A Neural Network Approach for the Optimisation of Watershed Management

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Abstract: Managing a catchment with a high proportion of agricultural land use for the supply of potable water supply is a difficult task if one has to maintain a reasonable balance between water quality demand and consequent restrictions for the farming industry. In this paper we present a neural net based method for finding optimized approximations to solve 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, Nitrogen Leaching

1. INTRODUCTION

In regions with little groundwater storage 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 with intensive agriculture. As a consequence, a water quality problem results which can be traced back mainly to two impacts: diffuse nutrient leaching from farmland on the one hand and improperly treated waste water from settlements on the other. In order to solve this problem innovative and flexible 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 federal state of Germany, which is managed by the Thuringian reservoir administration (TTV). Two thirds of the reservoir’s catchment of is used for intensive agriculture (Arbeitsgemeinschaft Trinkwassertalsperren e.V., 2000).

At present the diffuse nitrogen (N) input from agricultural land is compensated by field-specific measures. These contain land use fertilization 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. As the TTV has only a limited annual budget for compensation payments it is therefore interested in making the best use of it. They intend to impose restrictions only where it is necessary and want to control whether the farmers really restrict to the restrictions and keep in line with individual contracts.

The TTV supervises such restrictions with the help of the following procedures:

1. questioning of the farmers about the land use management of the individual fields,
2. mineralised nitrogen soil analyses (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 farmer’s answers to the questionnaires N-balances are derived and compared with the N_{min}-analyses. The significance of the N_{min}-analyses is limited because only five samples are taken once a year per field regardless of its size (Thres et al., 1998). A further difficulty is the fact that gauge measurements at the main inflow only reveal lumped information from the catchment area in total and not from individual farm fields. In addition these procedures only permit an evaluation of land use 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 launched 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 called IWES (Integriertes wasserwirtschaftliches Entscheidungs-Unterstützungssystem, Fink et.al., 2001). IWES is supposed to support TTV managers who are responsible for the generation of land use scenarios. This support should ensure that only land use scenarios characterised by the following properties are generated:

1. Reduction 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 is representing the project's 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. 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 (Figure 1). 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 transfer from the Lössau into the Weida-Zeulenroda reservoir, thus merging both catchments into one management unit. 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).

Figure 1. The location of the Weida-Zeulenroda and Lössau catchment.

4. THE HYDROLOGICAL MODEL

4.1 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, 1994/1996) is used. Since the measures for nitrogen reduction are applied to single agricultural fields the model must not only operate on the catchment scale but also on the plot level. WASMOD simulates both simultaneously and calculates 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, sub-catchments and relief units (slopes, sinks and plains) are assembled to smallest common geometries (SCGs). They in turn are linked by their topology and water and solute transport is routed between them as shown in Figure 2: The model calculates the water and substance balances in each of the SCGs and routes the fluxes to the next downstream polygon where the calculation starts again. This process ends at the receiving stream where all fluxes are added up. The sum represents the model output for the whole catchment.

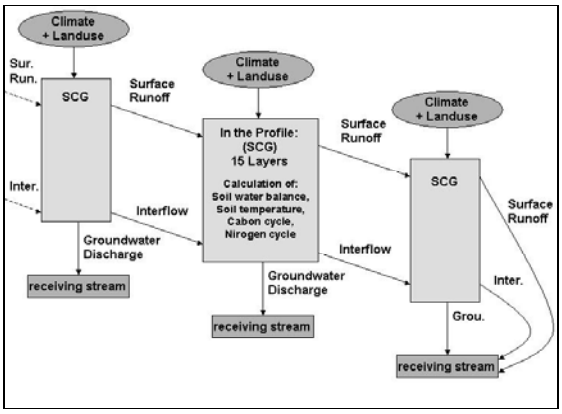

Figure 2. Model routing scheme of WASMOD.

WASMOD was developed to simulate this interactive process dynamics and therefore is the appropriate mean to evaluate the impact of land use change and scenarios of climatic change.

4.2 Results

In Figure 3 the simulated and observed runoff for the year 1976 at a daily time step is shown. The coefficient of determination (R^2) for our calculation amounts to 0.72. According to the simulation the base flow during the drought is too high but the general dynamic is well represented. However, we will furthermore improve the model performance and validations is in progress.

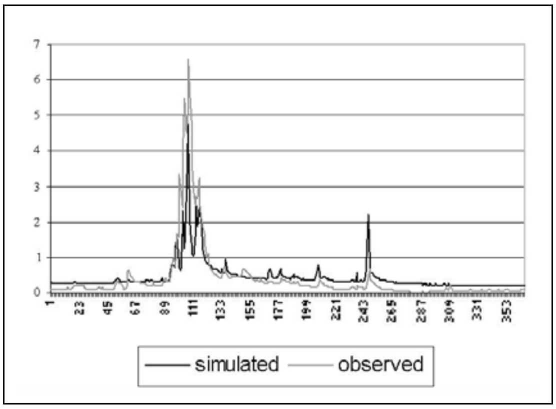

Figure 3. Simulated and observed runoff in m³/s of the gauge Laewitz (ca. 100km²).

Figure 4 and Figure 5 show the distribution of nitrogen output per year in the two main flow pathways: (i) Interflow (Figure 4) represents the lateral component and (ii) groundwater discharge (Figure 5) the vertical one.

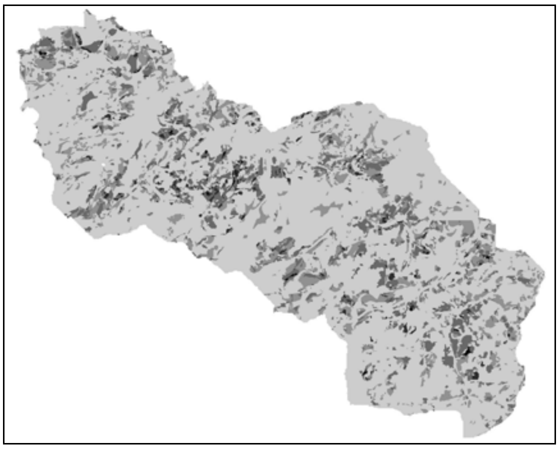

Figure 4. Nitrogen output due to interflow within the catchment of the gauge Laewitz (approx. 100km²). The darker colours indicate higher output.

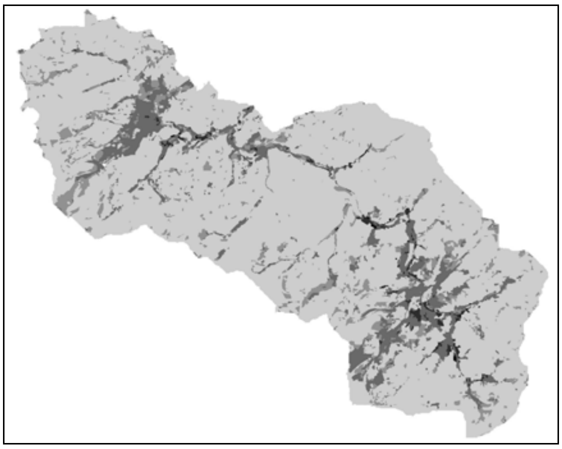

Figure 5. Nitrogen output due to groundwater discharge of the catchment of the gauge Laewitz.

Groundwater discharge is mainly controlled by the physical properties of the geological strata. The river valleys as well as the eruptive bedrock can be identified, as the underlying rock is more permeable. For the case of interflow discharge (Figure 4) the picture becomes more complex. It is caused by different crops on various soils, bedrock and topography conditions.

5. THE OPTIMIZATION PROBLEM

As the main objective of the TTV is to reduce nitrogen inflow into the reservoir the TTV intends to reduce the nitrogen fertilization and consequent leaching to a threshold value the water body is able to compensate by its internal biochemical dynamics. To compensate farmers income losses compensation payments must be done. Land use restrictions therefore must be agreed on in such a way that reduction of nitrogen leaching is maximised and consequent compensation payment is minimized. Consequently the core element of DSS developed is focusing on relevance of nitrogen reduction of the individual fields in relation to the threshold value set for the reservoir input.

The technique applied therefore comprises “real world” land use scenarios which can be accounted for by financial resources available for compensation. The intention of this strategy is to find the “best” land use scenario to produce the leaching threshold into the reservoir. The research problem is twofold: (i) there is a large number of scenarios to be examined, and (ii) hydrologic models are often too fine grained that it is hardly possible to consider all possible scenarios. 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. For a given configuration of land use on the specific fields this leaching is simulated by WASMOD.

6. THE NEURAL NETWORK APPROACH

Our optimization procedure applies the concept of neural networks (Gallant, 1995). Neural networks consist of simple autonomous processing units (neurons) which are joined by directed communication paths (edges). Each edge is parameterised 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 the input 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 characterised 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 (in our case the nitrogen threshold value defined by the TTV) as good as possible. Neural nets are therefore especially suited to solve optimization problems.

6.1 Representing the Catchment

Network topology: For the segmentation of the catchment we refer to the SCG used by WASMOD as modelling entities. We applied a modified Backpropagation network to represent the catchment. It possesses one neuron (fertilizer input) in the input layer and one neuron in the output layer, the latter is representing the catchment. 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 (fertilisation) 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 runoff and interflow 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 (fertilisation etc.) which are dependent on the current land use management of the SCGs.

Activation function: The activation functions represent approximations of the nitrogen discharge functions of the SCG neurons. In order to determine that function for each SCG neuron sampling points of the nitrogen discharge 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.

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 fertilisation). They are the parameters which will have to be optimised later on by our procedure.

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 6 shows a network (right part) which was computed from the data of a subcatchment with 762 SCGs (left part). 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, i.e. the position of each neuron in the figure corresponds to the position of the center of area of the associated SCG in the catchment.

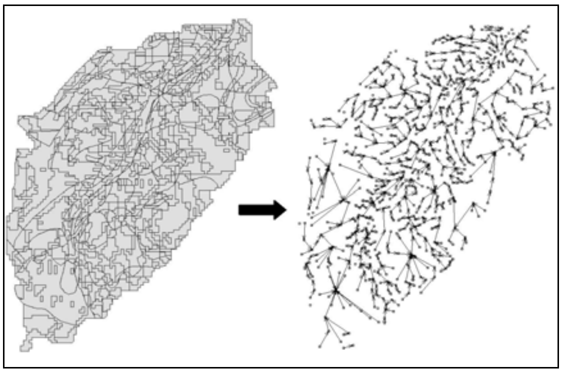

Figure 6. Neural Network – derived from the topology of a catchment area.

6.2 Formal NN Representation

The neural network represented in the last section can be formally described as follows.

Definition: The Hydro-NN is a tuple $(U, W, A, output, NET, ex)$ with:

1. U is a set of neurons with:
   (a) $U = U_1 \cup \ldots \cup U_n$ with $n \geq 3$,
   (b) $U_i \neq \emptyset$ for $i \in \{1, \ldots, n\}$,
   (c) $U_i \cap U_j = \emptyset$ for $i \neq j$,
   (d) $U_1 = \{u_{in}\}$ is the *input layer* with the input neuron u_{in},
   (e) $U_n = \{u_{out}\}$ is the *output layer* with the output neuron u_{out},
   (f) $U_{inner} = \bigcup_{1<i<n} U_i$ is the set of the *inner neurons*.
2. $W : U \times U \rightarrow R$ is the network structure with the following properties:
   (a) The corresponding graph is cycle free
   (b) within U_{inner} only connections between neurons of consecutive layers exist:
   $$\forall u, v \in U_{inner} : W(u, v) \neq 0 \Rightarrow u \in U_i, v \in U_{i+1} \text{ for } i \in \{2, \ldots, n-1\}$$
   (c) the edges
   $$W(u_{in}, v) \text{ for } v \in U_{inner}$$
   are called *fertilisation edges*
   (d) the edges
   $$W(u, v) \text{ for } v \in U_{inner}, u \in U_{inner} \cup \{u_{out}\}$$
   are called *runoff edges*
   (e) there is no fertilisation of the water body:
   $$W(u_{in}, u_{out}) = 0$$
   (f) the weights of the outgoing edges of the inner neurons are scaled, i.e.
   $$\forall u \in U_{inner} : \sum_{v \in U} W(u, v) = 1$$
3. A assigns a function $A_u : R \rightarrow R$ to every neuron $v \in U$ for calculating it's activation a_u:
   (a) for u_{in} and u_{out} holds:
   $$A_{u_{in}}(ex) = ex,$$
   $$A_{u_{out}}(net_{u_{out}}) = net_{u_{out}}$$
   (b) for all other neurons $u \in U_{inner}$ the activation a_u is calculated via a differentiable function f_u:
   $$a_u = A_u(net_u) = f_u(net_u).$$
4. $output$ is the output of the network, i.e.
   $$output =_{def} a_{u_{out}}.$$
5. NET assigns to every neuron $v \in U_i$ with $i \in \{2, \ldots, n\}$ a function
   $$NET_v : R \times (R \times R)^{U_{i-1}} \rightarrow R$$
   for the calculation of the network input
   $$net_v = ex \cdot W(u_{in}, v) + \sum_{u \in U_{i-1}} a_u W(u, v)$$
6. ex is the external input for the input neuron u_{in}:
   $$ex =_{def} 1.$$

6.3 Setting up the Network

The catchment area from section 3 was used to set up our network structure in the way described above. For the determination of the edge weights and activation functions we used the results of the WASMOD hydrological model. For this exercise five different fertilisation scenarios with uniform nitrogen inputs on all SCGs were defined:

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

In order to ensure robustness of our procedure and to represent a typical land use we not only simulated the five scenarios with the land use data from one single year, but also applied the complete five year crop rotation to represent the land use changes within the catchment:

- year 1: winter wheat
- year 2: winter barley
- year 3: maize
- year 4: summer barley
- year 5: winter rape

This crop rotation was derived from a detailed questioning of the farmers and evaluations of mapping data.

Based on the results from the five year modelling exercise we computed the average nitrogen discharge value for each SCG. Repeating this procedure for every scenario we obtained five sampling points − one for each scenario for the activation function.

From these five sampling points the activation functions of all SCG neurons as well as the weights on all edges of classes E1, E2 and E3 was derived. Finally values were assigned to all weights of edges of class E4 according to the fertiliser 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 polynoms (Figure 7).

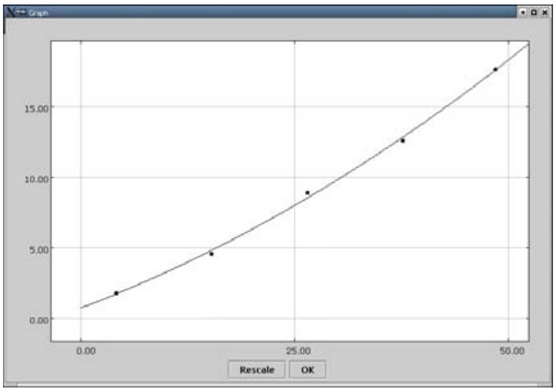

Figure 7. Example of a typical neuron activation function with sampling points, showing nitrogen discharge (y-axis) for given nitrogen input (x-axis) on a single SCG.

6.4 Solving the Optimization Problem

The network representing the catchment area can be seen as a restriction of the WASMOD model. Regarding the fertilisation 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 fertilisation 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 leaching properties. This search is performed with a modified Backpropagation procedure. Backpropagtion (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 minimised.

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 fertilisation 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 the land use scenario the optimization was starting with has to be modified. 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 the fertilisation edges (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 weigths of classes E1, E2 and E3 must not be changed since they describe some statical properties of our catchment.

6.5 Learning Procedure

Assuming a network with n layers and a target output t our learning procedure performed in the optimization step can be outlined as follows:

1. Propagate the value $ex \equiv 1$ through the net, the resulting value at the output neuron is $output$.
2. Calculate the error δ of the output neuron:
$$\delta_{u_{out}} := t - output.$$
3. Is $\delta_{u_{out}}$ smaller than some threshold value ε?
   - **yes**: We are ready.
   - **no**: Proceed with step 4.
4. $l := n$
5. Select layer $l := l - 1$. Is U_l an inner layer?
   - **yes**: Proceed with step 6.
   - **no**: Proceed with step 8.
6. For all neurons u of layer l, calculate the partial error δ_u:
   (a) calculate the network input of u:
$$net_u = \sum_{v \in U_{l-1}} W(v,u) a_v$$
   (b) calculate the partial error of u:
$$\delta_u := f_u'(net_u) \sum_{v \in U_{l+1} \cup \{u_{out}\}} \delta_v W(u,v)$$
7. Proceed with step 5.
8. Calculate and apply the weight adjustment for all fertilisation edges:
$$\forall u \in U_{inner} : W(u_{in}, u) := W(u_{in}, u) + \sigma \delta_u$$
   (σ is called the learning rate with $0 < \sigma \le 1$)
9. Proceed with step 1.

7. RESULTS

To test our network, we assigned the value 1 to the input neuron of the network described in section 6.3 and propagated that value through the network. The activation of the output neuron amounted to 74000kg N and deviated from the total nitrogen discharge as simulated 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 network amounted to 60000kg N. Thus, the failure of our network (difference between desired and actual output) amounted to 14000 kg N. Applying our modified Backpropagation procedure to the network, 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 8.

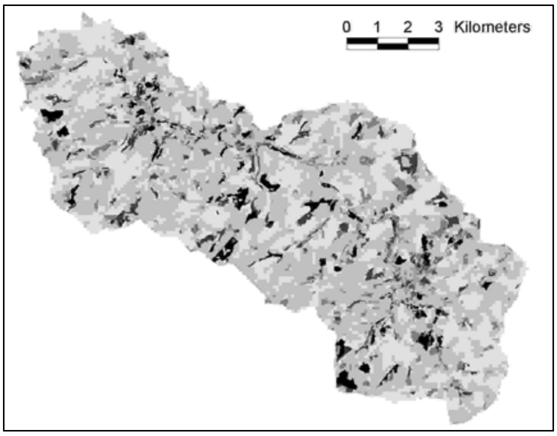

Figure 8. Fertilisation changes computed by a modified Backpropagation algorithm. The darker colours indicate higher changes.

In order to validate the fertilization changes calculated by our procedure we used the results to set up WASMOD again. After modelling the catchment with the modified fertilization inputs the change in the output of WASMOD amounted to 14800 kg N, i.e. 6% more than the predicted reduction. This result indicates that our approach is well suited to represent the behaviour of hydrological models like WASMOD.

Our optimization procedure ensures that the external nitrogen inputs (i.e. the fertilisation 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 fertilisations on irrelevant fields can now be used more efficiently to compensate fertiliser 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 fertilization related to the respective 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 in relation to the threshold 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

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