Neural Network Based Sensitivity Analysis of Natural Resource Models

[1]S. Kralisch, [1]M. Fink and [2]C. Beckstein

[1]Institute of Geography, [2]Institute of Computer Science
Friedrich-Schiller-University Jena, Germany
E-Mail: sven.kralisch@uni-jena.de

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EXTENDED ABSTRACT

The management of hydrologic catchments typically faces the challenge of keeping a reasonable balance between water quality demands and farming restrictions. In order to handle this problem it is most important to identify farming areas whose land use have a high influence on the nutrient leaching into the receiving stream. This identification can be regarded as a sensitivity analysis (SA). Changes in the land use of farming areas with high sensitivity usually promise an adequate relation between costs and benefits. In order to indentify sensitive farming areas, the processes responsible for nitrogen cycling and transport must be modelled first. Then a sensitivity analysis of the resulting model can be performed.

Unlike a SA of a model's output towards a small number of calibration parameters, this task is of exceptional complexity. Not only is the number of parameters that have to be considered proportional to the number of spatial model entities and thus possibly much higher. A SA regarding spatially distributed parameters becomes even more complicated if dependencies between parameters — in our case the catchment topology — must be considered. In this case all parameters have to be looked at simultaneously which leads to a massively multidimensional SA. For the catchment the problem arises when accounting for the lateral transport of water and nitrogen between farming areas. The simulation of these tranport processes is of high importance when looking at water and substances in mesoscale catchments.

We have developed a neural network based methodology (goal directed distributed SA – GDSA) which is suited to solve this problem. Given a distributed natural resource model that is suited to simulate nitrogen cycling and transport our GDSA comprises two steps: First a representation of the natural resource model is contributed in the form of a special neural network (HydroNet). Then the computational properties of the HydroNet are used to make a sensitivity analysis of the network model and thus of the natural resource model.

In order to show the power of the GDSA approach, we applied it to the problem of reducing nitrogen leaching from farming areas into a drinking water reservoir. As a first step, the model WASMOD (water and substance simulation model) was used to simulate the processes responsible for nitrogen cycling and tranport in a distributed manner. Then the resulting model was mapped onto the HydroNet in order to apply our neural network based SA method.

The results of the GDSA application to the WASMOD model show that our HydroNet is capable of representing the relationship between the distributed fertilization inputs to farming areas and the nitrogen discharge to the receiving stream nearly as well as WASMOD. The average yearly nitrogen outputs from single areas and the whole catchment calculated by the HydroNet deviate only marginally from those calculated by the physically based model WASMOD. The GDSA was also able to correctly predict those model entities that have a high influence to the nitrogen discharge modelled by WASMOD.

We also compared our GDSA approach to two conventional approaches for the solution of the above-mentioned management problem. The comparison shows that it is necessary to incorporate topological information because it has a major influence on the quality of the results. GDSA therefore seems to be a good choice of method in cases where many interdependent parameters have to be accounted for.

1. INTRODUCTION

In regions with little groundwater, reservoirs are a major resource for the supply of potable water. 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 and settlement waste water that is untreated or clarified inadequately.

A catchment management which is suited to face these problems must focus on the minimization of nitrogen discharge as well as on minimizing the resulting costs (e.g. compensation payments for farming restrictions). An obvious approach to meet this dilemma is the concentration on nitrogen reduction measures on especially sensitive areas, i.e. farmland areas which have a high influence on the nitrogen discharge to the reservoir. In order to do this the processes responsible for nitrogen cycling and transport must be modelled. Then a sensitivity analysis (SA) of the resulting model can be performed in order to identify sensitive areas.

This task is of exceptional complexity. A conventional SA — like the calculation of the sensitivity index (Nearing et al., 1990) — is typically applied to only a small number of calibration parameters. In our case the number of parameters that have to be considered is proportional to the number of spatial model entities which usually is much higher. A SA regarding spatially distributed parameters is even more complicated if the catchment's topology must be considered. In this case all parameters have to be looked at simultaneously which leads to a massively multidimensional SA. In our case the problem arises when accounting for the lateral transport of water and nitrogen between farming areas. The simulation of these tranport processes is of high importance when looking at water and substances in mesoscale catchments (Fink and Kralisch, 2005, Fink, 2004).

A computational model which is well suited to perform a SA towards a large number of parameters with dependencies is an artificial neural network (ANN, Gallant (1993)). Apart from beeing a flexible computational model, ANNs are able to

1. perform a SA of their outputs with respect to the regarding network parameters and
2. based on this SA apply changes to their setup in order to meet desired properties.

In ANNs these two steps — a SA followed by a corresponding adaption — are performed in an interleaved manner by special learning algorithms. We have utilized this ability for the development of a computational model that supports the solution of the abovementioned catchment management problem.

2. THE GDSA APPROACH

Given a distributed natural resource model that is suited to simulate nitrogen cycling and transport the development of the desired computational model was done in two steps:

1. A representation of the natural resource model was contributed in the form of a special ANN — the so called *HydroNet* (Kralisch et al., 2003).
2. Then the computational properties of the ANN where used to solve the management problem at hand.

The subsequent application of these two steps is referred to as *Goal Girected distributed SA* (GDSA).

2.1. ANN Design

The HydroNet is an ANN which is suited to represent distributed hydrological catchments and transport processes within these catchments. ANNs 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 signals received over incoming edges. This output is then propagated to neighbouring neurons. An ANN 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 (Gallant, 1993) that can fine tune these parameters in a way that the function computed by the ANN approximates a given continuous function arbitrarily well. ANNs therefore are especially suited to solve hard optimization problems.

2.2. HydroNet Structure

In the HydroNet, neurons represent management areas (i.e. farming areas) within the catchment. These areas are derived via GIS operations. The tranport of nitrogen within the catchment is represented by directed edges. The edges represent both vertical transport from the catchment areas to the groundwater (groundwater edges) and lateral tranport representing interflow between areas (interflow edges). The external input of nitrogen into the managament units (i.e. fertilization) is represented by edges (fertilization edges) as well. As an example, figure 1 shows lateral flow paths between spatial model entities of a small catchment and the resulting HydroNet with interflow edges.

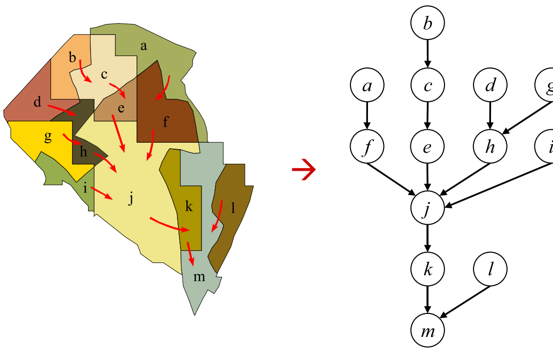

Figure 1. Catchment with spatial model entities and lateral flow paths (left) and corresponding HydroNet with interflow edges (right)

Each edge is provided with a weight value. This value corresponds to the amount of nitrogen which is transported via this edge. In the case of fertilization edges, the weight is identical to the annual nitrogen input to the corresponding spatial model entity. For interflow and groundwater edges, these weights represent the amount of discharge which leaves a model entity via the corresponding flow paths. As an example, a neuron representing an entity with 70 % nitrogen discharge to the groundwater and 30 % nitrogen discharge to neighboring entities will have an outgoing groundwater edge with weight 0.7 and an outgoing interflow edge with weight 0.3.

The HydroNet activation functions characterize the inidiviual ability of each management area to process nitrogen which was put into that area from outside. Figure 2 shows an example of a HydroNet with neurons, different types of edges and activation functions.

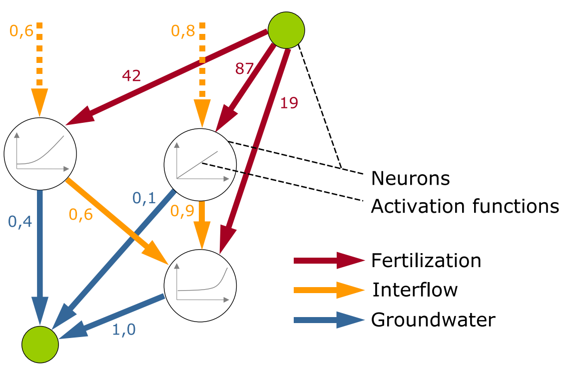

Figure 2. Edge types and activation functions of a HydroNet

2.3. HydroNet Learning Procedure

In order to identify management areas which have a high influence on nutrient leaching into the reservoir learning procedures can be applied to modify the HydroNet and thus model properties.

The HydroNet learning procedure is basically a backpropagation algorithm (Rumelhart et al., 1986) where the backpropagated failure signals are used for the SA step and corresponding local weight changes for the model adaption. Backpropagation attempts to iteratively change the edge weights in an ANN in such a way that a given error function on the output neurons of the net is minimised. This error function of course must be chosen so that it assumes its minimal value whenever the neural network produces its desired output. In the case of HydroNet this desired output is a given value for the maximum allowable nitrogen discharge to the reservoir. Contrary to standard backpropagation the HydroNet learning procedure only adjusts the weights of fertilization edges — all other weights stay fixed — and comprises specific stop criteria.

For a more comprehensive description of the HydroNet and its learning procedure please refer to Kralisch et al. (2003) and Kralisch (2004).

3. GDSA APPLICATION

3.1. Catchment Description

In order to evaluate our GDSA approach we applied it to a subcatchment of the drinking water reservoir Weida-Zeulenroda (figure 3). The catchment is located in the eastern part of Thuringia which is a federal state of Germany. It covers an area of about 102 km^2, its altitude varies between 355 and 565 m above sealevel. Two thirds of the catchment are used for intensive agriculture. The annual average precipitation here is only about 640 mm, the annual average temperature less than 7 °C.

3.2. Simulation Model

The natural resource model that we used for the GDSA application was WASMOD (water and substance simulation model) developed by Reiche (1994). WASMOD allows a fully distributed simulation of the nitrogen discharge from single spatial model entities (i.e. management areas). These entities are represented by polygons. The discharge is described as a function of soil, relief, land use and climate which are the basic input data. WASMOD not only accounts for the nitrogen input by fertilization and atmospheric deposition but also for the input by lateral inflow from neighbouring model entities.

Figure 3. Location of the Weida-Zeulenroda catchment (Kralisch et al., 2003)

3.3. HydroNet Setup

In order to map the WASMOD model to a HydroNet for each spatial model entity of WASMOD a corresponding neuron was created. The nitrogen fluxes within the catchment were then represented by directed edges between the corresponding nodes. The external nitrogen inputs for the model entities were represented by directed edges as well. To initially set up the weights of groundwater and interflow edges we used the discharge values calculated by WASMOD. The resulting HydroNet included about 15000 neurons with individual activation functions and more than 44000 edges.

In order to identify the neuron activation functions sampling points of the nitrogen discharge function of each model entity were calculated by WASMOD. Sampling points represent the entity's nitrogen output for a given input. These outputs were calculated with the help of fertilization scenarios which were applied to the whole catchment.

The scenarios we looked at represented 13 different nitrogen inputs on each model entity, varying from 0% to 120% of their standard fertilization. Each fertilization scenario was simulated for a time period of five years. This period is a typical planning horizon for the Thuringian Water Management who manages the catchment. The choice of five years also made sure that the scenarios could take effect on the single entities.

All sampling points were calculated under the assumption of an average land use and constant general conditions (i.e. soil, climate and relief). They were then used to approximate the HydroNet activation functions. For these approximations individual polyline functions (figure 4) were used. Comparisons with other function types (i.e. polynomial and exponential functions) had shown that polylines were especially suited to reproduce the nitrogen discharge (Kralisch, 2004).

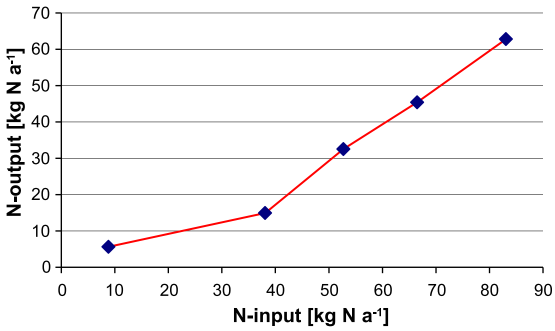

Figure 4. Polyline activation function based on five sampling points

3.4. WASMOD vs. HydroNet

In order to test the model qualities of the HydroNet we initialized the fertilization edge weights with annual standard fertilization values. After calculating the activations of all neurons the HydroNet output accounted for 225 Mg N a^{-1}. The overall nitrogen discharge to the catchment calculated by WASMOD accounted for 219 Mg N a^{-1} for the same time period. The deviation of only 2.9% shows that the HydroNet results fit those of the WASMOD model very well. A more detailed comparison of the calculated nitrogen discharge from single neurons and spatial model entities is shown in figure 5. The high coefficient of determination of 0.92 and a gradient of nearly 1 emphasise the high correlation.

3.5. Sensitivity Based Model Adaption

With a good ANN approximation of WASMOD at hand we then performed the second step of the GDSA — the goal directed adaption of the HydroNet model. For this purpose the HydroNet learning procedure was applied. During this procedure the weights of the fertilization edges were reduced according to the influence of the associated neuron on the HydroNet output. Before the learning procedure could be applied we needed to specify a value for the maximum allowable discharge into the reservoir. In order to see which minimum nitrogen discharge could be

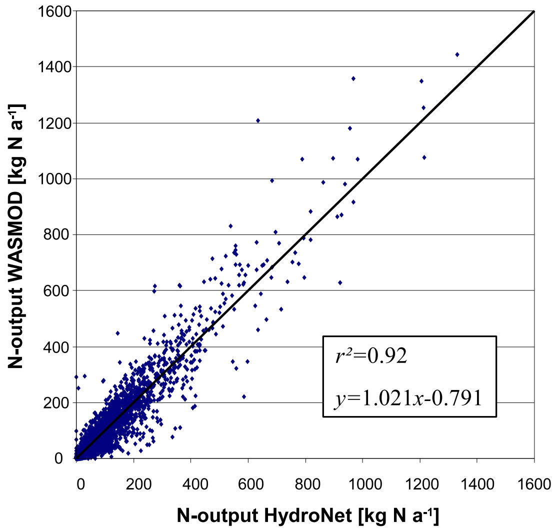

Figure 5. Deviations between calculated nitrogen discharge from neurons and spatial model entities

established we chose the following stop criteria for the learning procedure:

1. The HydroNet output accounts for a value of 0 kg N a^{-1} or
2. the changes in the HydroNet output between two consecutive steps of the learning procedure falls short of a given minimum (1 kg N a^{-1}).

The learning procedure stopped after a total of 518 steps of weight adjustments due to the second stop criterion. The HydroNet output for the new edge weights accounted for 168 Mg N a^{-1}. This means a total reduction of the proposed nitrogen discharge to the reservoir by 57 Mg N a^{-1} or 25%. Figure 6 shows the results for all spatial model entities. Here, each area is colored according to the percentage weight reduction of the fertilization edge of the associated neuron in the HydroNet. As can be seen very clearly the reductions are high especially on those areas that are situated near riparian zones.

3.6. Evaluating GDSA

In order to assess the quality of the GDSA results for our Weida-Zeulenroda scenario we used the calculated fertilization inputs to parameterize the spatial model entities of the WASMOD model. Then we again simulated the catchment's nitrogen discharge with WASMOD for a period of five years. During this time the fertilization inputs for the model entities stayed fixed as calculated with the learning procedure.

The WASMOD results show that the reduction of

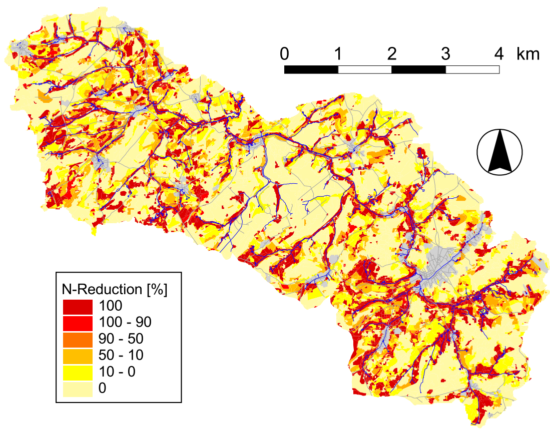

Figure 6. Results of the sensitivity analysis

fertilization has nearly no effect on the nitrogen discharge to the reservoir after one year (figure 7). Starting in the second year of reduced fertilization the discharge values start to respond. In the fifth year the nitrogen reduction in discharge reaches a value of nearly 33%.

In order to compare the WASMOD results to our predicted discharge reduction we used the five year average reduction. This is justifiable because we considered a five year period for the calculation of the activation functions as well. The average reduction within five years accounted for about 23%. Compared to the predicted reduction of 25%, this result shows satisfactory compliance.

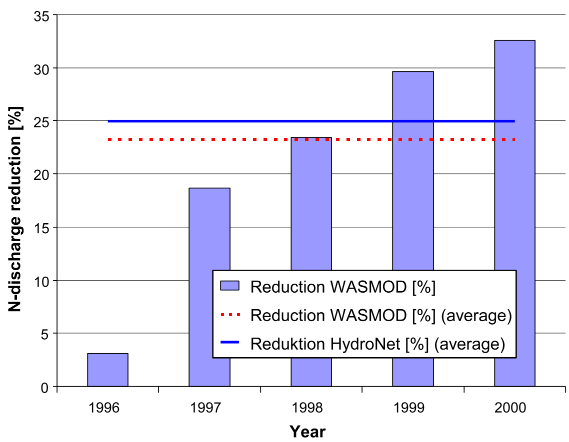

Figure 7. Reduction of nitrogen discharge to the reservoir modelled by HydroNet and WASMOD

3.7. Comparison with Conventional Approaches

We were also interested in how our GDSA approach compares to conventional approaches for the solution of the nitrogen leaching problem. As pointed out in the introduction, a conventional SA of a model's output towards a large number of spatially distributed parameters can not easily be done. In the case of WASMOD about 15000 parameters were to be considered. Even without taking the topology of the model entities into account this task cannot be done with WASMOD alone — it would lead to a very hard high-dimensional SA.

We therefore decided to compare GDSA to two non-SA-based conventional approaches that are frequently used in practice to identify areas that have a high influence to nitrogen discharge from the whole catchment. For this purpose we defined the following task: starting from the standard fertilization the overall nitrogen input for all spatial model entities should be reduced by an amount of 10%, 20% and 30%. The objective was to reach a maximum reduction in the nitrogen discharge to the receiving stream.

The first of the compared classical approaches simply reduces the nitrogen inputs evenly on all model entities (*even reduction*). This reflects the effects of establishing sanctuaries which allow only reduced fertilizer inputs. The second classical approach reduces the nitrogen inputs proportional to the entities' nitrogen discharge under standard fertilization conditions (*proportional reduction*). Note that both approaches ignore the lateral nitrogen transport between management areas. For both approaches WASMOD was used to predict the effects.

Each of the approaches — the GDSA one and the two classical — was applied to the abovementioned task. Figure 8 shows the results: The overall nitrogen input which is shown on the x-axis of the diagramm also includes nitrogen which is inserted to the spatial entities by atmospheric deposition. For this reason its values amount to about 8%, 16% and 24% rather than 10%, 20% and 30%. Assuming that WASMOD delivers correct results the following could be observed: The worst result was achieved by evenly reducing the fertilization inputs. The best result was obtained with the GDSA approach. The approach of proportionally reducing the fertilization inputs shows a result that lays in-between the others.

4. CONCLUSIONS

We have presented a new approach for the sensitivity analysis of spatially distributed parameters of a natural resource model: the goal directed distributed sensitivity analysis (GDSA). This neural network based approach is suited to take into account not only a large number of parameters. It also allows considering the topology that underlies the corresponding natural resource model. Our approach includes the transformation of a complex natural resource model into a neural network (HydroNet).

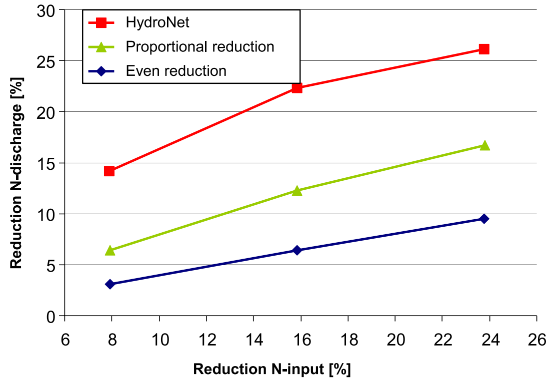

Figure 8. Comparison of the HydroNets results with two conventional approaches

The HydroNet is a computational model representing the relationship between the values of distributed parameters as inputs and the models output. We applied the GDSA approach to the model WASMOD which is able to simulate water and nitrogen fluxes within mesoscale catchments. The results show that the HydroNet represents the relationship between the distributed fertilization inputs into the models spatial entities and the nitrogen discharge to the receiving stream nearly as well as WASMOD. Moreover, the GDSA was able to correctly predict those model entities that have a high influence to the nitrogen discharge modelled by WASMOD. The identification of highly sensitive areas within the catchment as performed by the GDSA is a major step towards an integrated catchment management that accounts for processes on single areas as well as for the transport of substances between them.

5. ACKNOWLEDGMENTS

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