing the problem complexity.

The full results of the cyclical recourse model are presented in Table 7 for our baseline case. The land use percentages summarize the decisions for all non-leaf nodes in the scenario tree with $T = 3$ and $b_t = 3$ for all t. We observe that finalizing the construction decisions of wetlands in the first period is always more beneficial than installing them in later stages since it brings a higher benefit-cost ratio. Depending on the evolution of precipitation levels, most of the land is devoted to alfalfa, conventional soybean and conservation soybean, with both conventional and conservation corn substituted in year 2. Throughout our computational tests, permanent pasture and rotational grazing are never assigned to any cell with our current estimated parameter values described in Section 3. Therefore, we exclude those land use alternatives from all tables of results in the remainder of this section. Because it is cumbersome to present the full multi-stage solution, most of the rest of the results presented are limited to the expected land use decisions and the optimal expected profits over the whole study horizon.

We compute the expected land use proportion of alternative k in stage t as shown in Equation (48). To summarize the expected land use decisions over the whole study horizon, we use Equation (49).

$$\chi(t,k) = \frac{\sum_{s\in\mathcal{S}}\sum_{i\in\mathcal{I}}\sum_{j\in\mathcal{J}} p(s)\left(x^1_{ijkt}(s) + x^2_{ijkt}(s)\right)}{\sum_{i\in\mathcal{I}} J_i} \quad \forall t\in\mathcal{T}, k\in\mathcal{K} \tag{48}$$

$$X(k) = \frac{\chi(1,k) + c_2\chi(2,k) + c_3\chi(3,k)}{H} \quad \forall k\in\mathcal{K} \tag{49}$$

Table 7: Land use assignments from the cyclical recourse formulation with $\eta = 5$ ppm and $\rho = 2$ Mg/yr for the baseline case

Land use Alternative	Stage 1	Stage 2			Stage 3								
		H	M	L	HH	HM	HL	MH	MM	ML	LH	LM	LL
Wetland	1.52%	1.52%	1.52%	1.52%	1.52%	1.52%	1.52%	1.52%	1.52%	1.52%	1.52%	1.52%	1.52%
Conventional Corn	0.00%	13.32%	16.19%	4.72%	0.00%	0.00%	0.00%	0.00%	0.00%	1.35%	0.00%	0.00%	1.35%
Conservation Corn	0.00%	5.56%	4.55%	9.27%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
Conventional Soybean	32.72%	17.88%	16.86%	14.67%	28.16%	32.72%	26.64%	32.21%	32.72%	29.51%	31.20%	32.72%	29.51%
Conservation Soybean	9.95%	6.58%	6.07%	19.22%	15.01%	9.95%	20.74%	11.30%	9.95%	14.67%	12.82%	9.95%	14.67%
Alfalfa	53.96%	53.29%	52.95%	48.74%	53.46%	53.96%	49.24%	53.12%	53.96%	51.10%	52.61%	53.96%	51.10%
Permanent Pasture	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
Rotational Grazing	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
Switchgrass	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
Fruits and Veggies	1.85%	1.85%	1.85%	1.85%	1.85%	1.85%	1.85%	1.85%	1.85%	1.85%	1.85%	1.85%	1.85%

4.1.1 Sensitivity of Parameter Estimates

In view of the difficulty of estimating parameter values as described in Section 3, we explore the impact of variations in those parameter values on the results. Labor availability (N) at a watershed level is particularly difficult to estimate but dramatically restricts the land use design of the watershed. Table 8 indicates how the first stage decisions and expected profit vary with the value of N. We analyze alternative cases first by both reducing and increasing the baseline N value by 25% and 50%.

Table 8: Impact of changing labor availability from its baseline value

Land Use Alternative	50%	75%	**100%**	125%	150%
Wetland	1.85%	1.69%	1.52%	1.52%	1.52%
Conventional Corn	5.69%	7.65%	5.63%	8.04%	5.67%
Conservation Corn	5.94%	1.03%	3.10%	0.00%	5.24%
Conventional Soybean	19.95%	27.46%	24.86%	26.85%	24.19%
Conservation Soybean	18.01%	8.69%	10.91%	9.49%	9.36%
Alfalfa	41.87%	52.13%	52.13%	51.74%	51.16%
Switchgrass	0.00%	0.00%	0.00%	0.00%	0.00%
Fruits and Veggies	0.84%	1.35%	1.85%	2.36%	2.87%
Expected Annual Profit ($1000)	1,812	2,193	2,522	2,845	3,165

As the labor availability in the watershed area increases, the percentage of land devoted to fruits and vegetables also increases because of its high profitability compared to other land use alternatives. Yet, it uses a huge portion of the available labor, and the other land use assignment decisions take shape accordingly.

Profit estimates summarized in Table 3 are the other critical parameter values. With the baseline profit values for each land use alternative, our model prefers the soybean alternatives over corn and a significant alfalfa assignment is also made. However, market trends considerably affect profit levels. Here by taking market conditions from the previous year into account, we investigate an alternative realistic price example in which corn profit is increased by 5% and alfalfa profit is reduced by 15%. Table 9 presents the change in first stage decisions and expected profit under this price regime.

It is evident that the land use assignments are greatly affected by these prices. Instead of selecting soybean as in the original baseline price strategy, the model prefers corn. Also, alfalfa assignments are decreased, which results in even more land devoted to corn. These decisions require more wetlands and a greater emphasis on conservation rather than conventional management to meet the nutrient reduction targets.

Table 9: Expected land use decisions and expected annual profit under alternative prices for Markov chain model 1

Land Use Alternative	Baseline Prices	Alternative Prices
Wetland	1.52%	1.69%
Conventional Corn	5.63%	17.90%
Conservation Corn	3.10%	25.72%
Conventional Soybean	24.86%	6.86%
Conservation Soybean	10.91%	4.26%
Alfalfa	52.13%	41.71%
Switchgrass	0.00%	0.00%
Fruits and Veggies	1.85%	1.85%
Expected Annual Profit ($1000)	2,522	2,488

4.1.2 Relaxation of Nutrient Reduction Goals

Our baseline case is constructed from the nutrient reduction goals identified by the 2008 Gulf Hypoxia Action Plan. This plan requires a 45% nutrient reduction and Iowa State University et al. (2017) claims that Iowa as a whole must achieve 41% N and 29% P reductions to meet this objective. This amount is approximately equivalent to a nitrate-N concentration of 5 mg/L and P load of 2 Mg/yr for our watershed instance. In this section, we explore the economic impacts of alternative nutrient reduction aims for both nitrate-N concentration and P load. In Table 10 and Table 11, the changes in expected land use decisions resulting from alternative target nitrate-N concentrations and P loads are provided. Also, Figures 3 and 4 illustrate the change in expected annual profit with alternative nitrate-N and P targets.

Table 10: Impact of changing target nitrate-N on $X(k)$ for Markov chain model 1

Land Use Alternative	3 mg/L	4 mg/L	**5 mg/L**	6 mg/L	7 mg/L	8 mg/L
Wetland	1.35%	1.52%	1.52%	1.35%	1.69%	1.69%
Conventional Corn	3.01%	5.17%	5.63%	6.35%	5.51%	7.70%
Conservation Corn	2.23%	4.17%	3.10%	8.22%	10.56%	14.78%
Conventional Soybean	9.30%	21.80%	24.86%	30.19%	35.13%	33.62%
Conservation Soybean	15.54%	3.08%	10.91%	7.28%	15.91%	19.44%
Alfalfa	66.70%	62.41%	52.13%	44.52%	28.34%	20.92%
Switchgrass	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
Fruits and Veggies	1.85%	1.85%	1.85%	1.85%	1.85%	1.85%
Expected Annual Profit ($1000)	2,409	2,478	2,522	2,550	2,595	2,629

It is easily seen that as the η value increases, the percentage of land devoted to alfalfa decreases. As we allow more nitrate runoff, nitrogen stops being the limiting factor. Consequently, the land use percentage for corn and soybean increase. Similarly, as ρ is increased, the relaxation of the phosphorus constraint compels nitrate to again be the limiting factor and results in an increase in alfalfa. Allowing

Table 11: Impact of changing target P level on $X(k)$ for Markov chain model 1

Land Use Alternative	1 Mg/yr	1.5 Mg/yr	**2 Mg/yr**	3 Mg/yr	4 Mg/yr
Wetland	1.69%	1.52%	1.52%	1.52%	1.69%
Conventional Corn	0.00%	0.34%	5.63%	4.57%	4.61%
Conservation Corn	23.91%	20.69%	3.10%	3.12%	2.03%
Conventional Soybean	0.00%	0.67%	24.86%	31.23%	33.14%
Conservation Soybean	34.94%	34.11%	10.91%	3.00%	1.12%
Alfalfa	15.68%	40.81%	52.13%	54.70%	55.56%
Switchgrass	10.79%	0.00%	0.00%	0.00%	0.00%
Fruits and Veggies	1.85%	1.85%	1.85%	1.85%	1.85%
Expected Annual Profit ($1000)	2,252	2,455	2,522	2,527	2,529

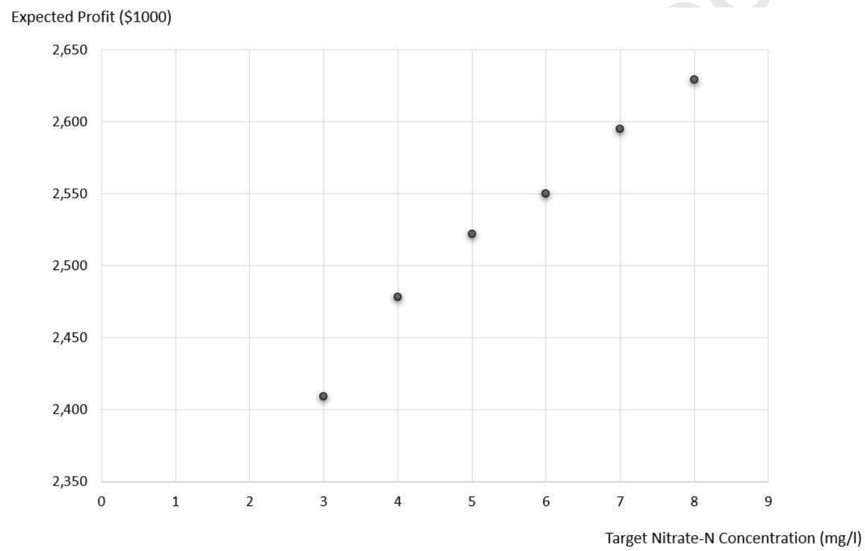

Figure 3: Expected annual profit with different targets Markov chain model 1

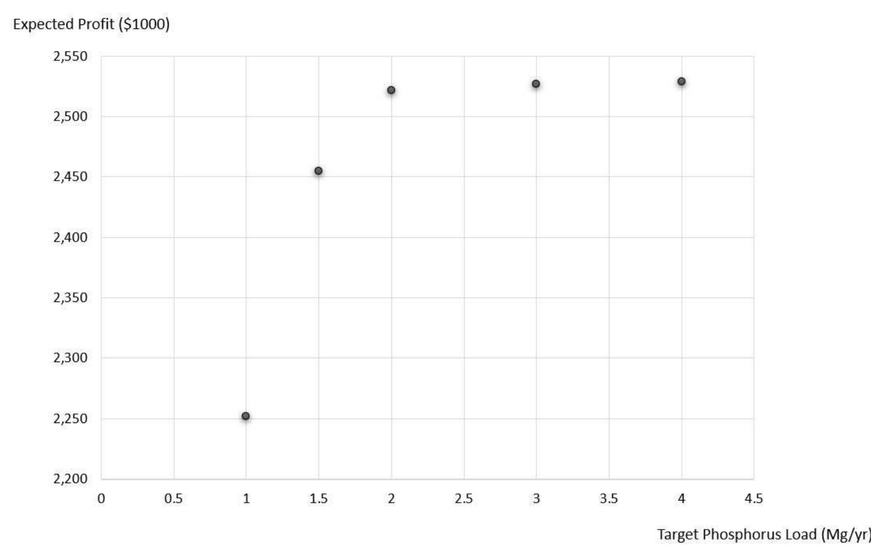

Figure 4: Expected annual profit with different nitrate-N targets for Markov chain model 1

ρ greater than 2 Mg/yr without changing η results in only a small profit increase, indicating that the nitrate-N constraint controls the land use allocations while the P constraint is not binding. Overall, it appears that the nitrogen goal is the more restrictive one. If the policy maker is able to alter the nutrient reduction goals, it is more valuable to focus first on the nitrate-N level.

4.1.3 Cyclical Recourse vs. Cyclical Chance-Constrained Formulation

A comparison between the results of the cyclical recourse and chance-constrained formulation exposes the effect of allowing flexibility in satisfying the nutrient reduction constraints. In the recourse formulation, nutrient reduction targets are enforced for every possible precipitation outcome each year; i.e., the requirements are met with probability one in every year t and scenario s. The chance-constrained formulation in Section 2.3.3 allows this probability to be altered for either nutrient in any year. This allows the policy maker to effectively ignore some low probability outcomes which negatively impact both profit and nutrient levels. In this section, we analyze how decisions and annual expected profit are affected as we change the probabilities of nutrient reduction constraint satisfaction. The results quantify the value of flexibility. In Table 12, expected land use decisions and annual profit of the baseline case for alternative values of $\alpha_t = \gamma_t$ for all t are provided. The case where the probability is set to 100% is equivalent to the recourse formulation.

Table 12: Expected land use decisions of baseline case with different values of $\alpha_t = \gamma_t$ for all t

Land Use Alternative	100%	95%	90%	85%	80%	75%	70%
Wetland	1.52%	1.69%	1.52%	1.52%	1.69%	1.52%	1.52%
Conventional Corn	5.63%	5.32%	4.87%	3.45%	6.30%	4.58%	5.68%
Conservation Corn	3.10%	3.87%	4.54%	7.21%	4.60%	6.42%	5.31%
Conventional Soybean	24.86%	28.93%	27.14%	30.11%	31.80%	31.11%	33.81%
Conservation Soybean	10.91%	6.41%	8.09%	6.57%	5.16%	7.09%	4.40%
Alfalfa	52.13%	51.93%	51.98%	49.29%	48.60%	47.42%	47.42%
Switchgrass	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
Fruits and Veggies	1.85%	1.85%	1.85%	1.85%	1.85%	1.85%	1.85%
Expected N Concentration over scenarios (ppm)	5.00	5.07	5.10	5.20	5.24	5.28	5.31
Expected P Load over scenarios (Mg/yr)	2.00	2.04	2.07	2.08	2.15	2.22	2.30
Expected Annual Profit ($1000)	2,522	2,529	2,534	2,537	2,539	2,543	2,545

As we lower the probability of satisfying both nutrient reduction constraints in all periods, expected alfalfa cultivation over scenarios is slightly decreased and that portion of land is allocated to corn and soybean which results in a higher annual profit.

4.1.4 Impact of Precipitation Uncertainty

The chance-constrained formulation also helps to demonstrate how incorporating uncertainty in the model improves the decision making. To assess the value of formulating and solving the multi-stage stochastic program, we investigate the impact of ignoring precipitation uncertainty.

First, we solve the cyclical single scenario model by setting the precipitation level in each year to its expected value. As a result, we obtain the results presented in Table 13.

Table 13: Expected value solution for $T = 3$, $H = 50$

Land use Alternative	Stage 1	Stage 2	Stage 3
Wetland	1.52%	1.52%	1.52%
Conventional Corn	0.00%	4.44%	0.00%
Conservation Corn	0.00%	4.90%	0.00%
Conventional Soybean	34.74%	28.42%	34.74%
Conservation Soybean	8.09%	6.41%	8.09%
Alfalfa	53.79%	52.45%	53.79%
Switchgrass	0.00%	0.00%	0.00%
Fruits and Veggies	1.85%	1.85%	1.85%
Nitrate-N feasibility	88.1%	72.6%	68.9%
Phosphorus load feasibility	88.1%	76.1%	69.7%

If we attempt to fix the decision variables to these values into our cyclical recourse stochastic programming formulation, we find the model to be infeasible; i.e., we do not meet nitrogen and phosphorus goals in every scenario s. Table 13 also provides information about frequency of meeting nitrogen and phosphorus goals at each stage according to scenario probabilities p_s.

To make a fair comparison between the expected value and stochastic programming formulations, we first fix the decision variables to their values in the expected value solution while solving the cyclical chance-constrained formulation with the probabilities of constraint satisfaction set to the percentage values provided in Table 13 for each stage and nutrient type. That is we set $\alpha_1 = 0.881$, $\alpha_2 = 0.726$, $\alpha_3 = 0.689$, $\gamma_1 = 0.881$, $\gamma_2 = 0.761$ and $\gamma_3 = 0.693$. In this way, we conserve feasibility for the expected value solution and observe a resulting annual expected profit of \$2,534 (in thousands of dollars). Second, we solve the chance-constrained formulation by using the same probability values again without fixing any values of decision variables. The resulting annual expected profit in thousands of dollars is increased by 0.3% to \$2,541. While this increase is admittedly small, it does demonstrate that allowing flexibility in how nutrient reduction goals are met over time and uncertain precipitation outcome can increase the profitability of land use decisions.

4.1.5 Impact of Precipitation Outcomes

Given the value of the multi-stage stochastic solution demonstrated in Section 4.1.4, it is natural to ask whether expanding the instance to include more finely discretized precipitation levels is worth the computational effort. Our baseline case includes 27 scenarios. Increasing b_t from 3 to 7 with $T = 3$ increases this number to 343. Table 14 presents the results of increasing the instance size in dimension. In all tests, the optimality gap for the mixed-integer programming solver was set to 1%; i.e., the solver was instructed to continue iterations until the value of the solution found could be guaranteed to be within 1% of the optimal value. However, the computation time limit was set to 12 hours. After investigated the computational burden of cyclical chance-constrained problem, we observe that our model manages to reach a 0.67% optimality gap within 641.2 s when Markov chain model 1 is used. On the other hand, when Markov chain model 2 is used instead, the optimality gap can be narrowed only to 2.01% within the 12 hour time limit.

Table 14: Impact of changing the outcome number for cyclical recourse problem

Land Use Alternative	Markov chain model 1	Markov chain model 2
Wetland	1.52%	1.52%
Conventional Corn	5.63%	5.74%
Conservation Corn	3.10%	3.21%
Conventional Soybean	24.86%	22.56%
Conservation Soybean	10.91%	13.74%
Alfalfa	52.13%	51.37%
Switchgrass	0.00%	0.00%
Fruits and Veggies	1.85%	1.85%
Expected Annual Profit ($1000)	2,522	2,520
Computational Time (s)	566.3	5421.6
Optimality Gap %	0.52%	0.97%

It is evident that the problem becomes considerably harder to solve as the total number of scenarios increases. In our test runs, when different numbers of precipitation outcomes were examined, we observed no significant change in expected land use or annual profit.

4.1.6 Value of Installing Wetlands and Cost of Meeting Nutrient Restrictions

In this section, we first solve the cyclical recourse formulation without permitting the construction of wetlands in any cells. By doing so, we calculate the amount of additional profit enabled by wetlands under the nutrient reduction constraints. We call this additional profit the value of installing wetlands, and it helps us to investigate how much incentive should be considered for landowners of the cells where wetlands are optimally constructed to meet the nutrient reduction goals. Secondly, we solve the cyclical recourse formulation assuming the policy maker is not trying to satisfy any of nutrient reduction requirements. That is, we maximize profit using the recourse model ignoring the nutrient reduction constraints. This helps us to identify the required regional investments and incentives to encourage landowners to cooperate and achieve the nutrient reduction goals.

Table 15 summarizes the results. The additional watershed annual profit of $337,000, that could be earned by ignoring the nutrient reduction constraints, corresponds to a suggested annual compensation of $570 for each ten-acre cell as incentive for adopting the socially-optimal land use decision. On the other hand, the reduction in annual profit of $124,000, that results from preventing the construction of the nine watersheds in the optimal solution, could be seen as a suggested transfer among landowners within the watershed. The owner of each of those nine cells should be paid $13,780 for sacrificing revenue from that land while enabling the neighboring landowners to earn more profit than they could without the benefit of the wetlands. Finally, note that even though the cost of fulfilling nutrient requirements is quite high, without any reduction constraints the resulting nutrient losses are substantially higher than the goals set in the Gulf Hypoxia Action Plan. Adding more spatial granularity while considering conservation practices separately in the model could moderate those results by capturing the ability of precision agricuture to simultaneously increase profit and reduce nutrient loss (Muth, 2014).

Table 15: Value of Installing Wetlands and Meeting Nutrient Restrictions

Land Use Alternative	Base Model	No Wetlands	No Nutrient Restriction
Wetland	1.52%	0.00%	0.00%
Conventional Corn	5.63%	0.00%	38.79%
Conservation Corn	3.10%	3.18%	0.00%
Conventional Soybean	24.86%	2.23%	54.68%
Conservation Soybean	10.91%	23.32%	0.00%
Alfalfa	52.13%	67.81%	4.68%
Switchgrass	0.00%	0.00%	0.00%
Fruits and Veggies	1.85%	1.85%	1.85%
Expected N Concentration (ppm)	5.00	5.00	24.53
Expected P Load (Mg/yr)	2.00	1.64	6.52
Expected Annual Profit ($1000)	2,522	2,398	2,859

5. Conclusion

In this study, we focused on the land use optimization of a watershed. We approached the problem from the perspective of a policy maker who is responsible for making land use decisions in a region. Such a policy maker must consider regional benefits but also fulfill the nutrient reduction requirements imposed by a higher authority. Besides, the decision maker must incorporate several factors including the planning horizon and uncertain precipitation which affects yield and nutrient loss considerably. Therefore, we built a multi-period stochastic mixed-integer program for land use decisions to maximize the agricultural profits of a watershed while meeting target reductions in nitrate-N and P levels under uncertain precipitation rates. We constructed the mathematical model based on watershed information collected from People in Ecosystems Watershed Integration (PEWI) (Chennault et al., 2016). The problem is inherently NP-hard because it is generalizes the stochastic assignment problem. Through an extensive computational study using the CPLEX commercial optimization software, we explored several questions which can facilitate the policy maker's work, identify crucial points in decision making and assist higher authorities or landowners with proper use of funding and incentives.

The formulation incorporated several parameters that are hard to estimate but have high impact on the optimal solutions. One is the total available labor force in the watershed, for which there are limited quantitative data due to migrant character of many agricultural workers. The other set of critical parameters are the profits of each land use alternative. In future work it would be worthwhile to consider explicitly modeling uncertainty in crop prices in addition to precipitation levels.

Nitrate-N concentration, P load and yield of each land use alternative depend on stochastic annual precipitation levels. In Section 4.1.4, we demonstrate that it is not possible to either reach an optimal profit or actually meet nutrient reduction goals by implementing a solution derived without considering precipitation uncertainty. Therefore, stochastic programming is needed to achieve optimality while meeting reduction targets.

The two variants of the multi-stage stochastic program provide insight into strategies for relaxing nutrient reduction goals. The simple strategy of relaxing the targets increases the profit of the watershed area as expected. Our results indicate that, under the current reduction goals identified by the 2008 Gulf Hypoxia Action Plan and Iowa Nutrient Reduction Strategy, nitrogen tends to be the limiting factor compared to phosphorus. Therefore, if there will be any concessions, nitrate-N constraint relaxation should be considered first. However, it is important to note that those results may be specific to the watershed instance examined. Further tests are required using different watershed data. The second relaxation strategy investigated in this study is to decrease the probability with which nutrient reduction targets are met. Instead of meeting nutrient reduction goals in every year and possible scenario with certainty, this strategy allows policy makers to ignore some scenarios with low probability outcomes that negatively impact both expected profit and nutrient levels. The chance-constrained formulation outperforms the solution to the deterministic expected value formulation by providing a more profitable way to achieve the same nutrient reduction amounts and incorporate flexibility for policy makers in meeting reduction targets.

Our model prioritizes the total prosperity instead of individual benefits of landowners through planning of a benevolent policy maker. Even if this viewpoint aligns with the INRS where statewide cooperation is assumed to achieve the nutrient reduction goals, the major concern is to ensure the cooperation of each landowner in order to implement socially optimal strategies. We investigate the amount of incentives required to ensure compliance of each landowner. Our results indicate that, although the expected compensation per landowner is admittedly not small, the resulting nutrient reduction is quite significant. However, it is necessary to expand the watershed analysis statewide to investigate to what extent Iowa can follow the optimal reduction strategies with reasonable economic sacrifices.

The current formulation can further be expanded by increasing the number land use options while elaborating individual conservation practices. Expanding the number of land use alternatives or adding more parameters modeled as random variables might require the use of decomposition methods for solving the resulting, larger scale, stochastic programs.

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Highlights of “Land Use Optimization for Nutrient Reduction Under Stochastic Precipitation Rates”

- A multistage stochastic mixed-integer program is solved to near-optimality
- Watershed-scale nutrient reduction constraints met with a loss in expected profit
- Nitrate reduction constraint limits feasibility more than phosphorus constraint
- A chance-constrained variant allows higher expected profit with relaxed constraints
- Economic incentives are derived for landowner compliance with social optimum