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# Choosing an Appropriate Hydrological Model for Rainfall-Runoff Extremes in Small Catchments

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**Abstract**

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Real and scenario prognosis in engineering hydrology often involves using simulation techniques of mathematical modelling the rainfall-runoff processes in small catchments. These catchments are often up to 50 km$^2$ in area, their character is torrential, and the type of water flow is super-critical. Many of them are ungauged. The damage in the catchments is enormous, and the length of the torrents is about 23% of the total length of small rivers in the Czech Republic. The Smědá experimental mountainous catchment (with the Bílý potok downstream gauge) in the Jizerské hory Mts. was chosen as a model area for simulating extreme rainfall-runoff processes using two different models. For the purposes of evaluating and simulating significant rainfall-runoff episodes, we chose the KINFIL physically-based 2D hydrological model, and ANN, an artificial neural network mathematical "learning" model. A neural network is a model of the non-linear functional dependence between inputs and outputs with free parameters (weights), which are created by iterative gradient learning algorithms utilizing calibration data. The two models are entirely different. They are based on different principles, but both require the same time series (rainfall-runoff) data. However, the parameters of the models are fully different, without any physical comparison. The strength of KINFIL is that there are physically clear parameters corresponding to adequate hydrological process equations, while the strength of ANN lies in the "learning procedure". Their common property is the rule that the greater the number of measured rainfall-runoff events (pairs), the better fitted the simulation results can be expected.

**Keywords**: flood prediction; infiltration; Jizerské hory Mts.; kinematic wave; neural network

Rapidly developing catastrophic situations caused by extreme rainfall-runoff episodes can often be encountered in small mountainous catchments, where changes in the runoff and sediment regime can be enormous. This is the situation for the creeks in the Jizerské Hory Mts., where the Smědá catchment was chosen as the case study for this paper. Convective high-intensity precipitation on a relatively small catchment area, its high inclination and the slope of the longitudinal profile of the river, channel destruction and its surroundings impacted by erosion often cause a great damage (Kovář & Křovák 2002).

An improvement in runoff prediction methods and in determining the volumes of flooding waves are of economic as well as environmental importance (Čamrová & Jílková 2006). *N*-year flood discharges are the basic hydrological sources for proposing measures against floods and erosion. Over the past few decades, growing importance has been given to the use of mathematical models of the rainfall-

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runoff process, based physically on infiltration, and to monitoring surface runoff and its movement on slopes and on hydrographic networks. This case study shows the ways of identifying the design runoff in small basins using the KINFIL model (Kovář 1992). This model combines the *CN* curves method and the solution of infiltration equations (Morel-Seytoux & Verdin 1981). The simulation of surface runoff is resolved by the kinematic wave model (Singh 1976, 1996), taking into account the detailed topography of the basin. The topographic terrain values are calcualted by ArcGIS software. The accuracy of these mathematical modelling methods and their connection to GIS systems is adequate for the accuracy of the mathematical description of physical processes and to the range and reliability of the data set used herein.

The second model used in this paper is an artificial neural network consisting of units called neurons that transfer and process information in the form of excitations. The training of the neural network can be imagined as modifications to the network parameters in such a way that the output neurons are excited by certain combinations of input signals (Rumelhart & McClelland 1986). The number of neurons and their connections are determined by the topology of the network. According to the function, we distinguish input, output, and intermediate neurons. The input neurons correspond with receptors, the output neurons are connected to effectors, and the intermediate neurons constitute the mediators of the information transfer between inputs and outputs (Lippmann 1987). These ways of excitation transfer are referred to as paths. The information is processed on paths by means of changes in the states of neurons along the corresponding paths. The states of all neurons and connections (synaptic weights) represent the configuration of a network. Training the neural network involves setting the configuration on the basis of data representing pairs of inputs with desired outputs. This approach is called supervised learning, and it most often utilizes gradient-based nonlinear algorithms, called error back propagation (Neruda *et al.* 2005).

The goal of our study is to compare the KINFIL and ANN approaches, to identify their strengths and weaknesses.

## MATERIAL AND METHODS

**Description of the Smědá catchment**. The river Smědá rises in the peat lands of the Jizerské hory Mts. It is the border flow between the Czech Republic and Poland (Figure 1a). Since 1957, a water level recorder has been installed in the Bílý potok station and a number of precipitation gauges have been set up in Hejnice, Nové Město pod Smrkem, Višňová, and Bílý Potok. This catchment with its measured rainfall-runoff episodes is often a source of flood disasters, which will be analyzed in this study. Table 1 shows the major physical-geometric catchment characteristics of the Bílý Potok downstream water level recorder.

The Smědá brook is classified as having class I and class II basic water quality – the water is classified as unpolluted or slightly polluted. Table 2 shows the basic hydrological data in the Smědá catchment, e.g. the average yearly precipitation and the *N*-years runoff values.

In the following description, the basic geological, soil, geomorphological, and land use characteristics of this part of the Jizerské hory Mts. are presented as a consequence of the effects of major rainfall-runoff episodes. For understanding the destruction in the area caused by high surface outflow and erosion processes, the following considerations should be taken into account:

- The geological basement of the Jizerské hory massif is composed of biotic coarse granular or porphyritic granite, easily eroded and crumbled into fine fractions.
- Most of the soils are shallow, light, coarse granular loamy-sandy soils of peat mountain Podzol type, peaty soils, and rocky rubble on steep slopes.
- The unsuitable structure and texture of the soils and the softness of the soil profile with a lack of humus means that the soils are easily eroded.
- The Jizerské hory Mts. have one of the highest precipitation frequencies and amplitudes of all Central Europe.
- Steep terrain slopes (30–50%) and quite long slope lengths (400–1000 m) provide conditions for gully erosion of whole areas.

Table 1. Physical-geometric characteristics of the Smědá catchment, Bílý Potok downstream gauge

| Characteristics | Value |
|---|---|
| Basin area ($km^2$) | 26.58 |
| Thalweg length (km) | 13.3 |
| Thalweg slope (–) | 0.069 |
| Altitude (m a.s.l.) | 497–1123 |
| Basin average width (km) | 1.96 |
| Basin slope (Herbst) (%) | 22.2 |

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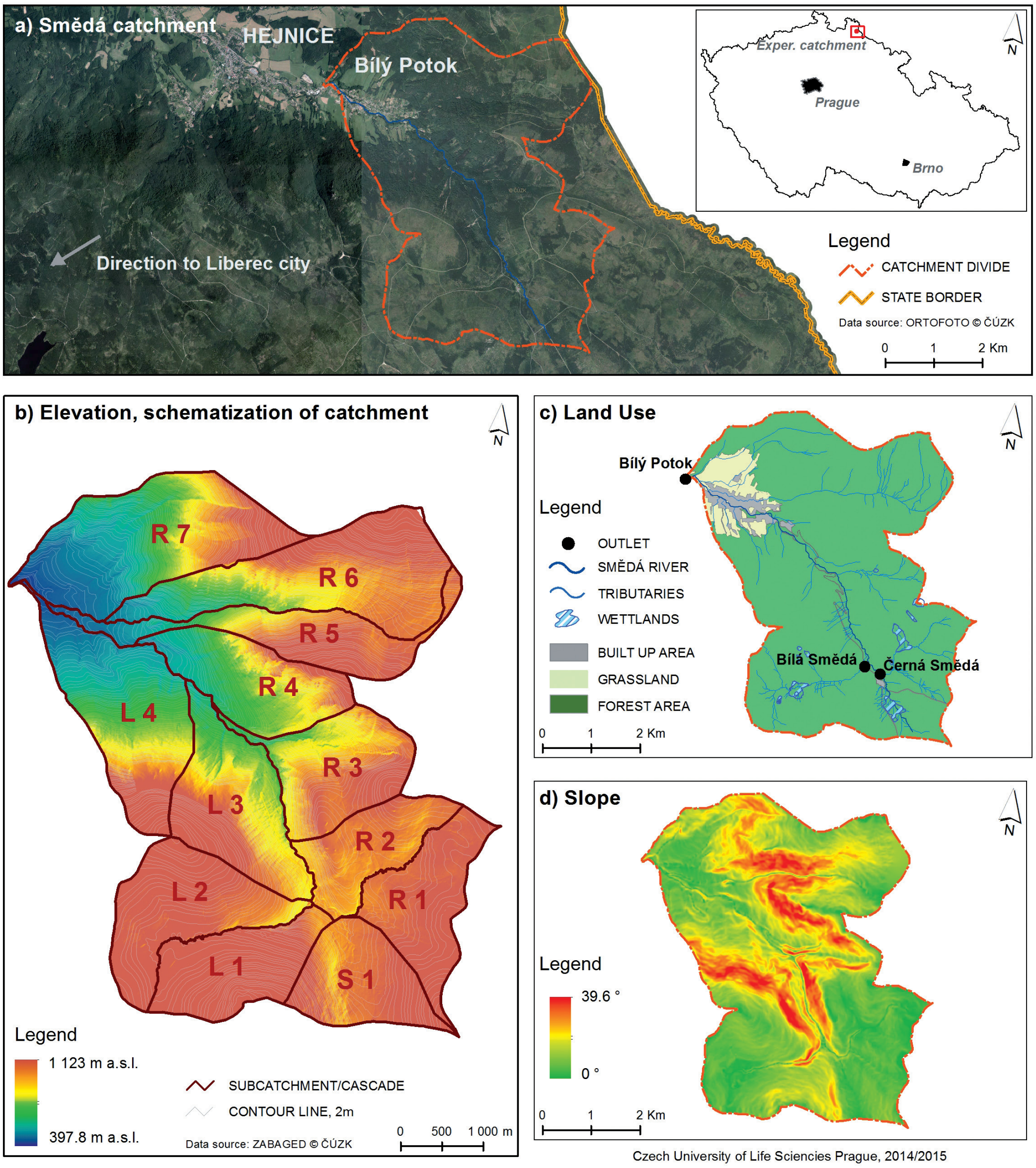


Figure 1. Main characteristics of the Smědá catchment

The vegetation in the Smědá basin consists mainly of spruce (80–90%), beech and maple trees (up to 15%). Dwarf pines occur in the peatlands, and birches and rowans are scattered in coppices. However, there is an intensive new planting programme, and the herbaceous small reed vegetation that has grown up in the clearings after deforestation is gradually being replaced. The species composition now being planted is different from the old species composition, and includes species that are more resilient to natural disasters, and that help preventing forest erosion and infiltration.

**GIS mapping of the Smědá catchment**. In the present study, GIS tools were used to create a digital model of the terrain (DMT), hydrological soil groups, economic land use, and the distribution into the subcatchments. We used ArcGIS 10.2 software tools, with the Spatial Analyst extension. The starting-point

Table 2. Hydrological data of the Smědá basin at Bílý Potok, the outlet station (Czech Hydrometeorological Institute)

| Smědá basin | Precipitation (mm) | Runoff | *N*-year runoffs ($m^3$/s) | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | | $Q_1$ | $Q_2$ | $Q_5$ | $Q_{10}$ | $Q_{20}$ | $Q_{50}$ | $Q_{100}$ |
| Bílý potok | 1426 | 1116 | 21 | 33 | 54 | 74 | 97 | 132 | 162 |

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materials were vector base datasets derived from the Orthophoto map and the Basic Map of the Czech Republic 1:10 000 (ZABAGED II), digital map BPEJ, and datasets downloaded from the HEIS database. The resulting products are the maps shown in Figure 1: Major characteristics of the Smědá catchment, comprising: (a) orthophotos, (b) height ratios and schematization of sub-catchments, (c) slope, and (d) land use. The synthetic product is a geographical map containing the hydrological information required for the KINFIL model. This data is compiled in Table 3 and shown in Figure 2, which provides a geometrical schematization of the sub-catchments, including land use. Table 3 provides a numbering system for the geometrized areas of the catchment (see Figure 2) away from the catchment boundary to the downstream gauge profile, distinguishing the upper segment (S) and the plates of the left (L) and right (R) side of the flow direction of the Smědá river.

**The KINFIL model.** The KINFIL model is based on a combination of infiltration theory, put forward by Green and Ampt and modified by Morel-Seytoux (Morel-Seytoux & Verdin 1981), and direct runoff transformation, resolved using a kinematic wave (Lax & Wendroff 1960; Kibler & Woolhiser 1970; Beven 1979; Singh 1996).

The task of the infiltration part of the model is to determine the parameters of saturated hydraulic conductivity $K_s$ and the retention coefficient of the suction pressure $S_f$ (for the state of field capacity *FC*).

Table 3. Schematization of the Smědá catchment

| Cascade/ subcatchment | Area (km$^2$) | Length of basin (km) | Plate | Area (km$^2$) | Average width (km) | Length (km) | Slope (–) | Grassland (%) | Forest (%) | Other area (%) | Built up area (%) |
|---|---|---|---|---|---|---|---|---|---|---|---|
| S1 | 1.64 | 1.86 | S 11 | 1.12 | 0.88 | 1.26 | 0.178 | – | 99.30 | – | 0.70 |
| | | | S 12 | 0.53 | | 0.60 | 0.114 | – | 94.60 | – | 5.40 |
| R1 | 1.84 | 1.35 | R 1 | 1.84 | 1.36 | 1.35 | 0.070 | – | 99.60 | – | 0.40 |
| R2 | 1.44 | 0.75 | R 21 | 0.96 | 1.93 | 0.50 | 0.097 | – | 99.60 | – | 0.40 |
| | | | R 22 | 0.48 | | 0.25 | 0.204 | – | 99.90 | – | 0.10 |
| R3 | 1.99 | 1.80 | R 31 | 1.08 | 1.10 | 0.98 | 0.213 | – | 100.00 | – | – |
| | | | R 32 | 0.91 | | 0.83 | 0.394 | – | 99.90 | – | 0.10 |
| R4 | 1.91 | 1.75 | R 41 | 0.97 | 1.09 | 0.89 | 0.243 | – | 91.50 | – | 7.80 |
| | | | R 42 | 0.95 | | 0.87 | 0.424 | – | 100.00 | – | – |
| R5 | 1.79 | 0.78 | R 51 | 0.10 | 2.29 | 0.05 | 0.119 | – | 100.00 | – | – |
| | | | R 52 | 0.41 | | 0.18 | 0.216 | – | 100.00 | – | – |
| | | | R 53 | 1.27 | | 0.56 | 0.269 | 1.10 | 81.10 | 1.70 | 16.10 |
| R6 | 3.30 | 1.49 | R 61 | 0.50 | 2.22 | 0.23 | 0.156 | – | 100.00 | – | – |
| | | | R 62 | 1.33 | | 0.60 | 0.218 | – | 100.00 | – | – |
| | | | R 63 | 1.47 | | 0.66 | 0.380 | 0.65 | 93.75 | 3.06 | 2.54 |
| R7 | 3.46 | 3.50 | R 71 | 0.40 | 0.99 | 0.41 | 0.180 | – | 100.00 | – | – |
| | | | R 72 | 1.68 | | 1.70 | 0.317 | 2.90 | 95.40 | 1.70 | – |
| | | | R 73 | 1.38 | | 1.40 | 0.147 | 34.70 | 42.50 | 15.00 | 7.80 |
| L1 | 1.79 | 1.18 | L 11 | 0.62 | 1.51 | 0.41 | 0.193 | – | 100.00 | – | – |
| | | | L 12 | 1.17 | | 0.77 | 0.147 | – | 99.70 | – | 0.30 |
| L2 | 2.25 | 1.23 | L 21 | 1.34 | 1.83 | 0.73 | 0.086 | – | 100.00 | – | – |
| | | | L 22 | 0.91 | | 0.50 | 0.154 | – | 99.93 | – | 0.07 |
| L3 | 2.33 | 1.48 | L 31 | 0.36 | 1.58 | 0.23 | 0.157 | – | 100.00 | – | – |
| | | | L 32 | 1.61 | | 1.02 | 0.415 | – | 98.40 | – | 1.60 |
| | | | L 33 | 0.36 | | 0.23 | 0.273 | – | 94.60 | – | 5.40 |
| L4 | 2.75 | 2.67 | L 41 | 0.23 | 1.03 | 0.23 | 0.171 | – | 100.00 | – | – |
| | | | L 42 | 1.03 | | 1.00 | 0.403 | – | 100.00 | – | – |
| | | | L 43 | 1.49 | | 1.45 | 0.164 | 24.70 | 52.00 | 2.00 | 21.30 |

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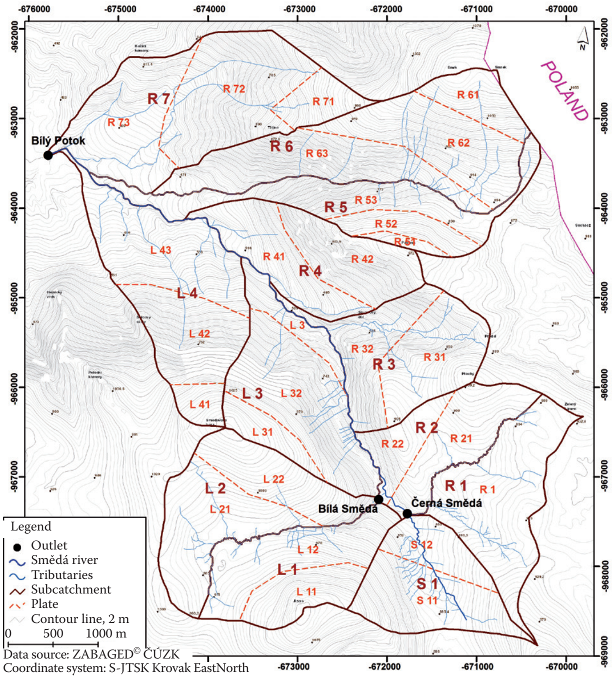


Figure 2. The Smědá catchment (BP) – distribution into sub-catchments

The solution makes use of previously derived relationships between these parameters and the values of the runoff curve numbers *CN* (US SCS 1986). The *CN* index values correspond with the conceptual values for soil parameters $K_s$ and $S_f$ (*FC*): $CN = f(K_s, S_f)$ (Kovář 1992; Kovář *et al.* 2014). The second component of the KINFIL model is the direct runoff transformation. The equation describes an unsteady flow, which is approximated by a kinematic wave. The kinematic equation has been converted into the finite difference form and resolved by the Lax-Wendroff explicit numerical scheme (Lax & Wendroff 1960). For practical solutions, the basin has been geometrized by being divided into two components: the cascade of planes and the convergent segments, so that the simulation of the runoff process corresponds with the topographical catchment areas.

For the rain files of rainfall-runoff episodes, the KINFIL model simulation is important for correct determining the value for the runoff curve numbers *CN* (US SCS 1992) for antecedent moisture conditions (average: *AMC* II), and also the default values for other parameters (actual: $CN_A$, volumetric: $CN_{vol}$), and consequently the hydraulic conductivity $K_s$ and sorptivity *S* (at the field capacity *FC*). The *CN* values, and therefore the value for the potential retention of the active upper soil zone, are influenced by the uses to which the mostly forested land is put. The forest hydrological conditions affect especially the interception, infiltration, and retention of water in depressions with no runoff and a ground cover layer of forest soil (humus leaf litter, *HLL*). The class of forest hydrological conditions (*CFHC*) is determined on the basis of the depth of the litter (*HLL* from 0 to 15 cm) and its compactness (*C*) classification. For these *CFHC* values, the average numbers of runoff *CN* curves have been derived by hydrologic soil groups (Kovář & Vaššová 2012).

The average value representation of the first grain category $I^{st}$ is 25–30%. To this class reaches saturated hydraulic conductivity $K_s$ values as high as 10 mm/h. On the basis of the humus compactness grade *CG* = 1 (depth to 5 cm), the forested surface of the basin may be classified into two hydraulic conditions (*CFHC* = 2) and for soil group C, subsequent $CN_{II}$ = 79 and for soil group B $CN_{II}$ = 69.

Table 4 provides a clear record of the numbers of runoff curve values. To calibrate the parameters of the model, it is necessary to choose characteristic couples of rainfall-runoff episodes in such a way that the rains were short and heavy, that the basin has already been saturated by previous rain, and that the peak flow was attained as soon as possible. This means that the episode should preferably be in category *AMC* III of the *CN* curve validity (i.e. low values for hydraulic conductivity and sorptivity at *FC*). Episodes with the characteristics reported in Table 5 were selected for calibration.

Variable $i_{max}$ in Table 5 is the highest rainfall intensity, $H_s$ is rain depth, $H_{s5}$ is the sum of previous rains for five days before the start of the episode, and $Q_{max}$ is peak flow. For the selected calibration episodes, we were aware that the period of 35–45 years that elapsed between the calibration and the validation

Table 4. Land division in the Smědá catchment, Bílý Potok downstream gauge

| Representation | Area (%) | HSG (%) | Weighted CN |
|---|---|---|---|
| Forests | 88 | 70 C | 0.70 × 79 = 55.3 |
| | | 18 B | 0.18 × 69 = 12.4 |
| Pastures (clearings) | 7 | 7 C | 0.07 × 79 = 5.5 |
| Arable land | 3 | 3 B | 0.03 × 79 = 2.4 |
| Built-up (urbanized) | 2 | 2 – | 0.02 × 98 = 1.9 |
| Total | 100 | 100 | $CN_{II}$ = 77.0 (rounded)<br>$CN_{III}$ = 89.0 |

HSG – hydrological soil groups; weighted CN – weighted average of curve number values

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Table 5. Selected runoff episodes (KINFIL) in the Smědá catchment (calibration)

| Episode No. | Date (start) of episode | $i_{max}$ (mm/h)[1] | $H_s$ (mm) | $H_{s5}$ (mm) | $Q_{max}$ (m$^3$/s) |
|---|---|---|---|---|---|
| 03 | 1/7 1971 | 10.1 | 77.3 | 50.5 | 33.75 |
| 04 | 20/6 1977 | 12.4 | 37.7 | 37.0 | 37.89 |

$i_{max}$ – highest rainfall intensity; $H_s$ – precipitation depth; $H_{s5}$ – sum of the previous rains for five days before the start of the episode; $Q_{max}$ – peak flow

Table 6. Simulation rating of episodes selected for parameter calibration in the Smědá catchment

| Episode No. | Date (start) of episode | Measured $Q_{max}$ | Calculated $QC_{max}$ | Difference peak (%) | Nash-Sutcliffe coefficient (–) |
|---|---|---|---|---|---|
| | | (m$^3$/s) | | | |
| 03 | 1/7 1971 | 33.75 | 40.22 | 19.17 | 0.62 |
| 04 | 20/6 1977 | 37.89 | 35.45 | 3.14 | 0.99 |

$Q_{max}$ – peak flow; $QC_{max}$ – computed peak flow

period in the KINFIL model has changed the status of land use in the Smědá basin to some extent. The simulation rating for the parameters used for calibrating the KINFIL model is shown in Table 6.

From the calibration criteria, only episode number 04 is fully acceptable (WMO 1984). When selecting the validation episodes, we focused on recent episodes (after 2008) (Table 7), indicating the volume of effective rainfall (i.e. runoff volumes) for each rain gauge station. Table 7 also shows the previous rainfall totals, the $API_{30}$ index, and the saturation class (II–III) for each episode. Table 8 provides the episodic volume values for $CN$ and the volume of the retention zone.

The volume values for the $CN_{vol}$ curves and the values for the retention zone volumes were calculated from the rainfall and runoff volumes according to a well-known methodology (Ponce & Hawkins 1996).

**The ANN model**. The inputs for the ANN model are short-history values of hourly precipitation and runoffs; the output of the network, representing the runoff value one hour ahead, is predicted on the basis of the history of hourly values of precipitation and runoff. The experiments demonstrated that a period of two or three hours was sufficient for good predictions. A further objective of the experiments was to minimize the free parameters, i.e. the size of the network. A two-hour runoff and precipitation history was therefore used during the experiments. The number of layers in the network has also been kept as limited as possible. It is known that, in theory, one hidden layer should be sufficient to obtain an arbitrarily relevant approximation of the functional dependence represented in the data. However, in our experiments there was a confirmation that the use of two (and sometimes more than two) hidden layers results in a smaller network. In all our experiments we have therefore used networks with four input neurons, one output neuron, and two layers of eight and five neurons, respectively. This rather small size has proved to be specific enough for the quantity of available data; larger networks have a tendency to over-fit the training data and achieve poor generalization.

Table 7. Status of catchment saturation 30 days before the start of the episode

| Episode No. | Start of episode | Total rainfall 30 days before the episode start (mm) | | | $API_{30}$ (mm) | Saturation class |
|---|---|---|---|---|---|---|
| | | Hejnice | Nové Město pod Smrkem | weighted average | | |
| Weight | | 0.830 | 0.170 | 1 | | |
| 1 | 29/10 2008 | 84.2 | 94.5 | 86.0 | 79.9 | II |
| 2 | 24/6 2009 | 195.4 | 226.1 | 200.6 | 186.6 | III |
| 3 | 2/6 2010 | 144.8 | 150.8 | 145.8 | 135.6 | III |
| 4 | 23/7 2010 | 88.9 | 97.3 | 90.3 | 84.0 | II |
| 5 | 6/8 2010 | 164.0 | 175.2 | 165.9 | 154.3 | III |

$API_{30}$ – index of previous saturation

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Table 8. Runoff episode heights and $CN_{vol}$ volume

| Episode No. | Start of episode | Rainfall | Q | A | $CN_{vol}$ (–) |
|---|---|---|---|---|---|
| | | | (mm) | | |
| 1 | 29/10 2008 | 54.6 | 26.3 | 37.3 | 87.2 |
| 2 | 24/6 2009 | 21.1 | 15.7 | 5.4 | 97.9 |
| 3 | 2/6 2010 | 44.8 | 38.6 | 5.7 | 97.8 |
| 4 | 23/7 2010 | 79.1 | 29.1 | 76.3 | 76.9 |
| 5 | 6/8 2010 | 199.7 | 136.8 | 63.5 | 80.0 |

*Q* – runoff; *A* – retention zone volume; $CN_{vol}$ – volume value of curve number

## RESULTS

**Results of the KINFIL model calibration and validation**. The results of parameter calibration for the KINFIL model are shown in Figure 3. The peak flows of the tested hydrographs were in accordance with the criteria assessment that was used (WMO 1984) only in the case of episode 04. The data for calibrating the KINFIL model parameters is presented in Table 6, and the results of the hydrograph simulations used by the model are shown in Figure 4.

According to the criteria of the World Meteorological Organization (WMO 1984), simulations with resulting coefficients in the range of 0.75–1.0 are applicable, using the same coefficient for model assessment (Table 9). The quality of the results is described by means of the Nash-Sutcliffe coefficient (Nash & Sutcliffe 1970) in Table 9.

Table 9. Validation results of the physically based model (KINFIL)

| Episode | | Nash-Sutcliffe coefficient | |
|---|---|---|---|
| 1 | 29–30/10 2008 | 0.61 | no* |
| 2 | 24–25/6 2009 | 0.77 | yes |
| 3 | 23–25/7 2010 | 0.89 | yes |
| 4 | 6–8/8 2010 | 0.81 | yes |

*coefficient lower than WMO limit

**Results of the ANN Model calibration and validation**. During the experiments, we employed the leave-one out methodology – the model was always calibrated using four episodes out of five, and the remaining fifth episode was used for validation. Figure 5 shows the calibration and validation results. In this case, a history of two hour worth runoff and precipitation values is used as an input of one training example with the output of runoff value one hour ahead. The main problem when calibrating the network was not the quality of approximation, but rather the generalization of the model for previously unseen data. The validation data error was therefore used during calibration as a stop criterion to prevent over-fitting. In particular, the relevant increase in the validation error was used as an indicator to stop the iterative training algorithm. The models were calibrated by the error back propagation method with a momentum term. The quality of the results is described by means of the Nash-Sutcliffe coefficient (Nash & Sutcliffe 1970) in Table 10.

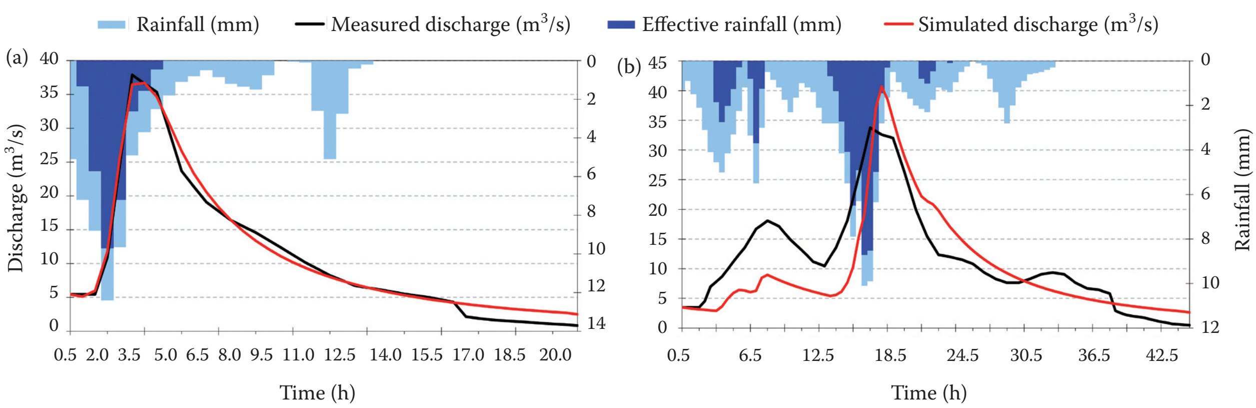


Figure 3. KINFIL calibration: Smědá 04, 20–21/6 1977 (a) and Smědá 03, 1–2/7 1971 (b)

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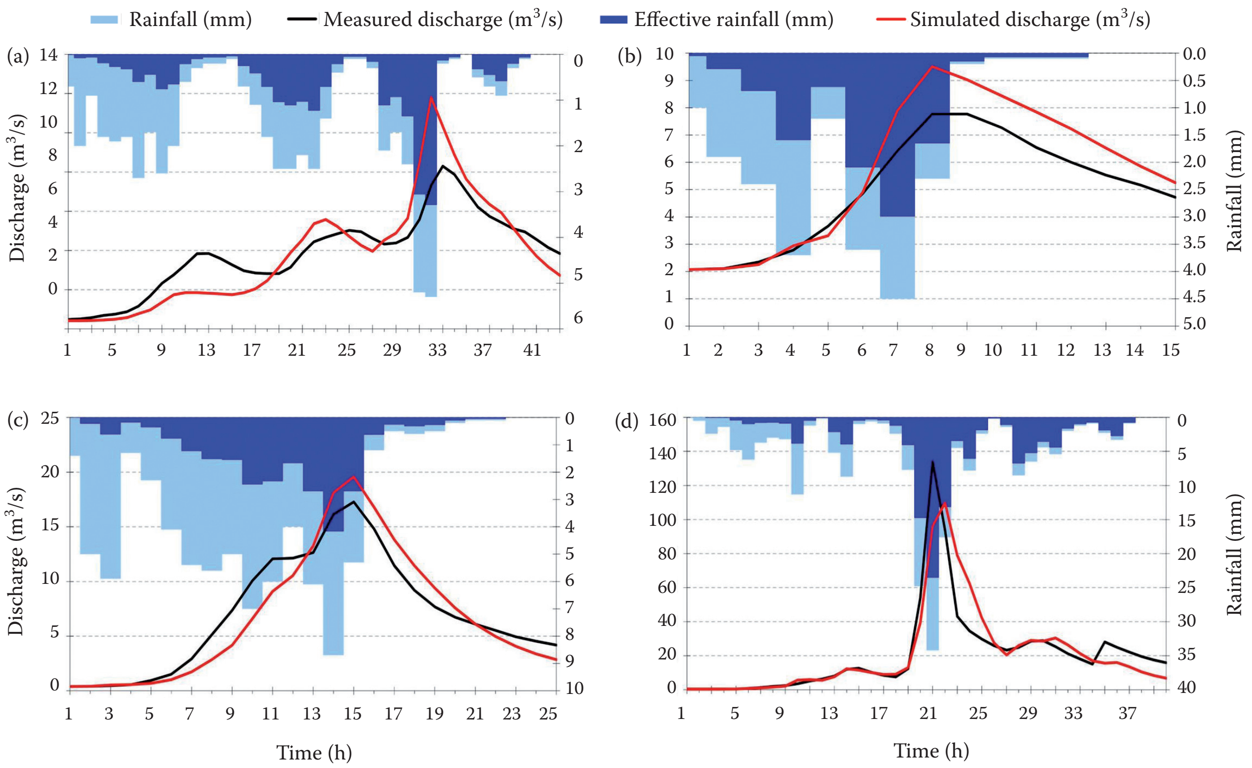


Figure 4. KINFIL validation Smědá: 29–30/10 2008 – episode 1 (a), 24–25/6 2009 – episode 2 (b), 23–25/7 2010 – episode 3 (c) and 6–8/8 2010 – episode 4 (d)

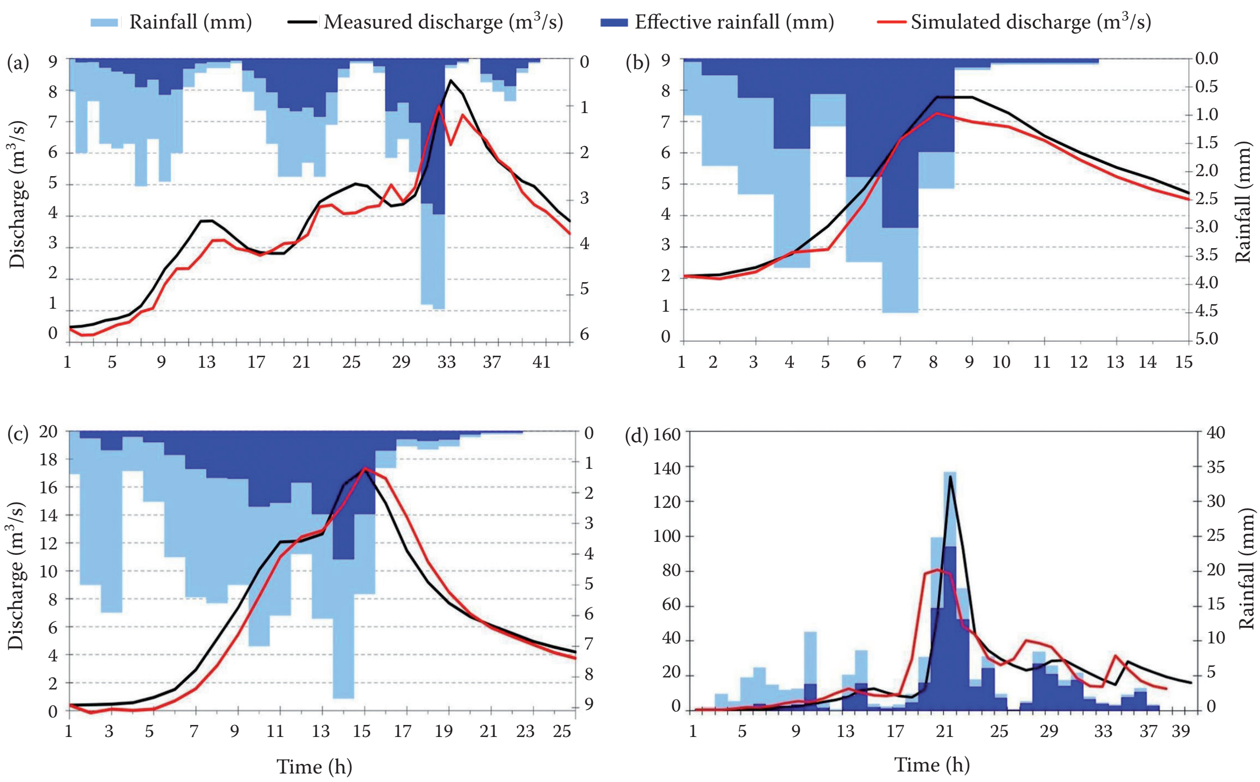


Figure 5. ANN Smědá: 29–30/10 2008 – episode 1 (a), 24–25/6 2009 – episode 2 (b), 23–25/7 2010 – episode 3 (c) and 6–8/8 2010 – episode 4 (d)

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Table 10. Validation results of the artificial neural network (ANN) model

| Episode | | Nash-Sutcliffe coefficient | |
|---|---|---|---|
| 1 | 29–30/10 2008 | 0.92 | yes |
| 2 | 24–25/6 2009 | 0.96 | yes |
| 3 | 23–25/7 2010 | 0.95 | yes |
| 4 | 6–8/8 2010 | 0.75 | yes |

## DISCUSSION

Concerning the KINFIL model, the essential question for hydrologists is which simplifications are right. Physically-based rainfall-runoff models attempt to link catchment behaviour with measurable properties (Beven 2001). However, scaling is a problem of magnitude. It is currently unclear whether this upscaling premise is correct. Catchment behaviour at larger scales can hardly be described by the same governing equations with effective parameters that somehow subsume the heterogeneity of the catchment (Kirchner 2009). Not only the subsurface conditions for unsaturated flow, but also the spatial distribution of the rainfall over a catchment area serve as good examples of heterogeneity. However, we tested the KINFIL model with four parameters only in order to avoid over-parametrization while keeping an adequate model structure (Perrin *et al*. 2001; Andréassian 2004).

The Smědá catchment in the Jizerské hory Mts. has a very non-linear rainfall-runoff process. The shallow peat soils are poorly permeable, and precipitation extremes often cause soil erosion and even landslides. The KINFIL model in the version with parameter derivation of saturated hydraulic conductivity $K_s$ and sorptivity $S$ (at $FC$), as a simple three-parameter model (along with Manning roughness $n$), has proved not to be entirely reliable for simulating extreme runoff. The derived parameters from two calibration cases are applicable (Table 6), but only three out of four validated episodes are fully acceptable (Table 9).

Unlike a physically-based model, the mechanism of the artificial neural network ANN model involves approximating the relationship between rainfall (an input to the system) and runoff (an output from the system) represented by the available historical data. In our case, the calibration process is based on training the network on data from several episodes, irrespective of the physical system, the structure, and the governing equations. The robustness of the model is based on two important factors. The first factor is the reliability of data representing the rainfall-runoff relations, while the second factor is the leave-one-out approach. It means that each simulation is calibrated on several episodes, and is validated on one episode that has not been used for calibration. All possible combinations of calibration and validation splits of the episodes were tested.

The most important issue that we had to address when calibrating the ANN model was over-fitting of the training data. The obvious non-linearity of the problem, represented by the data, calls for a more complex network design with a larger number of units. This conflicts with the rather small sizes of the datasets describing the episodes by means of one hour-based data. Thus, the networks of dozens of units in two layers have a tendency to capture too many details (maybe including rainfall measurement errors). The network parameters and the length of the training episode were therefore verified by means of the validation set results. Since our goal is not the best-possible performance of the training set, but relevant performance of the validation data, the models typically show better validation results than calibration.

## CONCLUSION

The rainfall-runoff processes in the Smědá basin are admittedly difficult to calibrate, especially in a model with a small number of parameters. Generally, the KINFIL model used here is a physically-based four-parameter 2D model (2 infiltration parameters and 2 transformations by a kinematic wave). When a version of the runoff $CN$ curves was tested, the resulting values were used for deriving two parameters, $K_s$ and $S$. Thus the four-parameter version was reduced to a three-parameter version. The selection of more recent calibration episodes (not from the 1960s and 1970s) would probably also help the simulation. We also assume that direct measurements of the soil hydraulic parameters using geo-statistical methods, instead applying $CN$ methods to derive both infiltration parameters, would bring more relevant results. However, a method of that kind would be very laborious.

In the case of ANN models, it has been demonstrated that neural networks in general have the ability to capture the non-linear nature of the rainfall–runoff relationship, and the results are to a degree comparable with those obtained using hydrological models. The application of neural networks in this area raised several issues that needed to be dealt with. Due to the low statistical frequency of extreme episodes, the ANN model has to be trained on selected data where

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these episodes are present, and most of the data is not of interest and has to be abandoned. Unfortunately, the amount of available data from extreme episodes is relatively small, taking into account the complexity of the inherent nonlinear relationship of the model. We therefore have to address the issue of a suitable network size. It has to be large enough for the problem to be modelled faithfully, but at the same time it should be small enough to generalize well. Our solution to this problem was to use the validation data performance as a stopping criterion during the calibration phase. This allowed us to stop the calibration before the algorithm started to over-fit the data. This problem should be further investigated in future, and several other methods for improving generalization should be employed. Ensembles of ANNs are a promising approach.

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