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Hydrological model coupling with ANNs

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Abstract

Model coupling in general is necessary but complicated. Scientists develop and improve conceptual models to represent physical processes occurring in nature. The next step is to translate these concepts into a mathematical model and finally into a computer model. Problems may appear if the knowledge, encapsulated in a computer model and software program is needed for another purpose. In integrated water management this is often the case when connections between hydrological, hydraulic or ecological models are required. Coupling is difficult for many reasons, related to data formats, compatibility of scales, ability to modify source codes, etc. Hence, there is a need for an efficient and cost effective approach to model-coupling. One solution for model coupling is the use of Artificial Neural Networks (ANNs). The ANN can be used as a fast and effective model simulator which can connect different models. In this paper ANNs are used to couple four different models: a rainfall runoff model, a river channel routing model, an estuarine salt intrusion model, and an ecological model. The coupling as such has proven to be feasible and efficient. However the salt intrusion model appeared difficult to model accurately in an ANN. The ANN has difficulty to represent both short term (tidal) and long term (hydrological) processes.

1 Introduction

Water management influences many aspects of our modern life and has many interdisciplinary fields. Water management deals not only with traditional tasks like safety and drainage, but also with our high living standards, health and environment. This results in the need for integrated computing and inter-disciplinary relations. Examples of hydrological models are rainfall-runoff models, free surface flow models and groundwater models. In these fields integrated models already exist, for example integration of groundwater and surface flow models, water quality and quantity models. Another example is integration of water quality in urban waters and waste water treatments.

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Other fields related to water management are biological and ecological models. Model coupling is necessary to answer complex questions.

Integration of different models is intensive in time and costs. Segmented software development is most successful. Conquer and divide is a common way to solve complex problems. The negative side is that a large amount of energy is necessary to integrate two different types of computer models. From a software point of view integration faces difficulties with import/export tools, data formats and software versions. A real online time connection tends toward hybrid systems. To build online connections or a hybrid system serious integration is needed. This is only cost effective if it is used intensively. Another possibility is making components that can be plugged into one central framework. Many initiatives have been launched. One of the problems is that all stakeholders and future users must adopt and consequently implement one standard. This for example requires exact definition of all interfaces and results in less flexibility. Furthermore there are commercial and practical problems like product support, source update and legal issues.

On the one hand water management requires answers from different disciplines and on the other hand it is difficult to connect computer models to one another. This research investigate the ability of ANNs to set up quick connections between hydrological computer models. With ANNs it is possible to make connections more easily without adjustments to software code or connections to a framework.

This methodology uses ANNs. The ANN is used as a fast simulator that operates as an interface between different computer models. The ANN simulates the output of the computer model. In the training period the ANN learns the model's behavior based on input and output. The only restriction is that the model or network does not change. In most situations coupling of a model is only interesting if the model is already calibrated and the design and building has finished. In this research, the focus is on four hydrological models. These models are described in the next section.

2 Model description

2.1 ANNs

The basic elements of ANNs are neurons that are connected by transfer functions in layers and a network. In mathematical terms a neuron k can be described by writing the following pair of equations (Haykin, 1999):

$$u_k = \sum_{j=1}^{m} w_{kj} x_j \tag{1}$$

$$y_k = \varphi(u_k + b_k) \tag{2}$$

where $x_1, x_2, \ldots, x_m$ are the input signals, $w_{k1}, w_{k2}, \ldots, w_{km}$ are the synaptic weights of neuron k; u_k is the linear combiner output due to the input signals; b_k is the bias and *phi* $(\cdot)$ is the activation function; and y_k is the output signal of the neuron. The sigmoid transfer function is the most common form of activation used:

$$\varphi(v) = \frac{1}{1 + \exp(-av)} \tag{3}$$

A few rules of thumb are available to design an ANN for hydrological modelling (Zijderveld, 2003; Hagan et al., 1996). The ANNs have to be trained to calculate the values of the synaptic weights. A measured or observed data set is necessary with known input and corresponding output values.

2.2 HBV rainfall-runoff model

For the rainfall-runoff model a lumped model of the Alzette Basin, Luxembourg is used (Fenicia et al., 2006). Many researchers have shown it is possible to simulate a HBV model with an ANN (Vos and Rientjes, 2005; Minns and Hall, 1996). Input is rainfall (P) and the potential evaporation (E_p). The output is the downstream discharge (Q). The size of the catchment area is 31 km^2.

2.3 River model in 1D-channel flow

For river flow, Duflow modelling software is used. There are several publications on simulating hydraulic flow, e.g. Bobovic and Abbott (1997); Dibike (2002); Price et al. (1998); Shrestha et al. (2005). Duflow is based on the one-dimensional partial differential equations that describes non-stationary flow in open channels. These equations which are the mathematical translation of the laws of conservation of mass and momentum (Stowa, 2002) read:

$$\frac{\partial B}{\partial t}+\frac{\partial Q}{\partial x}=0 \tag{4}$$

and:

$$\frac{\partial Q}{\partial t}+gA\frac{\partial H}{\partial x}+\frac{\partial\left(\alpha Qv\right)}{\partial x}+\frac{g\left|Q\right|Q}{C^2AR}=\alpha\gamma w^2 cos\left(\Phi-\phi\right) \tag{5}$$

The equations are discretized in space and time using the four-point implicit Preissmann scheme. The space between calculation points Δx is 3000 m, the calculation time step Δt is 30 min. Upstream the HBV rainfall-runoff model generates the inflow from the Alzette basin.

2.4 Salt intrusion in alluvial estuary

An estuary is the transition zone between the river and the sea. Alluvial estuaries have movable beds consisting of sediments of riverine and marine origin. The water moving in the estuary can either erode the estuary bed or it can deposit sediments. This results in a dynamic equilibrium situation. In this paper we chose the derivation of the steady state intrusion for the tidal average (TA) model. In the one-dimensional flow model, the dispersion at high water slack (D^{HWS}), varies with the tide and river flow (see Fig. 3). D_0^{HWS} is the high water slack dispersion at the downstream boundary.

The salt intrusion model was developed by Savenije (1986, 1989, 1993a,b, 2005):

$$\frac{S - S_f}{S_0 - S_f} = \left(\frac{D}{D_0}\right)^{\frac{1}{K}} \tag{6}$$

$$\frac{D^{\mathrm{HWS}}}{D_0^{\mathrm{HWS}}} = 1 + \frac{K a Q_f}{D_0^{\mathrm{HWS}} A_0} \left(\exp\left(\frac{x}{a}\right) - 1\right) \tag{7}$$

$$D_0^{TA} = D^{\mathrm{HWS}} \left(E/2\right) \cdot \exp\left(-\frac{E}{2a}\right) \tag{8}$$

where K is the Van der Burgh's coefficient, S, S_0 and S_f the salinity, salinity at the estuary mouth and fresh water salinity respectively. Q_f is the fresh water discharge, A_0 is the tidal average cross-sectional area at the estuary mouth and a is the cross-sectional area convergence length. Furthermore the predictive equation for the downstream boundary condition and the shape function apply:

$$\frac{D_0^{HWS}}{\upsilon_0 h_0} = 1440 \frac{E}{a} \sqrt{N_R} \tag{9}$$

$$E = H \frac{a}{h_0} cos\left(\epsilon\right) \tag{10}$$

$$Nr = \frac{\Delta\rho}{\rho} \frac{gh}{A_0} \frac{Q_f T}{E_0 \upsilon_0^2} \tag{11}$$

With E the tidal excursion, ϵ the phase difference between high water (HW) and high water slack (HWS).

2.5 Secchi-depth

The under water light climate is an important factor for the development of the aquatic eco-system. Growth of algae and water plants is strongly dependent on the availability of light under water. The contribution of optical active components to adsorption and diffusion of light is linear related to concentration of components. Total extinction of light for plants and algae in the most important wave length (400–700 nm) is described by the extinction coefficient K_d. The visibility is expressed and measured as the Secci-depth (d_S) Blom (1992):

$$d_S^{-1}=d_{S0}^{-1} + \beta_h \cdot E_{\mathrm{abs}(380)} + \beta_a \cdot C_{\mathrm{chla}} + \beta_d \cdot C_{\mathrm{det}} + \beta_m \cdot C_{\mathrm{min}} \tag{12}$$

in which:
d_{S0} background Secchi-depth, $E_{\mathrm{abs}(380)}$ absorption of light dissolved material at 380 nm, C_{chla} concentration of cholorofyl-a, C_{det} concentration of suspensive organic matter, C_{min} concentration of suspensive mineral matter. And, β_h contribution of humus acids to inverse Secchi-depth, β_a contribution of chlorofyl-a to inverse Secchi-depth, β_d contribution of detritus to inverse Secchi-depth, β_m contribution of floating matter to inverse Secchi-depth.

We assumed the concentration of suspensive organic matter C_{det} is related to the quotient of muddy river water and the saline sea water ($\frac{S_f}{S}$). This Secchi-depth model is implemented as a water quality model in the 1D-flow model.

3 Methodology

The goal of this paper is to couple four models with ANNs. An integrated hydrological model, simulating all four models, is also built in Duflow to compare the ANN results. The calculation starts with a HBV model simulating precipitation runoff from the Alzette basin. Starting point is a data set consisting of daily precipitation and potential evaporation data. The parameters of the HBV model were roughly set to realistic values. For

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our goal, connecting hydrological models, it was not necessary to calibrate the HBV models to observed values. We only used the rainfall and evaporation data to produce discharge values. This discharge time series is output of the HBV model and in the next phase it is the input for the flow model of the river. The river disperses into an estuarine area with tidal influence. In an estuary, salt intrusion depends on the dispersion of the flow model. Dispersion is a function of geometry, tidal movement (sea level) and fresh water inflow from the river. It is also a function of space expressed in x, the distance from a point along the estuary to the estuary mouth $x=0$ m. The last model, expressing the Secchi-depth or visibility of the water in the estuary, is modelled by a Duflow quality model.

3.1 Connection points

We focus on physical points in the model suitable for connection. Four ANNs models means three connection points. The first connection point is between the HBV model and the river model. The simulated discharge from the HBV model is discharge input to the river model. The second connection point is the downstream discharge of the flow model to the upper river discharge point of the estuary. The downstream boundary of the estuary is the sea level with saline water inflow. The third connection point is a certain point along the estuary where the Secchi-depth model is connected. Input is the quotient of muddy river water and marine water simulated by the salt intrusion model.

The connection of the ANNs happens completely outside the hydrological model. It is totally separated from the original computer model and hence from its computer interface. The water flows artificially between the four models.

3.2 Training

The most important step is to train the ANNs. The data set should contain enough physical events such as high and low flows. If this is not the case, there is the possibil-

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ity to create an artificial training data in a systematical way based on physical features such as mean sea level, maximum flow, amplitude at estuary mouth, typical time variations etc. Many of these parameters can be subtracted from the conceptual model. Basic statistical parameters of a data source also give shape to the input space. Selecting correct data sets is important (Doan et al., 2005). In Kamp and Savenije (2006) the authors showed additional optimisation of the original artificial data is possible in combination of a Genetic Algortihms (GA). The GA constructs a new training set by selecting different subsets from the original training set resulting in better performance of the ANN. In this paper this methodology was not applied because a daily dataset of five years was available.

Model coupling is only useful if the connection consist of a few variables at a convenient number of locations. For example, coupling of a groundwater model with a river model should require many connection points along the river bed. This would be impractical for this method. In this paper some general training rules are combined with specific system or model knowledge from the authors of the used hydrological models. In future research some general applicable rules should be available for training any physical model.

4 Simulations

4.1 Design and training

ANNs consist of an input layer, one or several hidden layers and an output layer. Each layer consists of one or more neurons and all neurons of two successive layers are connected. Every connection gives a signal to the next layer multiplied by a factor. The neurons transfer this signal with a transfer function. ANNs are described in detail by Haykin (1999). We used two hidden layers. The first hidden layer consists of 7 or 3 neurons. The second hidden layer consists of three hidden layers. All transfer functions are sigmoid functions (Eq. 3) except for the output layer which has a linear transfer function. The trainings function is Levenberg-Marquardt back propagation. A stepped delay line is used to simulate flow dynamics. In a stepped delay line the input at time t until n steps in history Q_{t-n} form the ANN's input:

$$\mathbf{Q}=\begin{pmatrix} Q_{t-1} \\ Q_{t-2} \\ \vdots \\ Q_{t-n} \end{pmatrix} \tag{13}$$

For indication of the length of the delay line, a graph of the cross-correlation between input and output signals can be made. This graph gives the correlation of a delayed input vector and the (target) output signal. Cross validation for early stopping is not used. The average epochs or calculation runs for the training phase is 50. The error measurement is mean squared error. All design and train parameters are optimised and based on the authors expert knowledge. For testing the root mean squared error (RMSE) is used. Also the Nash-Sutcliff efficiency index (R^2) and the Pearson's r-squared statistics (RSqr) for measurement of high flows are used:

$$\mathrm{RMSE}=\sqrt{\frac{\sum_{i=1}^{n}\left(Q_i-\widehat{Q}_i\right)^2}{n}} \tag{14}$$

$$R^2=1-\frac{\sum_{i=1}^{n}\left(Q_i-\widehat{Q}_i\right)^2}{\sum_{i=1}^{n}\left(Q_i-\bar{Q}_i\right)^2} \tag{15}$$

$$\mathrm{RSqr}=\left[\frac{\sum_{i=1}^{n}\left(Q_i-\bar{Q}_i\right)\cdot\left(\widehat{Q}_i-\widetilde{Q}_i\right)}{\sqrt{\sum_{i=1}^{n}\left(Q_i-\bar{Q}_i\right)^2\cdot\sum_{i=1}^{n}\left(\widehat{Q}_i-\widetilde{Q}_i\right)^2}}\right]^2 \tag{16}$$

where Q_i is the observed value, $\widehat{Q}_i$ is the modelled value and $\bar{Q}_i$ is the mean of the observed data and $\widetilde{Q}_i$ is the mean of the modelled data.

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4.2 HBV rainfall-runoff model

For the Alzette basin (Pfister et al., 2005) daily time series are available for five years (1996–2001) for precipitation and potential evaporation (see Fig. 1). A conceptual HBV model was available with calibrated parameters. From the cross-correlation graph of precipitation and the potential evaporation, a history of six delayed time steps is sufficient. For training this was the best fit for the input dataset. Both the precipitation and potential evaporation were delayed for six days. However, training and testing the ANN showed a more basic problem. The train set should contain enough high flows. In the training set a few high floods occurred. One extreme high flood in the test set did not even occur in the training data set. This resulted in a poor prediction of high flows and a RSQR of only 0.66 (see Fig. 6). Another difficulty for neural networks is the fact that a HBV model has different model states. The response in wet situations is much quicker than in dry periods, which are difficult training conditions.

Additional attention has to be payed to different time scales between the models. The HBV model for example calculates daily discharge values, while the flow model has a time step of 30 min. Another problem was connecting the HBV model into the integrated Duflow model. While the standard precipitation runoff model of Duflow had different parameters and a different implementation, it was not possible to use the standard RAM-object. The HBV model results were connected as flow boundaries.

4.3 River model in 1D-channel flow

The largest river section connects the inflow from the HBV model to the inflow of the estuary and has an average slope (I) of $1.2\times10^{-4}\,\mathrm{m}^{-1}$. The distance between the input and output point is 336 km. The cross sectional profile is 20 m wide (B), rectangular and uniform with no flooding area's for water storage (B_s). The discharge (Q) is 13 m^3/s at low flow, 50 m^3/s at high flow and 100–150 m^3/s in extreme situations. The water depth (h) is 1.6 m and the (steady state) water velocity ($\bar{v}$) at the top of the high water wave ($\partial h/\partial t=0$) can be described as a steady state flow according to

Manning-equation:

$$\bar{v} = \frac{1}{n} h^{2/3} \sqrt{I} \tag{17}$$

If we assume $Q=\bar{v}B_s h$ and substitute it in the law of conservation (Eq. 4), the high water wave velocity is (Savenije, 2001):

$$c = \frac{5}{3}\frac{B_s}{B}\frac{1}{n} h^{2/3} \sqrt{I} = \frac{5}{3}\frac{B_s}{B}\bar{v} \tag{18}$$

With n=0.025 (Manning) for clean, straight and uniform river bed, we find a theoretical c=1.03 m/s, and from the 1D-flow simulation model we find a wave celerity of $c=\frac{\Delta x}{\Delta t}$=1.00 m/s. A river flood upstream arrives 3 days and 20 h later in the downstream area (see Fig. 2). This is important for the stepped delay line used for training (Eq. 13). The input fitted quite well and resulted in RMSE=4.4 m^3/s and an efficiency of R^2=0.92 (see Fig. 6). The results are good because the hydro graph was symmetric and showed little deformation. In situations of large water storage and non-uniform cross-sectional profile this is not the case.

The time step of the HBV model is days, while the time step of the dynamic flow model is half an hour. The HBV model provides one constant value for a whole day. To prevent a stepped time series, the input of the flow model are smoothed.

4.4 Salt intrusion in alluvial estuary

The upstream boundary of the alluvial estuary is the fresh river inflow. Downstream the MSL is 2.0 m with an average amplitude of 1.25 m. The geometric profile is wide at the estuary mouth and small at the river mouth. The width varies as an exponential function with distance. The bottom level is constant (5.0 m). These are conditions for alluvial estuaries that fit the model as described by Savenije (Sect. 2.4). The output of the salt intrusion model is the salinity at a point 120 km upstream from the estuary mouth. In this point the salinity is influenced by both the fresh river discharge and the tidal movement at the estuary mouth (see Fig. 3).

The first process, the tidal movement (see Fig. 5), has a time period of one day. The variations of the discharge includes several days and is a much slower process (see Fig. 6). It is important to understand that it is difficult for one ANN to simulate both time scales in one training. To improve the performance the moving average value of discharge is used for input. This gives better results but introduces a larger error in the starting period when the model has to build a “history”. A technical problem was the implementation of the dispersion. The 1D-flow model dispersion was not a direct function of the sea-level and river discharge. Extra calculation of dispersion depending on time varying water levels and river discharges were performed. Training the ANN was difficult and gave poor results. Introducing a moving history was necessary but did not give satisfying predictions. Although both the sea level and river discharge have effect on salinity, it is difficult to separate these two processes.

4.5 Secchi-depth

The ecchi-depth is an indication for the light penetration under water. This value is in our model directly derived from the quotient of river and sea water. We assumed this is an indication of dissolved matter in the water column. Except for salinity, all other parameters are assumed constant and there are no external variables distinguished in this model. If the salinity is high, the assumption is that there is relatively much sea water hence less muddy river water. In that situation the concentration of dissolved material is low and the visibility is high. This results in a Secchi-depth which is proportional with salinity. Training an ANN on proportional variables with no time lags results in good results. This was also the case in our model with R^2=0.99 (see Fig. 6).

4.6 Model coupling and results

Models with the same input and output variables, for example water levels or discharges can be connected. In this paper we used a cascading model coupling. The line-up of the models is (1) the rainfall-runoff model producing a discharge, (2) the 1-D-

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flow model for the river in, (3) the salt intrusion model and (4) the Secchi-depth model. The HBV model produces a discharge for the river model, the river model simulates discharge for the estuary and the estuary model provides salinity for the Secchi-depth model.

In general the ANN are good input/output fitters (see Table 1). However, the predictions were not very accurate due to several problems (see Fig. 7). We performed an extra calculation and disabled the short-term processes by focusing on maximum daily salinity values. However this resulted in no better performance (see Fig. 8 and Table 1 last row). The problem with the HBV is the time delays and different system responses. River flow could be simulated well because the river had uniform cross-sectional area's and no flooding area's. The ANN of the estuary could hardly distinguish two processes with different time periods. The Secchi-depth was proportional to the salinity without any time delay and gave perfect results. The final, coupled model performs poorly. All errors are accumulated in a cascading modelling.

5 Conclusions

In this research ANNs are used to couple four hydrological models. For training and testing five years of daily precipitation and potential evaporation are used for training and testing. The models are coupled in a cascading model and compared to an integrated conceptual model. We found that it is possible to use ANNs for model coupling. The ANNs were capable to simulate the output of the different model components. The individual ANNs were tested and three of the four resulted in good results. However, the final model results are as accurate as the weakest link in the model chain. In this model simulation the salt intrusion model was not accurate enough. The ANNs could simulate the tidal movement (short term) but simulated at the same time the salt-intrusion (long term) inaccurately. In the next paper we will focus on a method to separate the short and long term processes for the salt-intrusion in an estuary.

We can conclude that model coupling as such has proven to be feasible and efficient, however the overall accuracy of four coupled models was not sufficient due to the poor performance of the salt-intrusion model.

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Table 1. Simulation results.

Model	RMSE	R^2	RSQR	RMSE coupled
HBV	11.5 m^3/s	0.51	0.66	11.4 m^3/s
River flow	4.4 m^3/s	0.92	0.93	13.7 m^3/s
Estuary	837 mg/l	0.38	0.62	1424 mg/l
Secchi-depth	0.004 m	0.99	0.99	0.636 m
Max.Salinity	1068 mg/l	0.25	0.61	1663 mg/l

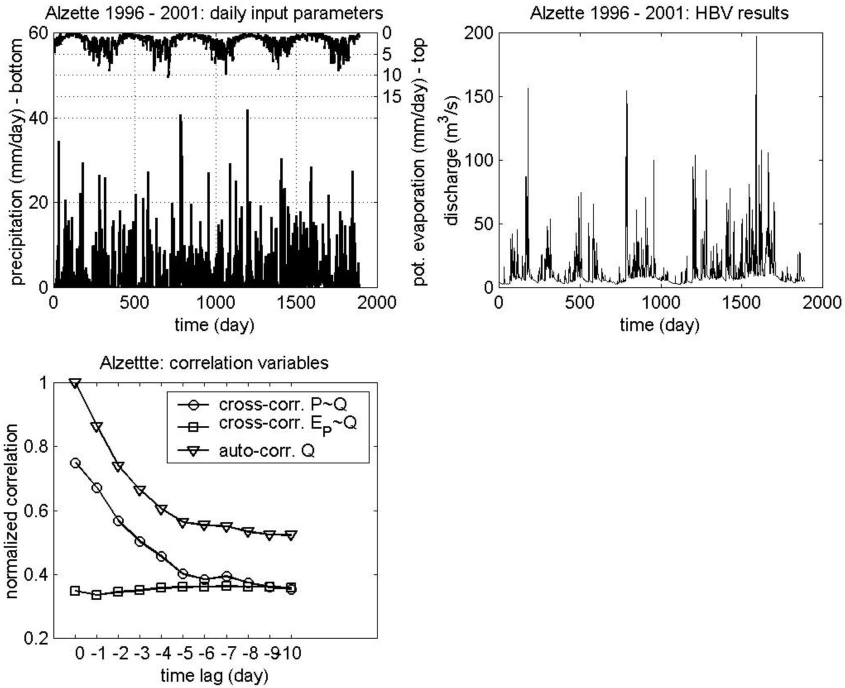

Fig. 1. Alzette basin.

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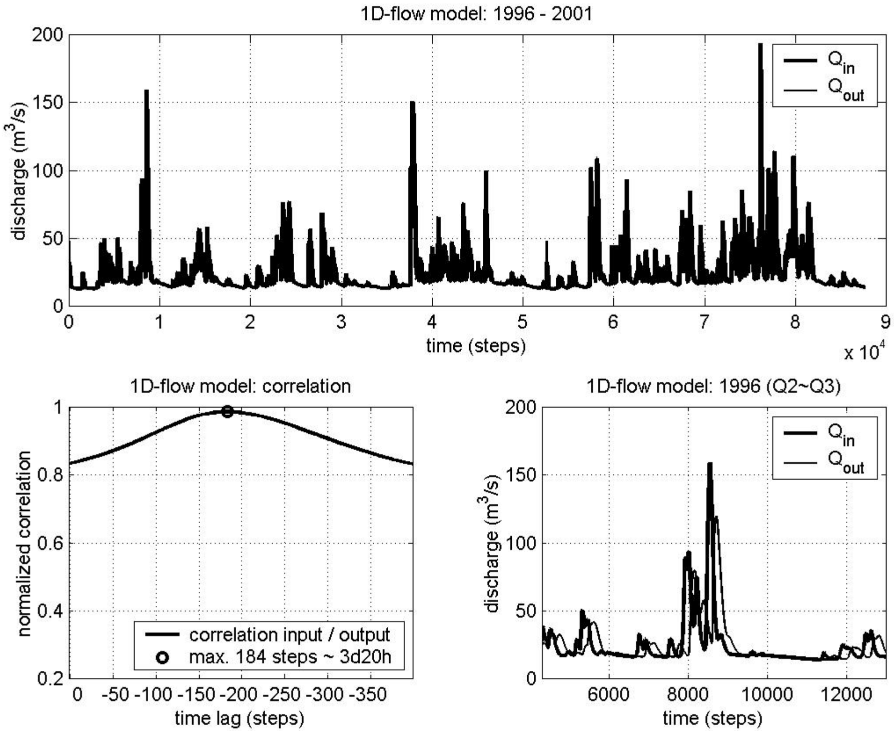

Fig. 2. 1-D-flow model.

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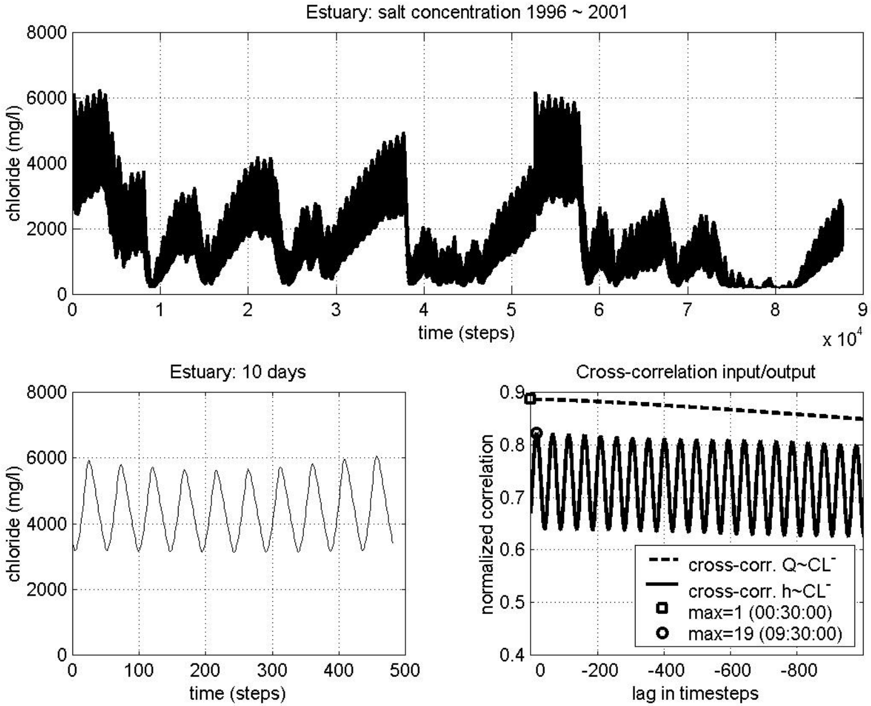

Fig. 3. Salinity in estuary.

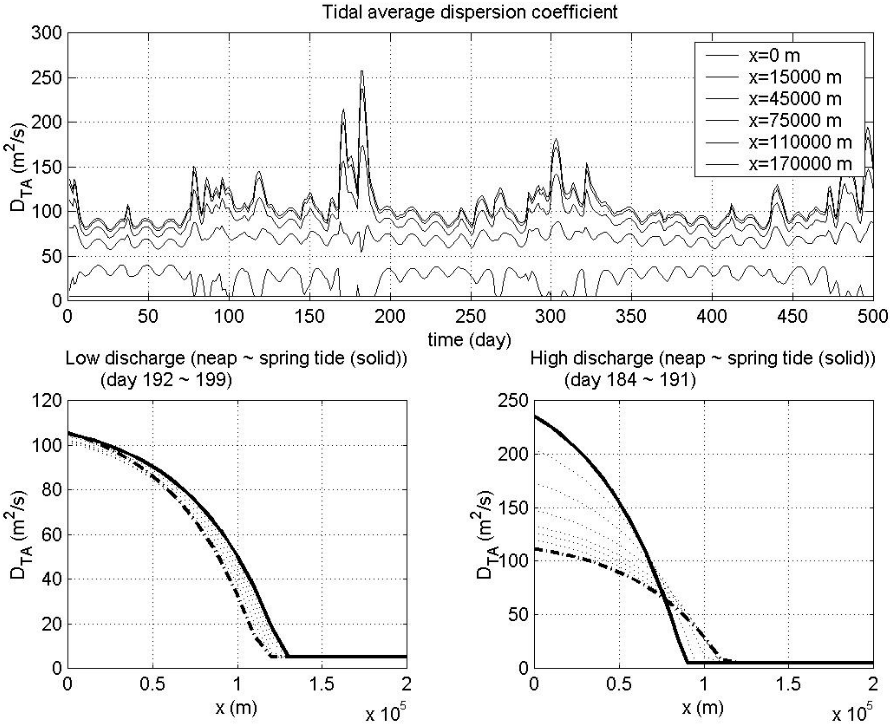

Fig. 4. Dispersion in estuary.

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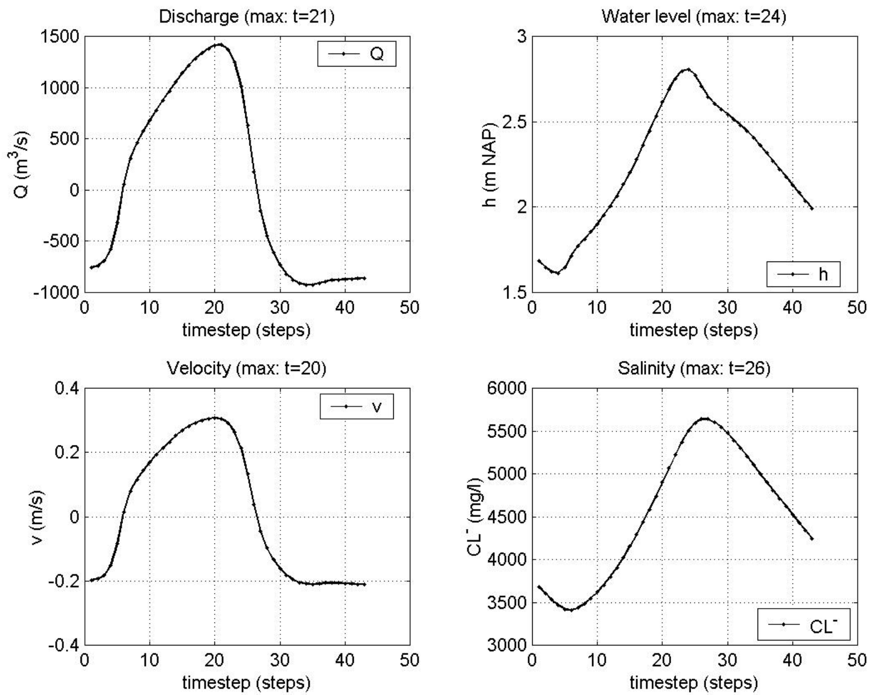

Fig. 5. Tidal movement in one point (SCH00004).

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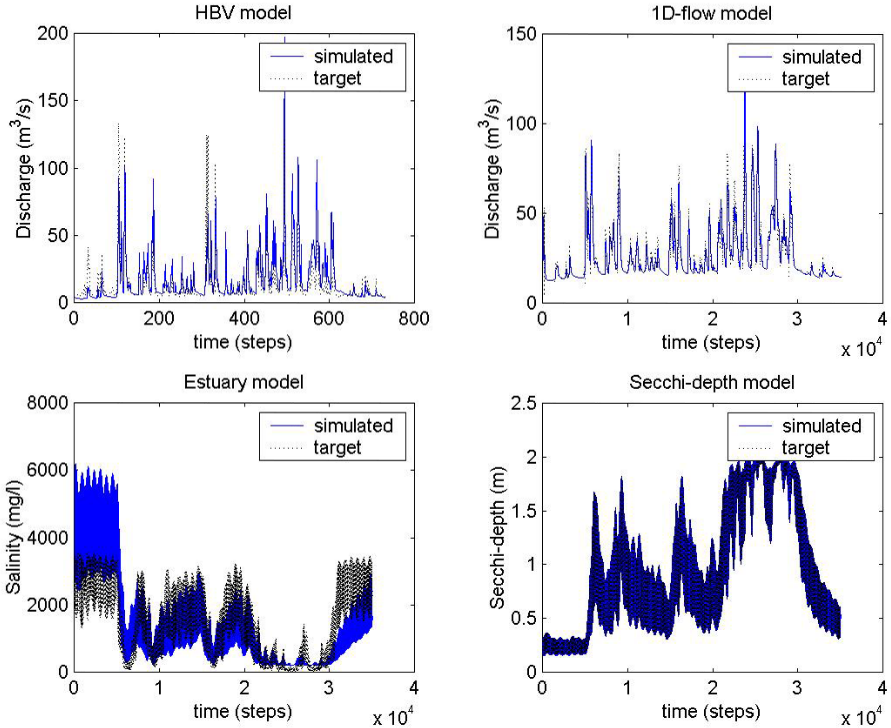

Fig. 6. Test results.

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Hydrological model coupling with ANNs

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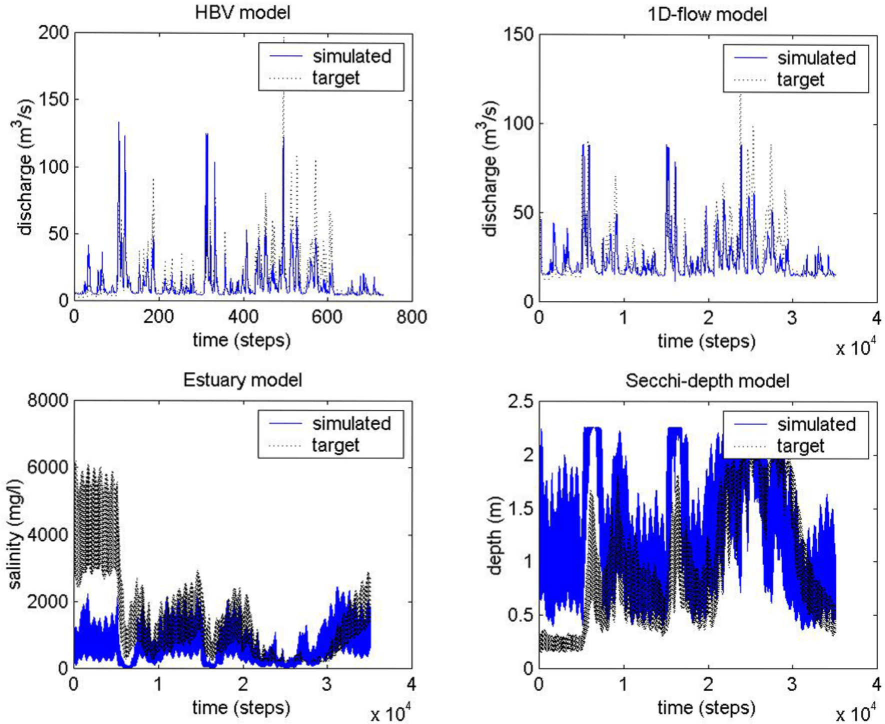

Fig. 7. Results connected models.

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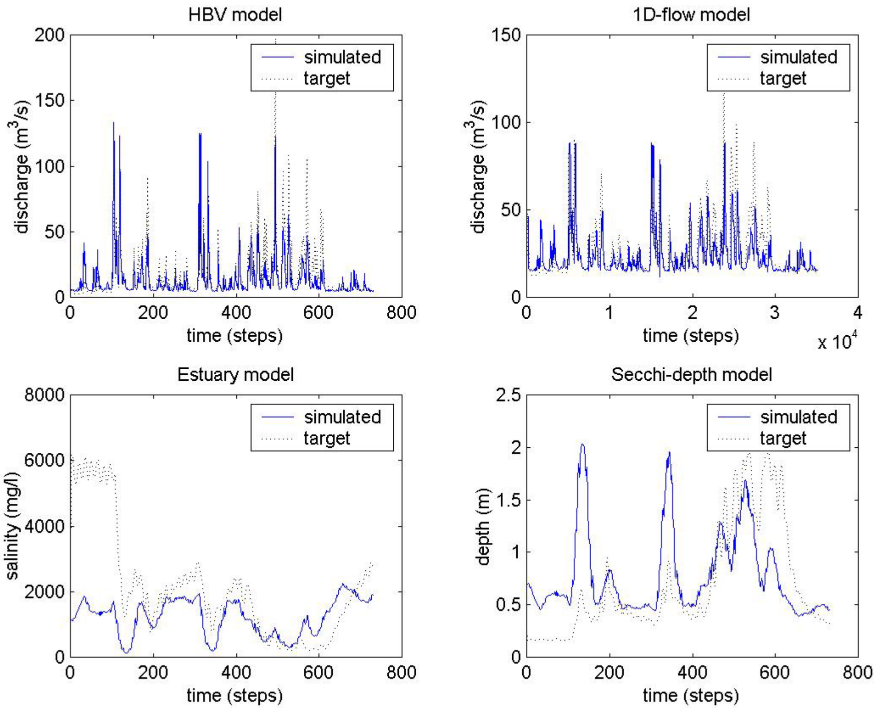

Fig. 8. Results connected models trained on maximum salinity.