

Using Neural Network Techniques to Optimize Agricultural Land Management for the Minimisation of Nitrogen Leaching

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Abstract: Managing a catchment for drinking water supply with a high proportion of agricultural land use is a difficult task if one has to maintain a reasonable well balance between water quality demand and consequent restrictions for the farming industry. In this paper we present a neural net based method for finding good approximations to solutions of this problem. This method is capable of "inverting" a hydrological model to identify land use scenarios that match leaching criteria defined for establishing a certain water quality level in the stream best. The method allows not only to simulate land use scenarios like hydrologic models do, but can search systematically for land use scenarios that fulfill specified criteria without worrying about complexity of combinational optimization.

Keywords: Groundwater; Modelling; Neural Network; Optimization; Water Quality

1. INTRODUCTION

In regions with little groundwater a major resource for the supply with potable water are reservoirs. Before Germany was reunited reservoirs in the eastern part were often built without accounting for the specific land use conditions in the contributing area. Reservoirs were even established in catchments which are mostly used for agriculture. As a consequence, a water quality problem results which can be traced back mainly to two influences: diffuse nutrient leaching from farmland on the one hand and settlement waste water untreated or clarified inadequately on the other. In order to solve this problem novel catchment management strategies have to be developed.

A reservoir system showing this controverse problem in a typical manner is the Weida-Zeulenroda-Lössau system located in eastern Thuringia (a federal state of Germany) which is managed by the Thuringian reservoir administration (TTV). Two thirds of the catchment of the reservoir is used for intensive agriculture [Arbeitsgemeinschaft Trinkwassertal-sperren e.V., 2000].

At the moment the diffuse nitrogen input from agricultural land is compensated by field-specific measures. These contain land use restrictions

which are based on legal rules and individual contracts between the TTV and the farmers. However, land use restrictions have to be compensated financially. The TTV has only a limited annual budget for compensation payments and is therefore interested to make the best use of it. They intend to impose restrictions only where it is necessary and want to control as well whether the farmers really restrict to the laws and keep in line with individual contracts.

The TTV supervises land use restrictions with the help of the following procedures:

1. questioning of the farmers about the land use management of the individual fields,
2. N_{\min} analyses of the individual fields and
3. measurement of the nitrogen concentration and the water amount at the main inflow of the Zeulenroda reservoir.

From the farmers answers to the questionnaires N -balances are derived and compared with the N_{\min} -analyses. The significance of the N_{\min} -analyses is low because only five samples are taken per field (regardless of its size) and only once per year [Thres et al., 1998]. A further difficulty is the fact that gauge measurements at the main inflow only allow statements about its catchment area and not about specific fields of this area. In addition these procedures only allow an evaluation of land use as

a whole and at a certain point in time. As a consequence an inspection of the efficiency of individual measures on different fields is hardly possible. Therefore it is very difficult to derive forecasts for alternative land use practices by means of past land use data.

2. THE IWES PROJECT

In order to find a solution to this management problem a research project was started in cooperation between the TTV and the University of Jena (Germany). The overall objective of this project is the development of an integrated decision support system for watershed management (IWES = Integriertes wasserwirtschaftliches Entscheidungs- Unterstützungs-system). The task of IWES is the support of TTV managers who are responsible for the generation of land use scenarios. This support should ensure that only land use scenarios characterized by the following properties are generated:

1. Minimization of the nitrogen concentration in the reservoir in order to
 - observe the legal boundary values for nitrogen concentrations and
 - reduce the expenditures for the management of the water body of the reservoir.
2. Minimization of the payments for the farmers.

The generation of land use scenarios which fulfill both objectives equally well can be understood as an optimization problem. Due to the enormous range of the parameters which must be considered this is a very difficult problem whose exact solution is intractable in practice. This paper therefore will present a procedure that finds good approximations to the optimal solutions.

3. MODEL PROPERTIES

An optimization procedure of the described kind cannot be built without knowledge about the relationship between the field-specific land use on the one hand and the nitrogen concentration in the reservoir on the other. For the computation of this relationship the water and nitrogen modelling tool WASMOD [Water and Substance simulation MODEL, Reiche, 1996] is used. Since the measures for nitrogen reduction are applied on single agricultural fields the model must not only operate on the catchment scale but also on the plot level. WASMOD can do both of this simultaneously. It allows to describe the nitrogen discharge as a function of soil, relief, land use and climate. An application of WASMOD presumes that GIS-layers of soil, relief, land use, river network,

subcatchments and relief units (slopes, sinks and plains) are assembled to smallest common geometries (SCG). A simplified routing scheme is shown in Figure 1. The model calculates the water and substance balances in each of the SCGs and routes the water and nitrogen flux to the next polygon where the calculation starts again. This sequence ends at the receiving stream where all fluxes are added up to the model output respectively catchment outlet.

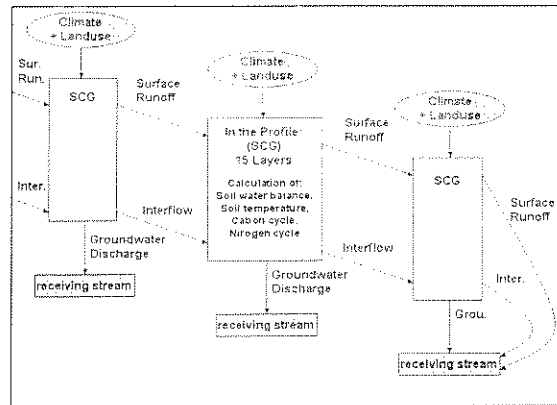


Figure 1. Model routing scheme of WASMOD.

Since WASMOD is able to directly model physical processes it is especially suited for the simulation and evaluation of land use and climatic scenarios.

4. STUDY AREA

The catchments of the reservoirs of Weida-Zeulenroda and Lössau are located in the Thuringian Slate Mountains and have an area of about 249 km². The reservoirs of Zeulenroda and Weida drain via the river Weida into the river Weisse Elster, and the Lössau reservoir drains via the river Wisenta into the river Saale. A tunnel viaduct connects both dams with each other. It permits water to be directed from the Lössau reservoir into the dam of Weida-Zeulkenroda and thus combines the two separated catchments into a single one. The altitude in this catchment varies between 270 and 650m over NN. Located in the rain shadow of the Thuringian Forest the annual average precipitation is only approx. 640mm. The annual average temperature is also low with less than 7° C. The geology is dominated by clay shists and eruptive rocks. The soils developed from this bedrock range from shallow rankers to well developed cambisols and fluvisols in the river valleys. The predominant part of the area is used for agriculture (67%) and forestry (27,5%). Settlements and traffic areas have a portion of 5,2% and water areas cover about 0,3% of the catchment [Thüringer Talsperrenverwaltung, 1999].

5. MODEL RESULTS

In Figure 2 the simulated and observed runoff for the year 1976 at a daily time step is shown ($R^2 = 0.72$). The baseflow during the drought is too high but the general dynamic is well represented. However further model improvements and validations are still in progress.

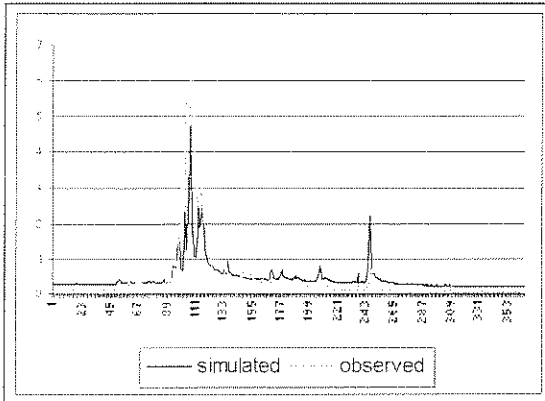


Figure 2. Simulated and observed runoff in m^3/s of the gauge Laewitz (ca. $100km^2$).

Figure 3 and Figure 4 show the distribution of nitrogen output per year in the two main flow pathways. The interflow (Figure 3) represents the lateral component and the groundwater discharge (Figure 4) the vertical one.

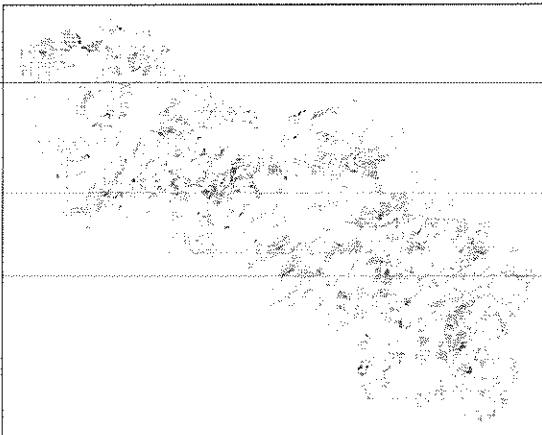


Figure 3. Nitrogen output due to interflow (15299 SCGs) within the catchment of the gauge Laewitz. The darker colours indicate higher output.

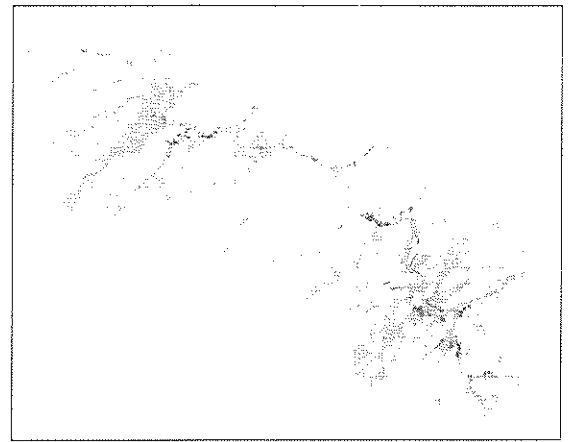


Figure 4. Nitrogen output due groundwater discharge of the catchment of the gauge Laewitz (ca. $100km^2$).

The groundwater discharge is mainly dominated by the geology. The river valleys are identifiable and the eruptive bedrock can be seen. This result is mainly caused by the more permeable rock. For the case of interflow discharge (Figure 3) the picture becomes more patchy. It is caused by different crops on various soils, bedrock and topography conditions.

6. THE OPTIMIZATION PROBLEM

In order to exert influence on the nitrogen balance of the reservoir, the TTV attempts to restrict the land use in the catchment area in a way that ensures that the amount of nitrogen from agricultural areas, which ends up in the reservoir is minimized. As mentioned above, these restrictions often involve compensation payments. Restrictions must therefore be exercised in a way that maximizes use with minimal costs. For this reason a procedure which can rate the specific fields according to their relevance for the nitrogen balance of the reservoir is at the heart of the decision support system currently under development.

A procedure often applied in practice is characterized by the creation of reasonable land use scenarios which can be accounted and managed with the available financial resources. The intention of this strategy is to find the scenario which causes a minimum total nitrogen input into the reservoir. For a given configuration of land use on the specific fields this input is estimated with the help of hydrological modelling. However, the number of scenarios which must be examined of course is very large. Additionally, modern hydrologic models are often such fine grained that it is hardly possible to consider all interesting scenarios with these models. We therefore developed a procedure that does not attempt to

always find exact solutions to this optimization problem. Its primary objective is to identify very good approximations to the exact solutions.

7. THE NEURAL NETWORK APPROACH

Our optimization procedure uses the concept of neural networks [Gallant, 1995] to do its job. Neural networks consist of simple autonomous processing units (neurons) which are joined by directed communication paths (edges). Each edge is parametrized with a numeric value (weight) which specifies the strength of the connection between the connected neurons and thus the ability to pass signals. A so-called activation function is assigned to each neuron enabling it to calculate an output signal dependent on signals received over incoming edges. This output is then propagated to neighbouring neurons. A neural net can therefore be seen as a machine which computes a function that is characterized by a possibly large set of parameters (represented by the weights). There are learning algorithms that can fine tune the parameters of a given neural net such that the function computed by this net approximates a given function as good as possible. Neural nets are therefore especially suited to solve hard optimization problems.

7.1 Representing the Catchment

Network topology: For the segmentation of the catchment we revert to the smallest common geometries (SCG) used by the model WASMOD. We use a modified Backpropagation network to represent the catchment. It possesses one neuron in the input layer and one neuron in the output layer. The catchment outlet is represented by the output neuron. The remaining neurons represent the catchment area in the following way:

1. each SCG is represented by a unique (SCG) neuron,
2. for an hydraulic linkage between two SCGs there is an (interflow) edge between the neurons representing the SCGs,
3. for an hydraulic linkage between a SCG and the catchment outlet there is an (groundwater discharge) edge between the corresponding neurons,
4. the input neuron is connected via (fertilization) edges to all neurons except the output neuron.

Since WASMOD distinguishes between two main runoff components (namely groundwater discharge and interflow), each SCG neuron possesses exactly two outgoing edges: via the interflow edge it is connected to another SCG neuron or (in special cases) the output neuron. The groundwater discharge edge connects the neuron to the output

neuron. We can distinguish between the following types of hydraulic linkages that are represented by edges in the network:

1. surface and interflow runoff between SCGs (class E1),
2. groundwater discharge from the SCGs into the catchment outlet (class E2) and
3. surface runoff and interflow from the SCGs into the catchment outlet (class E3).

The edges from the input neuron to SCG neurons (class E4) represent external nitrogen inputs (fertilization etc.) which are dependent on the current land use management of the SCGs.

Activation function: In order to determine the activation function of each SCG neuron sampling points of the nitrogen discharge function for the SCGs are calculated by WASMOD. The discharge function has the following properties:

1. It maps the amount of nitrogen which is applied to the SCG to the amount of nitrogen delivered from the SCG.
2. It takes into account all further location-specific characteristics of the SCG which are modelled with WASMOD.

The sampling points form the basis for a linear regression which is used to approximate the activation function of the neuron representing the SCG. The input and output neuron are assigned the identity function as activation function since they just have to transmit incoming data.

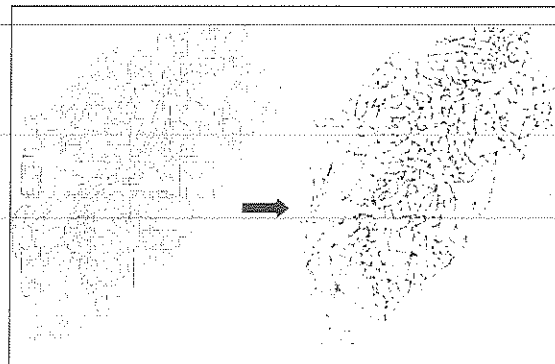


Figure 5. Neural Network – derived from the topology of a catchment area.

Edge weights: The weights at the outgoing edges of the input neuron (E4) correspond to the nitrogen input which is supplied to the SCGs (e.g. by fertilization). They are the parameters which will have to be optimized later.

The weights at the outgoing edges of the SCG neurons are computed with the help of WASMOD. They reflect the relevance of the discharge components of the SCG and thus the proportions of the transmitted nitrogen quantities.

Figure 5 shows a network which was computed from the data of a subcatchment area with 762

SCGs. In order to simplify the picture only edges of the class E1 are shown. As can be seen the spatial topology of the catchment is maintained in the net.

7.2 Setting up the Network

The catchment area described in chapter 4 was used to set up our network structure in the way described above. For the determination of the edge weights and activation functions we created for each crop 5 scenarios with uniform nitrogen inputs on all SCGs:

- scenario 1: no fertilization
- scenario 2: 50% of crop typical (normal) fertilization
- scenario 3: normal fertilization
- scenario 4: 150% of normal fertilization
- scenario 5: 200% of normal fertilization

Since we wanted to represent a common crop rotation in our sampling points as realistically as possible we used a 5 year time period with that typical crop rotation to simulate the nitrogen discharge with WASMOD. Within each year the land use on all SCGs was the same for all scenarios. Afterwards we computed average nitrogen discharge values for each SCG from the results. This also made sure that climatic fluctuations were not over-represented in our model results.

With the resulting 5 sampling points per SCG we set up the activation functions of all SCG neurons as well as the weights on all edges of classes E1, E2 and E3. Afterwards we assigned values to all weights of edges of class E4 according to the fertilizer inputs on the SCGs taken from an actual scenario.

According to the number of SCGs in the catchment the resulting network contained 15301 neurons and 45897 edges. As activation functions for the neurons we chose 2nd-degree polynomials (Figure 6).

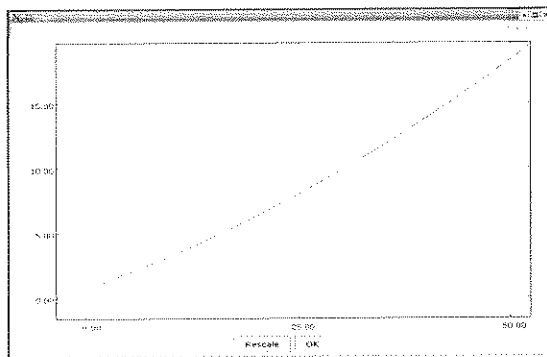


Figure 6. Example of a typical neuron activation function with sampling points, showing nitrogen discharge (y-axis) for given nitrogen input (x-axis).

7.3 Solving the Optimization Problem

The network representing the catchment area can be seen as a restriction of the WASMOD model. Regarding the fertilization regime, it can perform the same simulations of land use scenarios as WASMOD: after a value of 1 is applied to the input neuron and propagated through the net, the activation of the output neuron corresponds to the amount of nitrogen which is introduced into the catchment outlet from the entire catchment area. The specific land use scenario is represented by the parameters of the edges connecting the input neuron to the SCG neurons, i.e. the fertilization prescriptions for the individual SCGs.

Contrary to WASMOD our neural net representation of the catchment is not only able to simulate land use scenarios but also to systematically search for changes in land use scenarios to establish certain desired properties. This search is performed with a modified Backpropagation procedure. Backpropagation [Rumelhart et al., 1986] is a neural net learning method that attempts to determine the parameters of a neural net in such a way that a given (failure) function on the output neurons of the net is minimized.

The failure function in our case is given as a function (i) of the nitrogen input into the reservoir and (ii) of the costs involved by the restrictions that the TTV imposes on the land use (e.g. the compensation payments for fertilization reductions). Formally, the failure is the (squared) difference between the actual and the desired output of the output neuron. It is used to compute a change in the parameters of the neural net (for our procedure just the parameters that describe the connections from the input neuron to the SCG neurons, class E4). This change represents how to modify the land use scenario the optimization was started with. The parameters are changed repeatedly until the failure is sufficiently small.

Our learning procedure differs from the standard Backpropagation algorithm in the following way: After each step of determination of the partial errors on all SCG neurons we update only the weights of edges of class E4. As a consequence from that modification, our learning procedure possibly finds another local minimum of the error function than the standard Backpropagation procedure does. But it works correctly assuming the fact that the weights of classes E1, E2 and E3 must not be changed since they describe some statical properties of our catchment.

To test our network, we assigned the value 1 to the input neuron of the network described in section 7.2 and propagated that value through the net. The activation of the output neuron amounted to 74000 kg N and deviated from the total nitrogen

discharge computed by WASMOD by approximately 10%. The reason for that deviation is the inaccuracy of our activation functions. Nevertheless for our demands that accuracy is sufficiently high.

Afterwards we started the optimization procedure described above. Our target output from the neural net amounted to 60000 kg N. Thus, the failure of our net (difference between desired and actual output) amounted to 14000 kg N. Applying our modified Backpropagation procedure to the net, the failure became 0 (i.e. nitrogen output reached the target value) after 61 steps of weight adjustment. The changes of the weights and thus the changes in external nitrogen inputs on the SCGs to establish that reduction are shown in Figure 7.

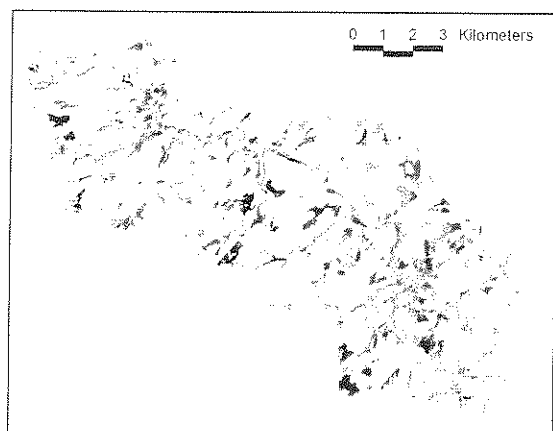


Figure 7. Fertilization changes computed by a modified Backpropagation algorithm. The darker colours indicate higher changes.

Our optimization procedure ensures that the external nitrogen inputs (i.e. the fertilization actions) are reduced especially on those SCGs, which have a high relevance for the nitrogen load of the catchment outlet. As a result the financial resources formerly used for compensating reduced fertilizations on irrelevant fields can now be used more efficiently to compensate fertilizer reduction on those fields which have the highest relevance for the system.

8. CONCLUSION

We have presented a new approach for the optimization of a given land use scenario of a catchment in order to obtain a specific nitrogen output from that catchment. Our approach includes the transformation of a complex hydrological model into a neural network. This neural network is a computational model representing the relationship between the nitrogen input resulting from the land use scenario to the nitrogen output into the catchment outlet. Contrary to classical

hydrological models this neural net can be used to tractably search for optimum land use scenarios wrt N-input into the reservoir. First applications indicate that a suitably designed neural network learning procedure will find near optimal solutions to the problem if the starting land use scenario is reasonable. Therefore the presented optimization procedure is an important step towards an integrated computer based decision support system design for watershed management.

9. ACKNOWLEDGEMENTS

We would like to thank the Thüringer Talsperrenverwaltung (TTV) for funding of this project and especially acknowledge the friendly cooperation with our colleagues from the TTV who are involved in this project.

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