Optimization methodology for land use patterns using spatially explicit landscape models

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Abstract

Spatially explicit ecosystem models allow the calculation of water and matter dynamics in a landscape as functions of spatial localization of habitat structures and matter input. For a mainly agricultural region we studied the nutrient balance as a function of different management schemes. For this purpose we formulated optimization tasks. This required the definition of performance criteria, which compare economic aspects, such like farmer’s income from harvest, with ecologic aspects, such like nutrient loss out of the watershed. The task was to calculate optimum land use maps and fertilizer application maps maximizing the performance criterion. We developed a framework of procedures for numerical optimization in spatially explicit dynamic ecosystem simulation models. The results were tested using Monte-Carlo’s simulation, which based on different stochastic generators for the independent control variables. Gradient free optimization procedures (Genetic Algorithms) were used to verify the simplifying assumptions. Parts of the framework offer tools for optimization with the computation effort independent of the size of the study area. As a result, important areas with high retention capabilities were identified and fertilizer maps were set up depending on soil properties. This shows that optimization methods even in complex simulation models can be a useful tool for a systematic analysis of management strategies of ecosystem use. © 2002 Elsevier Science B.V. All rights reserved.

Keywords: Spatial modeling; Ecosystem management; Agroecosystem modeling; GIS

1. Introduction

Simulation models are recognized as efficient tools for analysis of environmental processes, education, and decision making. The most fascinating ability of a model is the possibility to perform non-intrusive experiments over a system based on the theoretical and practical knowledge about processes and interactions.
In this context every model consists of a simulator which represents the environmental processes and connects control parameters (forcing functions, inputs) to output variables (indicators). The former ones, the control parameters, define management strategies in terms of the model variables. The latter ones, output variables, are used to describe the system behavior and to assess the considered management strategies.

To analyze the system and define most appropriate management practices, a number of scenarios are formulated and then fed into the model. The output results are then compared to choose the one that fits the requirements, the management goals best of all. The formulation of a management scenario, assessment and comparison of results requires considerable efforts. Instead of running numerous scenarios through the model and then comparing the results (see for instance Costanza et al., 2001), we may formulate a certain goal that we want the ecosystem to reach, and then let the computer sort through the numerous parameter and pattern combinations to reach that goal. In this case the variations of parameters and functions in the model input (control) are performed automatically, as well as the processing of the output. The core of this process is the algorithm of numerical optimization, which makes the decision on how to define the next scenario to analyze based on the available information about the results of previous model runs. This optimization procedure connects the scenarios, the simulation process and the performance criterion. Algorithms of optimization are capable of performing a systematic search in the space of control variables to find an input vector which controls the systems in the desired way, specified by the goal function.

In most cases to assess the outcome of a scenario in terms of environmental, economic, toxic or social aspects, more than one output variable needs to be considered. To compare different simulation scenarios we then need to integrate output variables into a scalar value (or to analyze a multidimensional decision problem). This function that we choose to integrate or aggregate the several output variables is called a goal function or performance criterion and is a mathematical formalization of the state of the system that should be maximized or minimized to reach the desired state.

2. Spatial optimization in environmental modeling

2.1. State of the art

Table 1 summarizes recent publications on spatial ecosystem management based on simulation models. We look at the model structure, the control variables, the goal function, the processes, and the spatial database used. The last column lists the location of the study area, if any.

Scope of ecosystem management problems ranges from forest management and timber harvest (Loehle, 2000; Tarp and Helles, 1997) to agricultural problems (Nevo and Garcia, 1996; Seppelt, 2000; Makowski et al., 2000) to general issues of land use change (Martínez-Falero et al., 1998), and to habitat suitability (Bevers et al., 1997). The models used differ in terms of mathematical structure. Modeling methodology ranges from aggregated dynamic models based on difference equations of exponential growth (Bevers et al., 1997; Loehle, 2000) to complex models based on systems of non-linear differential equations (Seppelt, 2000; Randhir et al., 2000). In terms of optimization methodology one can find a broad spectrum of approaches.

2.2. Problem classification

The last point is explained, if one analyzes environmental models in terms of mathematical structure. The optimization techniques in environmental modeling still differ considerably from one problem to another. This may be in contrast to engineering problems, where the optimization methods are usually the same as long as the model structure is defined by a system of ordinary differential equations, (Bulirsch et al., 1993). This especially so, when spatial problems are formulated and the mathematical heterogeneity of the simulation model increases (Seppelt, 2000).

Complexity of an optimization task depends on two factors: the complexity of the ecosystem
Table 1
Application of spatial optimization in landscape ecology in recent literature

<table>
<thead>
<tr>
<th>Reference</th>
<th>Model structure process considered</th>
<th>Control variables</th>
<th>Goal function</th>
<th>Algorithm method for optimization</th>
<th>Spatial DB scale GIS</th>
<th>Case studies/applications</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bevers et al., 1997</td>
<td>Time discrete migration and population dynamics for Rodiacid treatment</td>
<td>Location of reintroduction Rodiacid treatment</td>
<td>Habitat suitability function, HSI</td>
<td>Non-linear programming, stochastic variation</td>
<td>Grid</td>
<td>Badlands National Park, US; Buffalo Gap National Oark, South Dakota; Northern Great Olanes, US</td>
</tr>
<tr>
<td>Hof et al., 1999</td>
<td>Population dynamic</td>
<td>Timing of habitat protection for prairie orchid</td>
<td>Timber harvest water quality</td>
<td>0-1 integer programming</td>
<td>Grid ArcINFO</td>
<td>Sheyenne National Grassland, South East North Dakota, US</td>
</tr>
<tr>
<td>Lochlè, 2000</td>
<td>Experimental growth of forests</td>
<td>Timber harvest</td>
<td>Timber harvest water quality</td>
<td>Hierarchical structured linear programming (LP)</td>
<td>Grid</td>
<td>European Union</td>
</tr>
<tr>
<td>Makowski et al., 2000</td>
<td>Linear model equation system</td>
<td>Spatial distribution of agricultural land use</td>
<td>Ecological suitability, economic costs, social constraints</td>
<td>Baye’s approach to land use changes</td>
<td>Grid</td>
<td>Torrelague township, Spain, 2787 ha</td>
</tr>
<tr>
<td>Nevo and Garcia, 1996</td>
<td>Spatial distribution of agricultural land use</td>
<td>Habitat suitability (HSI) to wildlife species</td>
<td>Two stage non-linear optimization</td>
<td>Vector 1:5000</td>
<td>ArcView</td>
<td>Lonetree wildlife Management Area, North Dakota, US</td>
</tr>
<tr>
<td>Seppelt, 2000</td>
<td>Non-linear differential equation system/agroecosystem process</td>
<td>Planted crop, fertilization</td>
<td>Economic yield, ecological damages</td>
<td>Hierarchical dynamic programming</td>
<td>Vector</td>
<td>Harz forelands, Germany, 2 km²</td>
</tr>
<tr>
<td>Tarp and Helles, 1997</td>
<td>Timber harvest</td>
<td>Sustainable forest management</td>
<td>Simulated annealing (SA), linear programming (LP)</td>
<td>Vector</td>
<td>Vector</td>
<td>Boendermes Hegn, Denmark</td>
</tr>
<tr>
<td>Randhir et al., 2000</td>
<td>EPIC, see Williams et al., 1983</td>
<td>Land use</td>
<td>Water quality erosion</td>
<td>Spatial dynamic programming</td>
<td>Grid GRASS</td>
<td>Experimental watershed</td>
</tr>
</tbody>
</table>
model (number of state variables, degree of non-linearity etc.) and the spatial complexity (size of study area, grid cell size, number of spatially interacting processes). The more complex the simulation model is and the more spatial relationships are considered, the lower are the chances to succeed in the optimization. For such complex models, scenario analysis is usually the only feasible method. Fig. 1 shows a diagram of this relationship.

Scenario analysis compares the outcome of a given number of scenarios, which are identified with possible management strategies. Optimization procedures perform a systematic search over the whole control space automatically. Whereas, optimization tasks require much less effort in preprocessing and formulating the numerous scenario options, their computational complexity is incredibly high. The models described in Table 1 are considered in an optimization context. Therefore, they all required certain simplification or aggregation to allow optimization (Fig. 1). This was achieved either by aggregation of the model or aggregation of the study area, or both.

The only other option would be to improve the optimization procedures. Apparently, there is not much that can be done in this field. Nevertheless, we have tried to combine some well known procedures of optimization in attempt to increase their overall efficiency.

3. Problem formulation

3.1. Study area

For the development of an appropriate methodology for optimization procedures for spatial landscape models we focus on the problem of optimum land use patterns and optimum fertilization in a mainly agricultural region in Southern MD, USA. We have focused our studies on the Hunting Creek Watershed which is located entirely within Calvert County in MD, USA. The 22.5 km² large study area belongs to the drainage basin of the Patuxent River (2356 km²) which is one of the major tributaries of the Chesapeake Bay. Soil types are well drained, mostly severely eroded soils that have a dominantly sandy clay loam to fine sandy loam subsoil (Soil Survey, Calvert County, MD, USA, July 1971, 76 pp.). The annual rainfall varies between 400 and 600 mm. Main land use of the watershed are forest and agricultural habitats. Rapid population growth, development and change in land use and land cover have become obvious features of the landscape.

3.2. Modeling framework

The ecosystem model used for the regional model covers the processes of hydrology (above ground, unsaturated soil zone, groundwater), macrophytes and consumers as well as nutrient cycling (Voinov et al., 2000).

A conventional approach is to regionalize the model based on spatial aggregation to larger units, called elementary landscapes, elementary watersheds, elementary areas of pollution or hillslopes (Beven and Kirkby, 1979; Krysanova et al., 1989; Band et al., 1991; Sasowsky and Gardner, 1991). These units are considered homogeneous and form the basis for the hydrologic flow network. The smallest homogeneous unit may be called ecotope (Naveh and Lieberman, 1984).

If we are to consider scenarios of land use change, generated by the economic considerations, which were not envisioned in the design of the elementary spatial units this approach is inappropriate. The boundaries between spatial units

Fig. 1. Concepts of regional optimization solutions as found in recent literature.
are fixed and cannot be modified during the course of the simulation, which may be somewhat restrictive.

In our approach the modeled landscape is partitioned into a spatial grid of square unit cells. We present the landscape as a grid of relatively small homogeneous cells and run simulations for each cell with relatively simple rules for material fluxing between the cells (Sklar et al., 1985; Burke et al., 1990; Costanza et al., 1990; Engel et al., 1993; Maxwell and Costanza, 1995). This approach requires extensive spatial data sets and high computational capabilities in terms of both storage and speed. Spatial complexity increases cf. Fig. 1. However, the approach allows quasi-continuous modifications of the landscape, where habitat boundaries may change in response to socioeconomic transformations. This is one of the prerequisites for spatial optimization analysis, since it allows one to modify the spatial arrangement of the model endogenously, within the simulation procedures. With this approach, the model builds on the format of a raster-based geographic information system (GIS), which is used to store all the spatially referenced data included in the model.

3.3. Model description

The model is designed to simulate a variety of ecosystem types using a fixed model structure for each habitat type. The model captures the response of macrophyte and algal communities to nutrient concentrations, water and environmental inputs. These processes are driven by hydrological algorithms for upland, wetland and shallow-water habitats. It explicitly incorporates ecological processes that determine water levels or content of surface water and the saturated and unsaturated soil zone, plant production, nutrient cycling associated with organic matter decomposition and consumer dynamics. Therefore, the simulation model for a habitat consists of a system of coupled non-linear ordinary differential equations, solved with a 1 day time step.

The model is hierarchical in structure, incorporating the ecosystem-level unit model that is replicated in each of the unit cells representing the landscape. Although, the same unit model runs in each cell, individual models are parameterized according to habitat type and georeferenced information for a particular cell. The habitat dependent information is stored in a parameter database, which includes initial conditions, rate parameters, stoichiometric ratios, etc. The habitat type and other location-dependent characteristics are referenced through links to GIS files.

The unit models in each cell exchange matter and information across space. Surface and subsurface hydrology define the horizontal fluxes. This joins the unit models together. The spatial hydrology module calculates the amount of water fluxed over the surface and in the saturated sediment. The fluxes are driven by cell-to-cell head differences of surface water and saturated sediment water, respectively. Dissolved and suspended material (nutrients) is carried by water fluxes between cells. At each time step, first the unit model updates the stocks within each cell due to vertical fluxing and then cells communicate to flux matter horizontally, simulating flows and determining ecological condition across the landscape.

This model approach has been used to construct the Hunting Creek Model (HCM), a subwatershed of the Patuxent. The local dynamics in the HCM were similar to those developed in Patuxent Landscape Model (Voinov et al., 1999), but the spatial implementation, defined by the Study Area, and the spatial resolution were different. By focusing on a smaller subwatershed, we could make many more model runs, better calibrate the model, and refine our understanding of some of the crucial ecological processes and spatial flows in the ecosystem. A rather small study area was especially essential for the optimization procedures that require numerous computer runs of the model.

3.4. General notations

The observed region is denoted by a set of discrete grid points \( R = \{(i,j), n_i < i < N_i; m_j < j < M_j\} \). A grid cell of the map is denoted by \( z \in R \). Seven different land use type are considered: soybeans, winter wheat, corn, fallow, forest, cities and rural areas. \( c(z) \) denotes the land use (or habitat type) in cell \( z \). Controllable cells are \( L = \)
\{soybeans, winter wheat, corn, fallow, forest\}. \( R_c = \{z \in R | c(z) \in L\} \) denotes the grid points with controllable cells \( c(z) \in L \). Further general notations are:

\begin{align*}
H(c, z) & \in \mathbb{R} \quad \text{is the yield of crop } c \text{ (if any) harvested from cell } z \\
N(z, t) & \in \mathbb{R} \quad \text{is the amount of nitrogen that escapes from cell } z \text{ at time } t \\
F(c, t) & \in \mathbb{R} \quad \text{is the amount of fertilizers applied for the habitat type } c \text{ at time } t
\end{align*}

Without loss of generality we focus on the estimation of the total required amount of fertilizer. As time of fertilization is a crucial parameter for reduction of nitrogen leached, we use the distribution patterns recommended by the best management practices recommendations for the temporal allocation of the total fertilizer amount. These are similar to the results described in Seppelt (1999) derived from solutions of optimum control problems.

### 3.5. Global performance criteria

Our goal is to find out what is the optimum land use pattern and what should be the strategy of fertilizer application to reduce nutrient outflow out of the watershed and increase yield? For a definition of a performance criterion one has to take into account crop yield, fertilizer application and nutrient outflow. The first two factors are easier to compare if we operate in terms of prices. The revenue from the yield over the whole study area is \( A = \sum_{z \in R} p_H(c) H(c, z) \) where \( p_H(c) \) is the current market price of crop \( c \). The price of fertilizers applied is then \( B = p_F \sum_{z \in R} \sum_{t:1<T} F(z, t) \), where \( p_F \) is the unit price of nitrogen fertilizer. Obviously \( A \) is to be maximized while \( B \) is to be minimized, which means that \( A - B \) is to be maximized. \( A - B \) denotes the ‘economic’ part of the goal function.

There are different ways of modeling the ‘ecological’ part of the performance criterion. One possibility is to take into account the total amount of nutrients generated by all the cells in the study area, \( C = \sum_{z \in R} \sum_{t:1<T} N(z, t) \). This is the distributed nutrient leaching. More realistic, and comparable to measurements of gauging stations is to consider the amount of nitrogen in the outlet cell of the watershed \( z_0 \). This case takes into account the compensation mechanisms of uptake along the pathways of nitrogen while it travels across the watershed and estimate the actual water quality in the river estuary: \( C = \sum_{1<T} N(z_0, t) \).

In both cases \( C \) is to be minimized. The crucial problem is to integrate the ‘ecological’ part \( C \) and the economic part \( A - B \) to a scalar goal function. For this purpose \( C \) is to be expressed in units that can be compared with the dollar measure that we derived in \( A - B \). Without going into any further details at this point, let us simply assume a weighting coefficient \( \lambda \), and formulate the goal function as

\[ J = A - B - \lambda C. \]  

The optimization task is:

\begin{align*}
\text{Task 1:} \quad & \text{Find maps } c^* \text{ and } F^* \text{ which maximize } J \rightarrow \text{max.} \\
\end{align*}

### 3.6. Local performance criteria

A second approach is to define the local performance criteria in each grid cell. This is structurally a different way, because it aims to map the regional goal function onto the processes in a grid cell. The basic idea is to set up characteristic functions, which are part of the performance criterion and are spatially dependent, as part of the goal function.

Let us analyze, how the performance criterion from (Eq. (1)) may be reformulated in this context: the goal function is defined for every grid cell \( z \), as a function of \( z \). Let:

\begin{align*}
A(z) & = p_H(c) H(c, z) \quad \text{be the local profit from crop yield} \\
B(z) & = p_F \sum_{t} F(z, t) \quad \text{be the local cost of fertilizers applied, and} \\
C(z) & = \sum_{t} N(z, t) \quad \text{be the amount of nitrogen leaching produced locally}
\end{align*}
4. Optimization methodology

4.1. Numerical effort

Task 1 and 2 can be classified a combinatorial optimization problem. We are to sort through all the possible combinations of six available land use types over the study area. Assuming a homogeneous land use and discrete stages of possible total fertilizer input, for say six stages $F \in \{0, 25, 50, 75, 100, 150 \text{ kg/ha}\}$, Task 2 leads to $I_2 < |F| |L| = 36$ combinations. Considering that no fertilization takes place for $e \in \{\text{forest, fallow}\}$ we get $I_2 = 26$ combinations.

The number of possible combinations for Task 1 depends on the size of the study area $I_1 = |F|^{|L||R_c|}$. For example, for the Hunting Creek (Voinov et al., 2001) watershed, which is represented by $|R_c| = 1681$ controllable cells of $200 \times 200$ m², there are $I_1 = 3.2 \times 10^{64}$ different land use patterns. For a smaller subwatershed that covers 25% of the total area and $|R_c| = 483$ controllable cells there are still $I_1 = 4.7 \times 10^{53}$ possible land use patterns.

4.2. Grid search strategy on local problem

A simulation period of 551 days is considered. It covers the growth periods of all crops, starting with soybeans and ending with the harvest of winter wheat. Before planting and after harvesting a crop, fallow is assumed to be the land use type of the cell. Twenty minutes processor time is required for one simulation run of the entire model on a Sparc Ultra 10 Workstation. From this follows that a simple search through the entire control space of Task 1 is hardly appropriate.

The first step is to solve Task 2. The approach makes use of the ability of the landscape model formulated within the framework of the Spatial Modeling Environment (SME, see Maxwell and Costanza, 1995) to deal with spatially distributed information and to perform mathematical operations on maps. The terms $A(z), B(z) \text{ and } C(z)$ of the local goal function can be formulated as maps that are calculated using the spatially explicit model.

The solution of Task 2 performs a grid search through the entire control space assuming a homogeneous land use and identical fertilizer amounts for each cell. A series of maps for different combinations of crops and fertilizer application...
tion rates are generated and stored. Maximizing $J(z)$ for every grid cell depending on the pre-calculated maps of the goal functions $A(z)$, $B(z)$ and $C(z)$ solves the optimization problem. The result is a pair of land use and fertilizer maps that optimize the local performance criterion. This pair is then fed into a spatial simulation that is used to calculate the global performance criterion Eq. (1).

4.3. Disturbing a solution: Monte-Carlo’s simulation

One way of testing the results from the local optimization approach is to run a Monte-Carlo’s simulation based on the optimum land use and fertilization pattern. This Monte-Carlo’s simulation ‘disturbs’ the optimum solution stochastically and gives an estimate of how close the local solution is to the unknown optimum.

For the given problem of land use and fertilization optimization the algorithm can be described mathematically by a three stage stochastic process. Let $Z_i(z) \in [0, 1]$ be a random variable. A new land use is generated randomly if $Z_i(z) < p_1$ for cell $z$. This is done by a stochastic variable $Z_z \in \{\text{corn, soybeans, wheat, fallow, forest}\}$ such that

$$P[Z_i(z) = c(z) | Z_i(z) < p_1] = f(c).$$

For every cell $z$ the stochastically generated land use $c$ follows a distribution which is defined by a density function $f(c)$. The density function $f(c)$ is constant for the entire region and may be generated by a stochastic process, started before generating the stochastic land use map. Or, it may be derived from the distribution of a known land use pattern, for instance the optimum solution. With this set up three different types of Monte-Carlo’s simulations can be distinguished:

- $p_1 = 1$, $f(C)$ generated stochastically: land use patterns are generated from scratch, without any knowledge about a possible land use pattern;
- $p_1 = 1$, $f(C)$ derived from known land use patterns such as historic data or optimum local solutions: land use patterns are based on reallocations;
- $p_1 = 0.01x$ and $f(C)$ derived from optimum solution: land use patterns are disturbances of optimum solutions by a certain percentage $x$.

4.4. Genetic algorithm of global problem

As we have seen in the former sections the global optimization problem cannot be solved in terms of a combinatorial optimization problem. The application of iterative procedures, which are usually based on gradient search algorithms may be inappropriate since in many cases the derivative cannot be estimated neither analytically nor numerically. This is because of the complexity of the ecosystem model and the combination of discrete and continuous control variables.

Genetic algorithms (GA) offer a solution to the optimization problem based on the global performance criteria. The first step of GA is to define a representation of the control variables of the optimization problem to a genome. Based on the idea of ‘survival of the fittest’ a stochastically generated first population of a distinct number of individuals runs through an evolutionary process. GA determines which individuals of a population should survive, which should reproduce and which should die. New individuals are created based on the operations of cross over, mutation and gene migration.

An application of GA to an optimization problem requires three steps:

1. Definition of a representation.
2. Definition of the genetic operators.
3. Definition of the goal function.

The goal function for the problem in hand is given by Eq. (1). Common libraries support the second step. We used a C++ Library of Genetic Algorithm Components (GALib), see Wall (1996). The first step, the representation of the land use and fertilization patterns to a genome is defined as follows:

- Each controllable cell $z \in R_k$ defines a single gene $g_k$, $k = 1, ..., |R_k|$. The genome has the length $|R_k|$. Urban and rural cells have no representation in the genome as these are non-controllable cells.
- The location of the gene in the 1-dimensional array genome string is identified with the location of the cell in the grid map $k \rightarrow z = (i, j) \in R_k$. 

The land use type is a discrete attribute of a cell or gene. The fertilization amount can be approximated by a discrete value, see previous section. The control variables are therefore defined by an allele set $L = (c, F(c))$ for each gene.

Before starting the GA an initial population has to be generated, usually performed by cloning a given individual. We used different populations derived from the three stage stochastic process used for the Monte-Carlo’s-analysis. The initial population therefore bases on a stochastic variation of a local optimum land use and fertilizer pattern parameterized by the probability $p_1$.

Based on the GALib-Library the global optimization problem is solved. For each generation the algorithm creates an entirely new population of individuals by selecting from the previous population then mating to produce the new offspring for the new population. Each new individual of the population requires a run of the entire spatially explicit simulation model. The ‘survival of fittest’ strategy is implemented by evaluating the goal function Eq. (1). This process continues until the stopping criteria are met (determined by the terminator).

Fig. 2 summarizes the methodological concept described in a flowchart. There are two main branches which are used. Branch 1 starts with the estimation of characteristic function maps, which are the basis for local optimization. Branch 2 shows, how to work on the optimization problem without any knowledge of an appropriate initial guess of the solution.
5. Results

5.1. Local optimization

We focus on the methodological aspects of the proposed framework. Results in terms of landscape ecological issues will be shortly described in the following section. For detailed discussion of these results see also Voinov et al. (2001).

We start the analysis of the results with branch 1 in the flow chart of Fig. 2. Homogeneous control variables for each possible land use type and a certain fertilizer amount are set up: \( c(z) = c_0 \) for all \( z \in \mathbb{R}^2 \), \( F(z) = F_0 \) for all \( z \in \mathbb{R}^2 \). Running simulations runs within SME for all possible combinations in the step ‘grid search’, we derive maps \( A(z) \), \( B(z) \) and \( C(z) \) which are used to estimate the local optimum solution.

The estimation of local optimum land use maps does not require any computational effort. It sorts through all possible combinations in the maps \( A(z) \), \( B(z) \) and \( C(z) \). This easily allows parameter studies for the weighting parameter \( \lambda \). Fig. 3 shows the results of a parameter study for the weighting parameter \( \lambda \). Fig. 4 shows three maps of optimum land use derived out of this parameter study: optimum land use patterns for the \( \lambda \)-values 0.0 (upper left), 0.1 (upper right), and 5.0 (lower left) are displayed.

- A zero value of \( \lambda \) leads to a pathologic solution: the optimum solution is to plant the most valuable crop in the entire study area. Only villages, urban area and open water remains the same (non-controllable cells).
- An increase of \( \lambda \) introduces forest into the land use pattern. The more nutrient outflow is ‘punished’ by an increase of \( \lambda \), the higher is the fraction of forest in the study area.
- With an increase of \( \lambda \) agricultural cells change to crops with a better nutrient-up-take/yield-efficiency. This depends of the market prices of the crop.

Due to the minimal computation effort, these steps are embedded in the GIS Front end ArcView to offer simple result visualization. Fig. 4 shows a screen copy of the ArcView display with a parameter study of the land use distribution in the Hunting Creek Watershed.

5.2. Monte-Carlo’s simulations

An analysis of these results can be performed by a Monte-Carlo’s simulation. Fig. 2 shows Monte-Carlo’s simulations in two boxes in the mid column:

- Monte-Carlo’s simulation ‘from scratch’ correspond to the first box of branch 2, compare first item in section above. It performs an analysis of the variabiliy of the entire process and sets up an initial population for the genetic programming algorithm.
- The step after local optimization, which corresponds to the reallocation \( p_1 = 1 \) or the disturbance of an optimum solution \( p_1 < 1 \), item 2 and 3 of above section.

Fig. 6 summarizes the results of a couple of different Monte-Carlo’s runs. We used a smaller sub watershed for these analyses. This allowed us to generate more realizations. The first column in Fig. 6 shows histograms of the global goal function results according to Eq. (2). The goal function values are normalized by the goal function value derived by the local optimization. Values below unity denote simulation runs...
Fig. 4. Local optimum land use maps for $\lambda = 0.0$ (a), 0.1 (b) and 5.0 (c).

where the global goal function returns values below the local optimization. Values above unity denote that the local solution was improved. The second column shows the histogram of the yield in the study area in U.S. $/m^2$ for comparison.

Row one can be identified as Monte-Carlo’s simulation from scratch: the distribution of land use types $f(c)$ as well as the land use type and the fertilizer amount for each grid cell are generated by random. The second row derived $f(c)$ from the local optimization distribution. Row three and four of Fig. 3 disturb the local optimization land use pattern with the probability $p_1 = 0.1$ and 0.01. Obviously, a stochastic generation of land use patterns hardly identifies a map, which is optimum in terms of the performance criterion. From the last two rows of Fig. 6 one can derive, that an increase in the probability $p_1$ immediately leads to solutions which are far away from the solution from local optimization. The local optimization approach seems to be very close to a global optimum. However, there are land use patterns which are ‘better’ in terms of the global optimization. Are these land use patterns the ones that take into account neighborhood relationships of the control variables?

5.3. Statistical analysis

What are the driving parameters for the optimum solutions? The question can be answered by a simple bivariate correlation analysis based on the resulting land use and fertilizer maps and the spatial input data of the model. Table 2 summarizes the results of four correlation analysis studies of the optimum solutions to the set of weights $\lambda = 0.0, 0.1, 0.2$ and 1.0. However, the sample size is high (1690) we used non-parametric correlation according to Spearman–Rho (Davis, 1984) because a normal distribution of the resulting
Table 2
Correlation analysis of local optimization solution to underlying spatial data

<table>
<thead>
<tr>
<th>Variable</th>
<th>Porosity</th>
<th>Infiltration rate</th>
<th>Field capacity</th>
<th>Percolation rate</th>
<th>Hydrologic conductivity</th>
<th>Elevation</th>
<th>Aspect</th>
<th>Slope</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \lambda = 0.0 )</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>( c(z) ) Correlation</td>
<td>0.046</td>
<td>-0.28</td>
<td>0.20</td>
<td>-0.44</td>
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<td>-0.035</td>
<td>0.110**</td>
<td>0.197**</td>
<td>-0.075**</td>
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<td>-0.049*</td>
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<td>0.000</td>
<td>0.002</td>
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<tr>
<td>( c(z) ) Correlation</td>
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<td>-0.155**</td>
<td>0.134**</td>
<td>-0.178**</td>
<td>-0.199**</td>
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<td>0.413**</td>
<td>-0.471**</td>
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<td>-0.086**</td>
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<td>0.000</td>
<td>0.001</td>
<td>0.487</td>
<td>0.688</td>
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* Significant correlation according two-sided significance level 0.005 (Spearman–Rho).
** Significant correlation according two-sided significance level 0.01 (Spearman–Rho).
parameters cannot be assumed. Input data maps are the soil and the elevation maps. Parameters of the soil map are porosity (m³ pore space per m³ sediment), infiltration rate (m/day), field capacity (m pore space per m sediment), percolation rate (m/day), horizontal hydrologic conductivity (1/day). From the elevation map the aspects and slope are derived using GIS functions.

One general result is, that the fertilizer application always correlates with the habitat type: each crop gets its specific optimum amount of fertilizer.

Setting $\lambda = 0.0$ neglects any ecological issues of agricultural production and fertilization. The optimum solution is a land use map with the most valuable crop and a high fertilizer amount. The correlation analysis shows, that almost none of the important parameters for nutrient transport in soil are responsible for the land use map.

An increase of the $\lambda$-value shows significant correlation to the parameters of the soil map. For $\lambda = 1.0(z)$ and $F(z)$ show significant correlation with all parameters of the soil map. Weak correla-

Fig. 5. Screen shot of ArcView front end with the local optimization project.
tions are also identified to the parameters of the elevation map, especially to aspect and slope. This shows that spatial relationships (to neighborhood cells) find their interpretation in the locally optimum solution from the spatially explicit model!

Note that due to the large sample size, a small sample set is sufficient for a significant correlation. In general all correlation values are low. However, statistical analysis gave a validation of the derived results.

5.4. Genetic algorithms

The only way to answer the question about the importance of neighborhood relationships in the control variable maps is to set up an optimization procedure which can uses Eq. (2) for assessment. As we have seen from the results of the Monte-Carlo’s simulation, the application of GA based on an initial population from scratch will fail, because the variability of a population from scratch is much too broad. GA needs too much iterations to converge to the solution we derived by the local optimization approach (compare to Fig. 2 upper right).

We used a smaller subwatershed of the Hunting Creek for a detailed study of this behavior. Fig. 5 displays the convergence process of a GA run from scratch and the GA run from local optimum (smaller graph). Note, it took 300 generations (4500 simulation runs) to achieve 80% of the goal function value. For this reason the local optimum solution is used for the generation of the initial population, see Fig. 2 (lower part, mid column).

Configuring parameters of GA algorithms is more an art than a science (Wall, 1996). From the former results we can generate certain rules for the parameterization: a too broad variety in the initial population takes us away from the optimum. We set $p_1 = 0.01$ for the stochastic generation of the initial population. This has to be assured within each step when generating a new population: mutation probability should be much smaller than $p_1$, cross-over population should be equal to zero. To enable modifications in the population we set migration probability to a high value (0.9). The graph in Fig. 7(b) shows the results of the GA run started from the local optimum solution. The GA process clearly separates from the initial population and improves the optimum solution by 2%.

What are the changes compared to the local optimum solution? We compiled two maps to show the differences in each grid cell based on the best generation of GA set up by 15 individuals. Fig. 8 shows the results. The map in Fig. 8(a) shows the average fertilizer difference. The map in Fig. 8(b) presents the modified land use cells.

Only a small number of cells are changed: 43 out of 513 cells (8%). The distribution of land use types stayed the same. The global optimization by GA performed a reallocation of habitats. We expected a couple of solutions, which can improve the local solution. A complex problem like this might have multiple solutions. This would have led to various realizations (of habitat and fertilization maps) which change different cells compared to the initial solution from the local optimization. However, the map (b) shows that nearly all of the individuals in the best generation modified the same grid cells. Most of the modified cells belong the class where more then 13 out of 16 individual changed the cell in the same way.

An explanation why these are the crucial cells is hard to derive by statistical approaches, however that would allow further improvement of spatial optimization. Due to a broad spectrum of input data/maps and due to a very complex network of dynamic and spatial process in the simulation model, no significant correlation can be identified. Using principle component analysis we were not able to reduce state space for analysis. One possible approach is to perform a bivariate correlation of $c(z_0)$ and $F(z_0)$ to the neighborhood cells, (north-east, north, ..., south-west $c(z_0)$). Two topics make us expect illusory correlations: first, analysis of the entire region, using every grid cell (and its neighbors) as a repetition just gives a general answer, which is mainly driven by a global aspect of the global slope of the catchment. Second, SME uses linkages between cells which are no direct neighbors for the hydrological sub module (Voinov et al., 1999).
6. Outlook and discussion

Note that the only simplification, which has been introduced to derive a solution to this very complex optimization task, was to assume a weak dependency of the single parameters of the control variable maps upon the neighborhood. This allows us to set up a characteristic function for each grid cell of the model. In this contribution we focus on simple goal functions which assess the state of a certain grid cell only. However, this approach may be extended by the integration of the neighborhood of a given grid cell. For instance, if $R(z_0) = \{z \mid z \text{ borders } z_0\}$ denotes the neighborhood of $z_0$, the proposed framework is capable of dealing with goal functions defined on $R(z_0)$. This allows the assessment of habitat structures in the goal functions. Habitat suitability of certain species may be assessed with this extension.

The core question which lays behind the consideration of neighborhood relationships of the control input in ecosystems models, is how much does the synergistic effect of land use change matter for a given watershed? It is an exciting question to be investigated in the framework of optimization, see for example (Müller, 1998).

Building upon the background of the Spatial Modeling Environment the proposed framework is capable of answering different questions of landscape management. Run time solutions for optimization problems can be derived (for example in the ArcView front end) if it is possible to set up a local optimization criterion and if a global...
Fig. 7. Development of global performance criteria values during Genetic programming process: (a) the GA process ‘from scratch’; (b) the GA process started from a local optimum solution with a stochastically ‘disturbed’ of ‘mutated’ population.

Fig. 8. Analysis of GA results. The maps show the difference from one generation (15 individuals) of the GA to the local optimum maps for the sub watershed: (a) fertilizer amounts; (b) this maps counts how many individuals of the population have a different land use type than the local optimum solution. The small map in the center displays the extent and location of the subwatershed within the Hunting Creek watershed.
solution is not required. In this case the computation effort does not significantly depend on the size of study area. On the other hand, the use of GA for global optimization offers the ability of parallelization in the optimization process. In summary, this framework seems to be applicable to a large class of problems in landscape ecology. It offers an integration of simulation models and environmental management.

Acknowledgements

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References


