Optimizing Patterns of Land Use to Reduce Peak Runoff Flow and Nonpoint Source Pollution with an Integrated Hydrological and Land-Use Model

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ABSTRACT: The goal of this study is to develop and apply a methodology for delineating optimal land-use patterns that minimize peak runoff flow at watershed outlets by coupling a hydrological model and a land-use model. Under the assumption supported in prior research that nonpoint source (NPS) pollution is positively correlated with surface runoff volume, the model then yields land-use patterns that minimize nonpoint source pollution. A hydrological simulation model is developed with a modified and spatially explicit Soil Conservation Service (SCS) curve number method to analyze the geographical impacts of land uses. An optimization algorithm is integrated with the simulation model to evaluate different land-use patterns and their response to rainfall runoff events, and to search for optimal land-use patterns. This approach, applied to the southwestern basin of Lake Erie, Old Woman Creek Watershed (Ohio), yields optimal land-use patterns that reduce the peak runoff rate by 15%–20% under 1-, 2-, 5-, and 10-yr storms, compared to the

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current land-use pattern. The model results provide site-specific land-use guidelines and identify critical areas for conservation.

KEYWORDS: Land-use allocation, Optimization, Surface runoff

1. Introduction

The impact of water pollution from diffuse sources on surface waters has been of increasing concern during the past several decades. Nonpoint source (NPS) water pollution is the leading cause of water quality impairment ([Environmental Protection Agency] EPA, 2000; Novotny, 1999]. NPS pollutants are mainly transported by storm runoff to surface water bodies. Studies have been undertaken to trace these pollutants back to their sources, to understand transport mechanisms, and to investigate the impacts of land uses/cover on watershed hydrology (Jołánkai et al., 1999; Jordan et al., 1997; Bingner and Theurer, 2001; Moglen and Beighley, 2002; Novotny and Chesters, 1982; Singh, 1995). Using this knowledge, simulation and statistical models have been developed to 1) explain the land–water interaction, 2) quantify pollution loads, and 3) link pollutants to their sources. Quantitative modeling provides useful tools to analyze land–water interrelationships and to support management decision making with more scientific data.

Even with the use of models, land-use planning and decisions for watershed protection are often made inefficiently. Decisions regarding land-use conservation and the best management practices are often derived based on scenarios developed with regard to 1) land-use suitability, 2) generalized concepts of and guidelines for preservation, and 3) land-use projections for future development. Generally, a runoff model simulates the hydrological impacts of land-use changes under such a scenario. This ad hoc scenario method is widely used to determine the best management plans or to prioritize environmentally sensitive areas for preservation. Another limitation of the current approach is related to the shortcomings of hydrological models. Although fully distributed physical models are available, runoff simulation modeling based on the SCS curve number method is the most widely used tool because of its simplicity and good accuracy [EPA, 2001; (United States Geological Survey) USGS, 2001]. However, the results from this type of model represent the lumped effects of changing land uses and practices on the watershed, and are not spatially explicit. This is of little help for decision makers and planners because site design and planning requires very detailed physical information at a finescale. Site planning at the subdivision and parcel levels requires evaluating the effects of land-use patterns defined at a high level of spatial resolution.

Instead of the scenario approach, optimization is an alternative approach for comprehensive land-use–water resources planning. Optimization is a procedure finding the best or optimal solution of a problem that can be formulated mathematically with decision variables, an objective function, and constraints. An optimization model integrates all relevant decision information in a systematic fashion, formulates different planning alternatives (Skjei, 1972), and investigates
the behavior of decision variables (Hopkins, 1974). This technique has been widely applied to comprehensive land-use and water resources planning.

When applied to land-use planning, optimization has been used to allocate different land-use types/activities to specific locations/zones in order to control and stimulate regional economic activities and to maximize economic benefits at minimal cost (Lundqvist and Mattsson, 1983; Gilbert et al., 1985). However, land-use allocation models often overlook the effects of land allocation on surface water bodies.

Applications of optimization techniques to water resource problems have mostly focused on point source pollution control and the development of efficient regional water resource plans meeting water quality standards, including 1) the determination of the capacity and location of water treatment facilities, 2) the choice of pollution abatement techniques, and 3) the design of piping network systems (Deiniger and Su, 1973; McNamara, 1976; Graves et al., 1972). There are a few optimization models handling nonpoint source pollution associated with land-use activities (Haith, 1982; Das and Haimes, 1979; Hopkins et al., 1981). However, the runoff/erosion processes are very much simplified in these models due to computational difficulties. Fixed levels of nonpoint source pollutant loadings are assumed for different land-use types and used as coefficients in the optimization models (Haith, 1982; Das and Haimes, 1979). These loadings do not properly reflect the real phenomena. Also, subwatershed hydrographs are used to represent the runoff characteristics of each land-use type and are integrated with a land-use model to find optimal allocations (Hopkins et al., 1981). This modeling approach is not spatially detailed and cannot address the locational impacts of on-site land-use allocations.

To improve land-use optimization modeling for surface runoff and nonpoint source pollution control, we present an integrated hydrological-land-use optimization model. The impacts of on-site land-use changes are evaluated with a process-based runoff simulation model within the framework of a land-use optimization algorithm. This algorithm is based on the standard principles of nonlinear programming, using the gradient as direction of steepest ascent, and leads to local optima. However, because the objective function cannot be expressed in closed mathematical forms, its derivatives are numerically approximated by using the simulation model. This model allocates land uses, accounting for land-use constraints and the hydrological effects of changing land uses. By linking these two models, the direct impacts of changing land uses at specific locations are evaluated, and the results are used for land allocation.

In summary, the objectives of this research are as follows:

- to understand hydrological responses to land-use changes in a watershed,
- to evaluate the locational/spatial impacts of land uses,
- to identify and prioritize target areas for land-use conservation,
- to develop an optimal land-use pattern to reduce nonpoint source pollution at watershed outlets, and
- to produce guidelines for land-use conservation and planning.
2. Methodology

An optimization model is formulated to allocate land uses so that the peak runoff rate at the watershed outlet is minimized. To implement the model, a simple, accurate, and spatially explicit hydrological model is necessary. In order to produce realistic land-use management plans, the land-use optimization model should be able to reflect current land uses/practices and the land planning policy in the watershed.

NPS pollution is assumed to be positively correlated with a storm runoff. This assumption is widely accepted, and numerous statistical and simulation models of NPS pollution have been built on the basis of this assumption (Jolánkai et al., 1999; Jordan et al., 1997). The physical equations describing soil erosion and transport capacity are also expressed as a function of surface runoff volume and peak runoff rate (Bingner and Theurer, 2001). Previous studies have concluded that reducing storm runoff decreases nonpoint source pollution. The proposed model reduces the peak discharge rate instead of the total runoff volume, because the peak discharge rate is influenced by the intensity of rainfall, unlike the surface runoff volume. The peak discharge rate can be a more sensitive indicator of detrimental hydrological impacts, such as on-site flooding. The peak discharge rate is calculated as a function of runoff volume and time of concentration. It is linearly related to the volume of storm runoff, and the time of concentration is assumed to be invariant with land-use changes, in contrast to runoff volume (Bingner and Theurer, 2001). The model can be easily expanded to account for actual NPS pollution by linking NPS pollution generation to land use.

2.1. A hydrological simulation model

To investigate the locational impacts of land-use changes on watershed hydrology, the runoff model is implemented as a cell-based distributed system. The model is developed at a high resolution (30 m). Since all the spatial data used for input parameters in the hydrological simulation are provided at the 30-m resolution, this resolution is a natural choice for modeling and eliminates the need to aggregate spatial data. The model is therefore able to account for detailed spatial variations within the watershed and hopefully to provide better estimates.

Two types of models were considered: physically based and empirically based. A physically based model is developed from the mathematical equations describing the runoff phenomena. These equations, the Saint Venant equations, have been found to be too complex and difficult to implement. They have been simplified to become the kinematic wave model, the diffusion wave model, and the dynamic wave model for practical computer modeling (Chow et al., 1989; Singh, 1995). However, these simplified versions of physical models are still too complicated for the purpose of this research. When combined with the optimization model, the runoff model is required to simulate the storm runoff change with respect to land-use changes occurring in every cell. The high-resolution hydrological simulation and the consequent optimization process require huge computer resources. Because the improvement of physically based models is beyond the scope of this study, these models are not further considered.

A typical empirical model is based on the statistical analysis of field data to
determine the rainfall–runoff processes. The curve number is developed to link the impacts of on-site land uses and soil types to the storm runoff. Due to its simplicity and good accuracy, this model has often been used. The conventional SCS curve number models yield lumped effects of land-use changes in a watershed, a subwatershed, or a field, but cannot account for the spatial effects of land-use changes [McCuen, 1982; (United States Department of Agriculture) USDA, 1986].

To meet computing resource constraints and to evaluate the locational impacts of land-use change, the SCS curve number method is modified to create a spatially explicit runoff model. A spatially explicit hydrological model in a geographic information system (GIS) environment was implemented by Moglen and Beighley (Moglen and Beighley, 2002) by applying a spatially weighted and dynamically changing curve number for each cell. Similar to this GIS approach, the proposed model is implemented by considering the watershed as a networked system of flow cells. The distributed cells are interconnected through flow paths and form a stream network system within the watershed boundaries (Maidment, 1993). Then, two model assumptions are made: homogeneity and linearity. The physical properties of the cells are assumed to be homogeneous. The second assumption is based on the fact that the runoff process tends to be linear as the flow increases (Pilgrim and Cordery, 1993; Olivera, 1996). In this model, linearity is assumed at the water cell level as well as at the watershed level. This assumption leads to the application of proportionality and superposition principles in the model.

Using the SCS curve number method, the volume of storm runoff is

\[ Q = \frac{(P - 0.2S)^2}{P + 0.8S}, \]

where \( Q \) is the volume of runoff, \( P \) is the precipitation, and \( S \) is the retention parameter, which is estimated from the runoff curve number (CN) by Equation (2):

\[ S = \frac{100}{CN} - 1. \]

Details on this method are provided by McCuen (McCuen, 1982), the USDA (USDA, 1986), and Bingner and Theurer (Bingner and Theurer, 2001).

Under the assumption of homogeneity applied at the watershed or catchment level, the conventional SCS approach calculates the curve number as a weighted average for the modeling unit, watershed or catchment, and updates it with changes in land use/cover. In the proposed model, the curve number is explicitly calculated for a given cell under the assumption of homogeneity at the cell level. The runoff volume \( Q \) then characterizes the cell.

Under the linearity assumption, the runoff process at the cell level is described by a first-order linear differential equation (Chow et al., 1989),

\[ \frac{dS_i}{dt} = I_i - Q_i - \lambda_i S_i, \]

where \( S_i \) denotes moisture storage, \( I_i \) the input, \( Q_i \) the runoff, \( \lambda_i \) the loss coefficient, and \( i \) the \( i \)th flow cell. Equation (3) applies the principle of conservation of matter and states that the change in the water content of cell \( i \) \((dS_i/dt)\) is equal to the balance between inflows \((I_i)\) and outflows \((Q_i)\) and \((\lambda_i S_i)\). This process is illustrated
in Figure 1 in the case of a hypothetical path made of three consecutive cells. In this model, the precipitation periods \( P \) are assumed to be uniformly distributed over the watershed.

Since the watershed system is assumed to be linear, the properties of linearity, proportionality, and superposition are applied. The runoff process is analyzed at the flow cell level, then at the flow path level, then at the subwatershed level, and finally at the whole watershed level, down to the outlet. The runoff over a flow path is obtained by summing up the storm runoffs occurring at the flow cells along the flow path (see Figure 1). The total runoff at the watershed outlet is obtained by summing up the runoffs occurring along all flow paths within the watershed (Olivera, 1996):

\[
Q_p = \sum_{i \in p} Q_i \quad \text{(volume of storm runoff from a flow path),} \\
Q_{sw} = \sum_{p \in sw} Q_p \quad \text{(volume of storm runoff from a subwatershed),} \\
Q_w = \sum_{sw \in w} Q_{sw} \quad \text{(volume of storm runoff from the watershed),}
\]

where \( i \) is the \( i \)th flow cell along flow path \( p \), \( p \) is a path within subwatershed \( sw \), which is a subset of watershed \( w \). By adopting this cell routing approach based on the linearity assumption, the distributed water flow cells are integrated systematically into a whole watershed, and the SCS method can be used as a spatially explicit model. While the method of cumulating runoff from cell to watershed is adapted from Maidment (Maidment, 1993), the distributed SCS method is an original contribution of this research.

Similar processes are applied to estimate the time of concentration. Travel time is determined for each cell according to its flow type: overland flow, shallowly concentrated flow, or channel flow. The flow type is determined by the TR-55 method (USDA, 1986). The topography of the watershed is investigated in detail regarding its slope, path direction, and aspect. The travel times of all the flow paths to the watershed are calculated, and the maximum travel time is selected as the time of concentration. After calculating the time of concentration and the total amount
of runoff, the peak runoff rate is determined using the extended TR-55 procedure (Bingner and Theurer, 2001). The peak rate is determined as follows:

\[
Q_p = 2.7777777778 \times 10^{-3} P_{24} D_a \left[ \frac{a + (cT_c) + (eT_c^2)}{1 + (bT_c) + (dT_c^2) + (fT_c^3)} \right],
\]

where \(Q_p\) is the peak discharge (m s\(^{-1}\)); \(D_a\) the total drainage area (ha); \(P_{24}\) the 24-h effective rainfall over the total drainage area (mm); \(T_c\) the time of concentration (h); and the constants \(a, b, c, d, e,\) and \(f\) are the unit peak discharge regression coefficients, which are determined by the ratio of initial abstraction (\(I_a\)) to 24-h precipitation (\(P_{24}\)). Refer to Bingner and Theurer (Bingner and Theurer, 2001) for the values of these coefficients. The model is storm-event based and assumes the SCS hydrograph.

### 2.2. Land-use optimization model

The goal of the land-use optimization model is to allocate land uses/activities for surface runoff control, so that the peak discharge at the watershed outlet is minimized. The focus is on reducing the hydrological impacts (the peak discharge rate) of the spatial land-use patterns and on delineating the critical areas for conservation. The resulting land-use patterns can then be assessed exogenously to the model with respect to other factors, such as land ownerships, field size, and financial constraints.

The mathematical program for land-use allocation is formulated as

\[
\min f(x) = \text{peak runoff rate at the outlet},
\]

which is subject to

\[
\sum_{i=1}^{n} x_{il} = T_l \quad \forall l = 1, 2, \ldots, m,
\]

where \(x\) is the vector of the decision variables:

\[
x = (x_{i1}, x_{i2}, \ldots, x_{il}, \ldots, x_{in})
\]

\[
x_{il} = \text{land-use decision variable representing the amount of land-use l in cell i (\(\forall i = 1, 2, \ldots, n\)),}
\]

\[
T_l = \text{total amount of land-use l in the watershed.}
\]

The runoff from each cell \(i\) is characterized by its soil type, its land-use type, topography, and precipitation. The land-use constraint (7) is related to the total land amounts planned in the watershed.

While the mathematical formulation of Equations (6)–(7) seems very simple, there are many challenges in solving this optimization model. First, the hydrological processes characterizing the rainfall–runoff event cannot be formulated analytically in a closed mathematical form. Therefore, it is impossible to write a simple mathematical expression for the land–water interactions in the objective function. Second, the nature of the objective function is unknown. The spatial impacts of land-use changes on storm runoff are clearly nonlinear, but unknown. This nonlinear relationship is made evident by the runoff–land-use
equations (1), (2), and (5). Equations (1) and (2) show that 1) a change in land use modifies the CN, 2) the soil infiltration capacity $S$ is then modified according to the CN, and 3) the volume of runoff is changed nonlinearly according to soil moisture and precipitation. Equation (5) demonstrates how the peak runoff rate is nonlinearly determined by the runoff volume and the time of concentration. Third, the assumption of cell homogeneity requires that the decision variables $(x_{il})$ be integer (0 or 1), indicating the absence or presence of a specific land-use type (i.e., urban, agriculture, or conservation). Therefore, the model should be an integer program. Finally, the model’s high resolution requires a very large number of land-use decision variables, thus a very large program.

To overcome the above modeling challenges, the following approach is taken. First, the storm runoff simulation model is combined with the land-use optimization model in order to analyze the objective function numerically, as proposed by Guldmann (Guldmann, 1979), with the nonlinear objective function linearly approximated. The assumption of the cell land-use homogeneity is relaxed, allowing mixed land uses in a given cell. Thus, the land-use variables $(x_{il})$ are taken as continuous rather than Boolean (0 = not assigned, 1 = assigned). Under this relaxation, the land-use variable $(x_{il})$ in a given cell $i$ is defined as a proportion (0–1) of different land-use types (i.e., urban, agriculture, and conservation). This relaxation allows for solving the problem using nonlinear optimization techniques. It is then necessary to add a constraint verifying that the sum of the different land-use variables in a given cell always adds up to 1. The new formulation is

$$\min f(x) = \text{peak runoff rate at the outlet},$$

which is subject to

$$\sum_{i=1}^{n} x_{il} = T_{l} \quad \forall \ l = 1, 2, \ldots, m$$

(9)

$$\sum_{l=1}^{m} x_{il} = 1 \quad \forall \ i = 1, 2, \ldots, n$$

(10)

$$x_{il} \geq 0.$$

(11)

The number of decision variables is the product of the number of cells in the watershed and the number of land-use types $(n \times m)$. A high resolution implies that the number of decision variables is very large. To deal with this problem, land uses are grouped into three categories: urban, conservation (grass/woods), and agriculture.

The nonlinear optimization problem is solved using sequential linear programming, also known as the method of convex combinations (Wagner, 1975; Venkataraman, 2002). The key of this method is the linear approximation of the nonlinear objective function, using a first-order Taylor’s series expansion. The linear approximation of the original function, $f(Z)$, is

$$f(Z) \approx f(X^k) + \sum_{j=1}^{J} \frac{\partial f(X^k)}{\partial x_j}(z_j - x_j^k),$$

(12)

where
1) \( f(Z) \) is the linear approximation of the original function;
2) \( X^k \) is \( k \)th trial point, \( X^k = \{x^k_j\} \); and
3) \( Z \) is any point in the neighborhood of \( X^k \), \( Z = \{z_j\} \).

With this linear approximation, the programming goal is now changed to minimize the second term, the sum of the first derivatives, subject to constraints (10)–(12), and the model becomes a linear program. The advantage of using linear programming is that very large programs can be solved with this technique, in contrast to the size limitations of earlier techniques, such as dynamic programming (e.g., Hopkins et al., 1981).

Next, it is necessary to find the optimal step size (\( t \)) along the gradient \( (Z - X^k) \), with components \( (z_j - x^k_j) \). To do so, the objective function is evaluated for steps varying in the interval (0–1) with increments of 0.01. The step size yielding the minimum runoff is the optimal one. Then, the decision variables are updated using Equation (13):

\[
x^k_j + 1 = (1 - t)x^k_j + tz_j, \quad t \in [0, 1].
\]

However, the linear approximation is not straightforward because the objective function is not analytically closed. To overcome this difficulty, the partial derivatives are approximated by a finite difference method (Guldmann, 1979). This method numerically evaluates changes in the objective function (storm runoff at the watershed outlet), resulting from very small changes in land uses, cell by cell and land use by land use. The objective function is, each time, computed using the hydrological simulation model. The partial derivatives are approximated as

\[
\frac{\partial f(X)}{\partial x_{ki}} \approx \frac{\Delta f(X)}{\Delta x_{ki}} = \frac{f(X + \Delta X) - f(X)}{\Delta x_{ki}}, \quad (14)
\]

where \( f(X) \) is the peak discharge rate.

The objective function cannot be characterized regarding convexity or concavity. Therefore, the optimal solution cannot be guaranteed to be the global one. Since the model involves minimization, the objective function should be convex to guarantee global optimality, with a positive semidefinite Hessian matrix everywhere. As this Hessian matrix cannot be formulated and analyzed, the alternative (second best) is to solve the model with a large number of different initial conditions and to select the best solution. However, this approach does not guarantee obtaining the global optimum. This is clearly an area for further research.

The hydrological simulation and the land-use optimization are programmed in MATLAB. The model runs on a PC Pentium IV with 1.6 GHz. Because of the model’s large scale, the interior point method is used as linear programming solver. The flowchart of the model is presented in Figure 2.

3. Data sources and processing

The modeling approach requires extensive spatial data characterizing the study site, including 1) digital elevation models (from the USGS); 2) surface water features (National Hydrography Dataset, from the USGS–EPA); 3) soil data (from the Soil Survey Geographic Database); and 4) land-use information (from the Ohio
Department of Natural Resources). The land-use/cover information is interpreted from images provided by the Landsat Thematic Mapper and taken in September and October 1994. The data are all provided at the 1:25,000 scale with a 30-m resolution.

The spatial data are preprocessed to derive watershed and subcatchment boundaries, using ArcGIS. The soil data are further analyzed to cluster them into SCS hydrological soil groups. Map Unit Use File (MUUF) soil databases are used for soil data analysis. Seven different land-use/cover types are identified by image interpretation. Land-use practices in the watershed are assessed through personal interviews and published statistics on agricultural practices [for more information see the USDA Web site for the National Agricultural Statistics Service (http://www.usda.gov/nass/); Conservation Technology Information Center, 2002]. The CN and the Manning’s roughness are chosen to reflect land-use conditions at the study site. The CNs for various land-use and soil types are presented in Table 1. The seven land-use categories are regrouped into three land-use types (i.e., urban, agriculture, and conservation), according to the similarities of their land-cover and hydrological characteristics, to reduce the number of the decision variables in the optimization model.

### Table 1. The CN for different land-use and soil types.

<table>
<thead>
<tr>
<th>Land-use type</th>
<th>USDA land-use classification and conditions</th>
<th>Soil A</th>
<th>Soil B</th>
<th>Soil C</th>
<th>Soil D</th>
<th>Manning’s roughness</th>
</tr>
</thead>
<tbody>
<tr>
<td>Urban</td>
<td>72% impervious</td>
<td>81</td>
<td>88</td>
<td>91</td>
<td>93</td>
<td>0.075</td>
</tr>
<tr>
<td>Agriculture</td>
<td>Single rows and crop residue Good condition</td>
<td>64</td>
<td>75</td>
<td>82</td>
<td>85</td>
<td>0.04</td>
</tr>
<tr>
<td>Shrub</td>
<td>Brush Fair condition</td>
<td>35</td>
<td>56</td>
<td>70</td>
<td>77</td>
<td>0.037</td>
</tr>
<tr>
<td>Wooded</td>
<td>Woods Good condition</td>
<td>30</td>
<td>55</td>
<td>70</td>
<td>77</td>
<td>0.600</td>
</tr>
<tr>
<td>Open water</td>
<td>Open water Natural channel bed</td>
<td>—</td>
<td>—</td>
<td>—</td>
<td>—</td>
<td>0.037</td>
</tr>
<tr>
<td>Nonforested wetland</td>
<td>Herbaceous Good condition</td>
<td>0</td>
<td>62</td>
<td>74</td>
<td>85</td>
<td>0.130</td>
</tr>
<tr>
<td>Barren</td>
<td>Fallow Bare condition</td>
<td>77</td>
<td>86</td>
<td>91</td>
<td>94</td>
<td>0.050</td>
</tr>
</tbody>
</table>

(Source: Ohio Department of Natural Resources, 2002 and USDA, 1986)
Prior to implementing the optimization model, the hydrological model is calibrated using actual flow data. The model is a single-event distributed system. In calibrating an event-based model, the design storm serves as input, and the hydrological model calculates the stream runoff. The design storm can be specified by 1) a precipitation depth at a site, 2) a design hyetograph with a time distribution, or 3) an isohetal map (Chow et al., 1989). To validate the model with more realistic data, the design storm is determined by using historical data on site, rather than the published isohetal map. Also, an assumption is made about the rainfall pattern. Since the data are only available in daily steps, it is assumed that the precipitation follows SCS rainfall time distribution. The return period for the design storm is determined using the extreme value type-I probability distribution function (Chow et al., 1989; Haan, 2002).

Flood frequency is then analyzed, with observed stream data and the Bulletin 17B method [(Interagency Advisory Committee on Water Data) IACWD, 1982]. The log-Pearson-type-III distribution is used as a base method for flood analysis. After determined the frequency curve, the stream runoff rates corresponding to the probabilities of 1-, 2-, 5-, and 10-yr storms are determined. The results of the hydrological model solved with the estimated design storms are compared with the stream runoff rates estimated from the flood frequency analysis. The flood analysis uses stream gauge data over the period 1987–2002. Daily precipitation data are obtained from the National Weather Service Center from the period 1985–2002. Only rainfall data are considered for this analysis, as the CN is primarily applicable to unfrozen soil conditions. The results of the model calibration analyses are presented in Table 2. In comparison with the actual monitored values, the simulation model appears to provide reliable outputs (all within 95% confidence intervals). The large confidence intervals are due to the relatively small samples (15 observations of streamflows), which may result in a biased estimation. Also, the simulation model does not consider evapotranspiration, which may lead to overestimating the streamflow.

### 4. Applications and results

#### 4.1. Description of the study area

To illustrate its applicability, the model is applied to a subcatchment of an agricultural watershed along Lake Erie. The Old Woman Creek watershed is located in the southwestern basin of Lake Erie between Cleveland and Toledo, Ohio. It is a small watershed, with a total area of 68.6 km², and stretches across the

<table>
<thead>
<tr>
<th>Return period (yr)</th>
<th>Design storm (cm)</th>
<th>Observed mean peak flow rate (m³ s⁻¹)</th>
<th>Simulated mean peak flow rate (m³ s⁻¹)</th>
<th>95% confidence interval (m³ s⁻¹)</th>
</tr>
</thead>
<tbody>
<tr>
<td>12</td>
<td>2.8811</td>
<td>0.9508</td>
<td>0.9377</td>
<td>0.5446</td>
</tr>
<tr>
<td></td>
<td>4.9347</td>
<td>8.8030</td>
<td>7.1342</td>
<td>5.7142</td>
</tr>
<tr>
<td></td>
<td>6.1638</td>
<td>15.6292</td>
<td>18.1865</td>
<td>11.0592</td>
</tr>
<tr>
<td></td>
<td>6.9776</td>
<td>20.1845</td>
<td>28.3018</td>
<td>14.9837</td>
</tr>
</tbody>
</table>

Table 2. Hydrological model calibration results.
boundaries of two counties, Huron and Erie. The watershed stream drains into Lake Erie. In recognition of the importance of this freshwater estuary, this area is preserved by state and federal regulations and is designated as the Old Woman Creek State Nature Preserve and National Estuarine Research Reserve. The goal in applying the model is to delineate optimal land-use patterns, identify priority areas, and provide land-use guidelines for watershed protection. The location of the study area is presented in Figure 3.

The total number of cells in the subcatchment is 1732, predominantly used for agricultural purposes (79%). Conservation land use (grass/wood) represents 13% of the area, and the remainder of the cells represents water. Only one cell is identified as urban (with a built-up structure). There are three types of soils (A, B, C), and cell slope varies between 0.0005% and 9.3%. Soil type A has the most desirable characteristics, with the highest infiltration rate. The soil infiltration capacity declines from soil A to soil C. Excluding water cells, the total number of decision variables is 4773 (1591 cells \times 3 land uses). The physical characteristics of the subcatchment are presented in Figure 4.

4.2. Results and discussion

Three research questions are investigated with the model. 1) Does the spatial land-use pattern have an impact on the storm runoff? 2) How does the optimal spatial land-use pattern change with respect to storm size? 3) How should urban sprawl take place? Note that land is allocated only to minimize storm runoff, without reflecting other purposes of buffers, such as providing wildlife habitat, preserving floodplain, or providing recreational and aesthetic benefits.

To answer the first question, the problem is set up to retain the initial (existing)
total land-use allocation during the optimization process: 79% of the land for agriculture, 13% for conservation, and 1 cell for urban activities. All cells, except water cells, are assigned a land use. A 1-yr storm is used.

To illustrate the complexity and irregularities (e.g., discontinuities) of the objective function computed with the simulation model, Figure 5 shows the computed peak runoff rates (i.e., the objective function) for various step sizes and for three iterations in the optimization process. The step size \( t \) [see Equation (13)] varies between 0 and 1. In the first iteration, the function is minimized at \( t = 1 \). In the second iteration, it is minimized at \( t = 0.2 \), and in the third one at \( t = 0.8 \). The
pattern of variations in the objective function is characterized by abrupt discontinuities. The optimal step size at each iteration provides the initial point of the next iteration.

The results point to a 21.7% reduction in the peak runoff rate with a 1-yr storm. The spatial pattern has the following features: 1) it preserves the areas with high infiltration rates (soil types A and B), 2) it reduces agricultural development around the water courses, and 3) it protects upland watershed areas from development. These findings are in line with published recommendations for management plans for nonpoint source pollution control (Herson-Jones et al., 1995). The urban land use (admittedly very small: 1 cell out of 1591) is permitted primarily near the watershed outlet. Agriculture moves away from the water courses. Intensive agriculture (i.e., with a high proportion of agricultural land use in a given cell) is not allowed over high-infiltration soils (A and B). This is clear when comparing the agricultural land-use pattern with the soil type of the watershed (Figure 4). Conservation land uses display similar characteristics. A high density of conservation land is assigned to areas with a high infiltration capacity. The previously urban cell is replaced by conservation land. The optimal land-use pattern suggests that grass/woods should be spread all over the watershed, with an overall watershed vegetation density of 15%, rather than concentrating this type of land only around the streams. However, areas adjacent to the stream have a higher density of conservation land (approximately 22%). This may imply that a small stream filter is effective for a 1-yr storm to control the surface runoff, if the overall watershed is covered by grass/woods.

The mixing of conservation lands and agricultural land may be unrealistic in practice. However, implications may be drawn from the results. Agricultural lands in the subcatchment are assumed to be straight row crops and covered with crop residues. Crop residue cover conditions are applicable in the hydrological model if residues are on at least 5% of the surface throughout the year. The model result (adding 15% of vegetation over agricultural fields) may suggest more conservation tillage practices, which could yield runoff control effects equivalent to a 15% vegetation density. However, it is clear that the mixing of land uses at the cell level is a limitation of the model, due to the relaxation of the integer constraints.

Overall, the optimal pattern for a 1-yr storm suggests retaining surface runoff on site, using vegetation, and therefore minimizing its delivery to the stream. This technique is the most recommended management practice (Novotny and Chesters, 1982). Figure 6 displays the optimal land-use patterns.

The second question is whether the watershed responds differently to different storm sizes. Although runoff tends to be linearly related to storm size, the relationship between land use and the rainfall–runoff process is clearly nonlinear, as Equations (1), (2), and (5) show. This nonlinear relationship is clearly demonstrated in the analysis of the direct runoff of different curve numbers for different rainfall depths by the USDA (USDA, 1986). Optimal land-use patterns are derived under 1-, 2-, 5-, and 10-yr storms. No change is made in the total land-use constraints from the first simulation (79% for agriculture, 13% for conservation land, and 1 urban cell). The results in Table 3 show that the optimization model successfully reduces the peak runoff by 15%–20%. The optimal land-use patterns vary across different storm sizes. The following can be observed: 1) vegetation
buffers along the stream are effective for small storms (1 and 2 yr), but not for larger ones (5 and 10 yr), and 2) the subcatchment is covered with a vegetation density of approximately 15% to minimize the runoff.

Conservation land uses near the water courses increase for smaller storms (1 and 2 yr). However, these lands under a 10-yr storm display little vegetation density variations between the stream buffer zones and other subcatchment areas, indicating the ineffectiveness of stream buffers to control large storm runoff. Shifting from a 1- to a 2-yr storm, agricultural land-use intensity near the water course is reduced by approximately 10%, indicating that more buffers around the stream are effective to control the runoff for a 2-yr storm. However, if the storm is larger, agricultural activities near the stream are no longer significantly reduced. Instead, agricultural activities in areas with high infiltration capacity are reduced with larger storms (5 and 10 yr). High-density vegetation appears in areas with a high infiltration capacity (soil A and B). The areas with soil A have the densest vegetation. Figure 7 displays the optimal land-use patterns for different storm sizes. (The optimal land-use patterns for a 1-yr storm are presented in Figure 6.)

The third question is how urban sprawl should take place in order to minimize storm runoff problems at the watershed outlet. To answer this question, the total urban development area is increased to represent 5% of the subcatchment.

**Table 3. Storm runoff vs optimal land-use patterns.**

<table>
<thead>
<tr>
<th>Storm size</th>
<th>Current pattern (m$^3$ s$^{-1}$)</th>
<th>Optimal pattern (m$^3$ s$^{-1}$)</th>
<th>Improvement (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 yr (28.9 mm)</td>
<td>0.13870</td>
<td>0.10923</td>
<td>21.1</td>
</tr>
<tr>
<td>2 yr (49.35 mm)</td>
<td>2.34123</td>
<td>1.93997</td>
<td>17.1</td>
</tr>
<tr>
<td>5 yr (61.64 mm)</td>
<td>5.32164</td>
<td>4.42405</td>
<td>16.9</td>
</tr>
<tr>
<td>10 yr (69.77 mm)</td>
<td>7.996370</td>
<td>6.65693</td>
<td>16.8</td>
</tr>
</tbody>
</table>
Accordingly, the total agricultural land is decreased by the same amount. The analysis is conducted with a 1-yr storm. The results, presented in Figure 8, show that urban sprawl should be avoided in areas adjacent to the streams. Dense urban development takes place near the watershed outlet or far from the streams. The areas with high infiltration (soil A and B) are used for low-density urban development.
development mixed with vegetation, but the surroundings of urbanized areas are protected with dense vegetation to control the storm runoff into the stream. Overall agricultural activities become more intense, allowing for decreasing activities in the stream buffer zone. Instead, denser vegetation is allocated near the streams.
5. Conclusions

The proposed integrated model generates optimal land-use patterns to reduce the storm runoff peak at the watershed outlet. The method allows for evaluating land-use changes at specific locations. Built into the optimization framework, land-use constraints are systematically verified, and an optimal land-use pattern is derived. It should be emphasized that the land-use allocation and the identification of prioritized areas for conservation are determined solely under the goal of controlling storm runoff. Preservation goals, such as the protection of aquatic wildlife or floodplains, are not considered.

The model provides useful results. The optimal land-use pattern reduces the peak runoff by 15%–20%. The results recommend the following: 1) allocate dense conservation land to areas with high infiltration capacity, 2) reduce the urban and agricultural intensity around the stream with vegetation buffers, 3) protect upland watershed areas from development, and 4) buffer urban areas with vegetation. These actions are to reduce the generation of storm runoff on site and its delivery to the stream. Different spatial patterns are recommended for various storm intensities. The stream buffers are ineffective for larger storms. The simulation results from a 10-yr storm point to little difference in vegetation density between the buffer zones and the other areas, emphasizing the ineffectiveness of stream vegetation buffers to control runoff from large storms. The results suggest protecting areas with high infiltration rates with denser vegetation to reduce storm generation on site instead of controlling its delivery to the stream. These different spatial patterns identified for various storm intensities can help decision makers, planners, or engineers by giving them an insight into how flexible land-use conservation planning should be. The findings from the optimization model are in agreement with general recommendations for conservation, but also provide site-specific and detailed guidelines for management actions.

The optimization model is nonlinear. Therefore, the optimal solution cannot be guaranteed to be the global one without knowing the property of the objective function. Since the proposed model evaluates the objective function numerically through simulation, it is not possible to analyze the objective function analytically to assess its concavity. To overcome this problem requires the generation of optimal patterns with different initial settings to better understand the behavior of the objective function. Analysis of the distribution of the local optima and their determinants remains an area for further research. The model results provide mixed agricultural and conservation land uses, which are due to using continuous decision variables and may be unrealistic in practice. This result could, however, be used in actual land-use management practices if realistic land-use patterns comparable to these mixed land uses could be delineated, possibly by allocating the optimal aggregate land-use mix to individual cells in a spatially acceptable pattern. Model improvements to correct for this limitation also remain an area for further research.

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References


