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FUZZY-LOGIC BASED RAINFALL RUNOFF MODELLING BY USING SOIL MOISTURE MEASURMENTS AS REPRESENTATIONS FOR SYSTEM STATE

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Abstract Due to the high spatial and temporal variability of soil moisture, point measurements may not always be sufficient to represent the actual system state of a basin. A fuzzy model using the Takagi-Sugeno-Kang approach has been set up with soil moisture and rainfall data as input variables in order to predict the actual runoff of the catchment's outlet. Four soil moisture probes from the hydrological test site Duerreych (Black Forest / Southwest-Germany) were selected, each of them representing a particular runoff generation process (saturation excess flow, infiltration excess flow, slow and fast interflow, return flow). The fuzzy model was calibrated manually. The simulated hydrographs were very similar to the measured values. The pattern of rule activation reflected the complex, highly non-linear behaviour of the basin. The fact that it has been possible to predict the hydrologic response on rainfall by a fuzzy modelling approach leaded us to the conclusion, that measurements of soil moisture at representative locations can be used as representation for the actual system state.

Résumé A cause d'une variabilité spatiale et temporelle de la humidité du sol très élevée, mesures locales ne sont pas suffisant pour représenter l'état actuel d'un bassin versant. Un modèle de logique floue (approche Takagi-Sugeno-Kang) a été construit avec humidité du sol et précipitation comme variables d'entrées pour prévoir le débit actuel du bassin versant. Quatre sondes d'humidité du sol dans le bassin d'observation de Duerreych (Foret noir / Allemagne Sud-ouest) ont été choisies. Chacun représente un procédé particulier de génération d'écoulement (écoulement par saturation, ruissellement hortonien, écoulement hypodermique rapide et retardé, écoulement de retour). Le modèle de simulation à base de logique floue a été calibré manuellement. Les hydrogrammes simulés étaient très semblables aux valeurs mesurées. Le modèle de l'activation des règles a reflété le comportement complexe et fortement non linéaire du bassin. Le fait qu'il a été possible de prévoir la réponse hydrologique sur des précipitations par une approche de logique floue nous a conduit à la conclusion, que des mesures de l'humidité du sol aux endroits représentatifs peut être utilisée comme représentation pour l'état actuel du système.

Key words fuzzy logic; rainfall runoff modelling; soil moisture; time domain reflectrometry (TDR)
Mots clefs logique floue; modèle pluie-débit; humidité du sol; réflectométrie dans le domaine temporel (TDR)

INTRODUCTION

Soil moisture plays a crucial role concerning rainfall runoff transformation (RRT) processes. In literature the term soil moisture has very different meanings: It is used as a description for real system state as well as for model system state but is measured only at point scale. The high temporal and spatial variability of soil moisture makes it difficult to regionalise single point measurements to the whole basin as needed for distributed catchment models. Because "in watershed rainfall-runoff transformation … initial and boundary conditions are critical issues" (NRC 2003), this raises the question if the available measurements would constrain the system state enough to allow for a prediction of hydrologic response (Zehe & Blöschl 2004). In addition runoff generation is a highly nonlinear process and threshold processes are observed in many cases (Grayson et al. 1997, Casper 2002, Chifflard et al. 2004), e.g. saturation excess flow starts when soil storage capacity is filled. Scherrer & Naef (2003) investigated flow processes during intense precipitation at the plot scale and distinguished dominant runoff generation processes by considering mainly soil and topographic properties. However, the upscaling of this information to catchment scale has not yet been solved satisfactorily.

The hypotheses of this study are that (a) measurements of soil moisture at locations representing dominant runoff generation processes may describe the actual basin state so far that the prediction of hydrologic response is possible. (b) The degree to which these field measurements constrain the actual basin state can be examined by applying data-driven models, such as artificial neural networks (ANN) or fuzzy systems. In this study a fuzzy system has been chosen because it allows for a backward interpretation of the results due to its transparency. In the past decade several fuzzy logic based models have been applied in flood forecasting (Stüber et al. 2000, Hundecha et al. 2001, Nayak et al. 2005, Chang et al. 2005) but only for large basins with upstream water level measurements as input data. In this study a fuzzy system has been built up for a small basin using soil moisture and rainfall as input variables and runoff as conclusion.

STUDY AREA

The 7 km^2 Dürreych basin (Fig. 1) is part of the mountainous Triassic sandstone landscape of the northern Black Forest. The river has formed outcrops of the stratigraphic sequence from the upper Perm (Oberrotliegendes) to the red sandstones of the Trias. Periglacial slope deposits cover most of the basin. The soils range from permeable cambisols to podzols with different degrees of stagnic properties. The mean annual precipitation is about 1500 mm. Elevation ranges from 590 to 950 m a.m.s.l.. The Duerreych creek provides a mean annual discharge of 125 l s^{-1} at the basins outlet (lowest measured discharge: 17 l s^{-1}, mean annual maximum: 3450 l s^{-1}).

Soil moisture in the Duerreych basin is significantly affected by podzolic illuvial horizons and periglacial layers with reduced permeability (Waldenmeyer 2003). On plateaus these hydraulic discontinuities can lead to stagnic conditions, whereas on slopes they induce occasional interflow (Fig. 2). On the other hand, less podzolised soils or cambisols on the other hand cause percolation as a result of the sandy and rocky substratum. According to the pattern of soil types the plateau area dominates runoff generation during moderately moist periods. Only during very wet periods interflow distinctly contributes to runoff. After dry periods, however the basin’s response even to intensive rainfall is damped and very delayed. During extreme rainfall events the event properties are outranking the basin properties in their importance (Casper 2002).

MATERIAL AND METHODS

Field data

From 1997 to 2001 the investigation area was equipped with two meteorological stations (FF and FH, see Fig. 1), time domain reflectometry probes (TDR) to measure soil moisture at the same site, data loggers at the outlet (DUE) and at four sub-basin sites measuring discharge, hydrochemical and hydrophysical parameters (Casper et al. 2003). Moreover, from 1998 to 1999 two additional soil profiles (B1 and B2) were equipped with TDR-probes, tensiometers and suction cups for soil water. All 18 TDR-probes (2 and 3 rod probes from IMKO Inc./Germany) were installed horizontally in soil depths between 8 and 90 cm. Soil moisture was logged in time intervals of 1 or 2 hours.

For the selection of the TDR sites a GIS analysis was performed using a digital elevation model and a wetness index derived from the forestry site map (Casper et al. 2006, Waldenmeyer 2003). Consequently the four sites feature different characteristic runoff generation processes:

(a) Site FF is located on the plateau region. It reacts very fast and represents saturation excess flow on a stagnic podzol.

(b) Site FH is located on deep slope deposits. Since this sandy-loamy cambisol shows high infiltration rates and has no lateral inflow. Percolation is the dominant process. Surface runoff is only possible as infiltration excess flow.

(c) Site B1 is located on a steep hillslope (35°). The soil type is podzol. It shows permanent slow interflow in the layer above the iron pan. Fast interflow is observed when the soil profile becomes saturated up to the organic horizon and then macropore flow and pipe flow dominate (Fig. 2).

(d) Site B2 represents a sandy cambisol with lower infiltration rates than at FH with additional lateral input (mainly return flow) during large rainfall events (percolation predominant for small and medium events, extreme events lead to saturation excess flow).

In October 1998 an extreme flood was captured with a return period of 150 years that featured a runoff coefficient of about 0.4. During the whole observation period this was the only non-snow influenced runoff event that led to a saturation of the entire soil profiles B1 and B2.

Fuzzy logic-based models

So called fuzzy models base upon the fuzzy set theory (Zadeh 1965). This theory differs from the classical theory of sharp sets in the way that a *fuzzy set* consists of ordered pairs of values, $(x,\mu_a(x))$, where x is an element of the usually numerical basic set A and where $\mu_a(x)$ is the degree of membership of x. This degree of membership is allocated by the membership function μ_a whose values lie the interval [0,1]. The value 1 indicates that x belongs entirely to the fuzzy set, $\mu_a(x)=0$ indicates that x does not belong to the fuzzy set at all. Values in between mean that x belongs to the set to some degree. A sharp set is a special case of a fuzzy set, if the membership function can take only the values 0 and 1.

The range of the model input values which are judged necessary for the description of the situation are used as linguistic variables. For each of them, two or more fuzzy sets are defined representing different states. A linguistic term can be associated with each of the fuzzy sets, e.g. *wet* or *dry*. Theses definitions can be used to formulate several logical IF … THEN rules.

The rule premises describe system states and can include sub premises usually combined by AND-Operators, e.g. x_1 = *wet* AND x_2 = *dry*. Accordingly, the rule consequences describe system response in the system state represented by the according premise. One method often used to design the fuzzy inference is the Takagi-Sugeno-Kang approach (Takagi & Sugeno 1985). Here the rule consequence consists of a linear function $f(e_1,\ldots,e_n)$.

The evaluation of a fuzzy rule basis e.g. for the concrete determination of the runoff value is in principle shown in Fig. 3. The left side shows the fuzzyfication of the (sharp) input values e_1 and e_2 and the aggregation of the inference values of the individual rules (degree of fulfilment w_i) e.g. over a *min* operator for the premise conjunction. The degree of fulfilment describes how strongly the system is in the condition described by the according rule. As the crossover between system states is not sharp, several of the values w_i will be greater than zero. For each rule a result $Q_{i,a}$ of the linear conclusion equation is calculated. The total result over all rule conclusions is calculated by weighting the results of each rule on the basis of its degree of fulfilment. Using this inference, a highly nonlinear system behaviour can be approximated although each single conclusions is linear.

We decided to use Fuzzy Logic for system modelling, because of its important advantages:

(a) With IF... THEN rules existing knowledge concerning the RRT process can be formulated directly and established in the system structure.

(b) The parameter identification for the rule consequences in the used fuzzy model approach of Takagi-Sugeno-Kang (TSK) can be achieved by a procedure for statistic optimization which produces a model with minimum error over the training data. Additionally methods with general constraints or specific limits for the parameters can be used for the system adaptation task. This allows to tune the optimization process with a priori knowledge.

(c) The generated system model is transparent and the firing of particular rules can be interpreted by according physical system states.

(d) All steps required for building up the system model can be implemented in computer algorithms. By this means an automated process is produced for system generation. With this technique it is possible to generate a system model very fast and economically.

In a practical view the modelling of the fuzzy system bears two substantial aspects: firstly the structure identification and secondly the parameter identification. The structure identification task has to identify the fuzzy terms and the primary rule base using different sources of information. Here, it is possible to exploit a priori knowledge over system relations. This knowledge can be formulated in form of simple rules. In addition different statistic and analytic methods known from data mining can be applied.

The first step generating a fuzzy model is the definition of input and output variables. In the case of a RRT process model, the output variable describes the water level or the runoff value, which has to be predicted. Input variables are measured values from the given catchment area, e.g. runoff, rainfall, temperature or soil moisture. In the next step the input variables have to be partitioned into suitable fuzzy sets. Thereby the total number, shape and position of the fuzzy sets have to be specified. Then suitable rules have to be determined on basis of meaningful combinations of the fuzzy sets covering the input space of the application. A priori knowledge can help to partition the input space manually. On the other hand fuzzy-cluster algorithms or heuristic algorithms could be used for automatic partitioning.

There exist different strategies for the optimization of the conclusion parameters. Due to the fact that the optimization may be seen as a typical least square problem, it can be achieved automatically by suitable algorithms from existing software packages (Stüber et. al. 2000 or Gemmar et. al. 2006). This approach produces parameters with minimal RMS concerning the used training data. Additionally, a priori knowledge can be integrated, e.g. if reasonable intervals for certain parameters can be defined.

The development of such an automatically optimized models showed several disadvantages in this special case of a small catchment:

(a) The catchment was observed for two years. Within this time, some probes failed several times at different points in time. Only spaces of time, where all probes are available can be used to identify parameters automatically. A further subdivision into training and validation data reduces the available data too far for automatic identification.
(b) Low water dominates in the period of time mentioned. The resulting model will tend to describe low water periods better than the flood waters by using the complete data set for automatic parameter identification. The usage of only the flood water periods leads to under-determined systems as too few data is available. Our intention is to describe the flood waters as precise as possible accepting deviations in low water periods.
(c) Models that produce results with a small time lag between calculated and measured peaks will be rated worse than models that predict the peak at the right point in time with a

wrong quantity using RMS. Our intention is to produce models that predict the correct amount of water allowing time lags of some hours.

Additionally, the simple model structure, the small number of parameters, the transparency of fuzzy models and the usage of our visualization combined with expert knowledge allow for manual tuning of the parameters in a first approach.

Considering the author's intention and the limitations mentioned, first results of a manual optimization are presented in this paper.

MODELLING

Structure identification

The selection of suitable soil moisture time series as input data was performed using statistical analysis (e.g. frequency distributions) and cluster analysis whereas the input data have met the following criteria:

(a) not very noisy measurement signals

(b) more or less the same saturation value for the whole observation period

(c) clearly different and plausible behaviour for different moisture conditions that allows for an identification of thresholds

Thus one respectively two time series were selected for each site as seen from Table 1 and fuzzy sets (dry - intermediate - wet) were defined for the selected. For the latter different runoff events as well as soil hydraulic parameters such as field capacity and permanent welting point were considered. This led to membership functions of trapezoidal and triangular shape respectively, as shown in the graphs of Fig 3.

Consequently unsharp relations between soil moisture state at every site and discharge behaviour, based on a more or less subjective perception of the system were formulated as fuzzy rules. Equation (1) gives an example of one fuzzy rule. Here the actual runoff Q_a as conclusion has been calculated using an unit hydrograph *uh* with *n* timesteps for the Duerreych basin. Q_b equals a nondynamic base flow of 100 l s^{-1}, *p* denotes the precipitation, *t* is the actual time and k_r is a weighting factor for the *r-th* rule.

$$\text{IF FF = wet AND B1 = dry AND ... THEN } Q_a = Q_b + k_r \cdot \sum_{n=1}^{n} (uh_n \cdot p_{t-n}) \qquad (1)$$

Fig. 4 shows two characteristic unit hydrographs for the Duerreych basin. A one unit impulse results in two different discharge response functions depending on the moisture state of the basin. In this paper only unit hydrograph 1 has been used but the implementation of the second steeper unit hydrograph could be worthwhile for wet conditions.

If all permutations of possible premises are formulated, some of them do not show degrees of fulfilment greater than zero within the observed period. However, the formulation of rules for every possible system state is very important in order to make the system robust.. There is still a possibility that someday a situation fulfilling this premise will occur. Therefore all combinations of moisture states have to be considered even if they do not occur during the observation period. The conclusion of the rules never fulfilled can be estimated using the values of related states. Thus 36 fuzzy rules have been defined.

Parameter identification

Due to the necessity that none of the probes may fail to determine the system state, only few runoff events are available in the time series. Some of them showed influence of melting snow and thereby the number of events is reduced additionally. Based on this limiting facts, one of the remaining medium events was selected randomly.

Figure 5 shows this event and part of the development user interface. Besides the calculated discharge, the measured discharge and the precipitation, the degree of fulfilment w_i for each rule in every time step is visualized in the background of Fig. 5a using grey values. The darker the grey, the higher the degree of fulfilment. Using this visualisation, periods where w_i of one rule is significantly higher (darker) than the other ones were observed. In this periods, single parameters k_r of the corresponding rule can be determined. By using this method, most of the rule's parameters could be identified. The ones that never dominate could be estimated using the k_r of rules showing adjacent system states.

RESULTS

For the calibration event (Fig. 5) one can easily see how the basin's system state shifts on the rising limb of the hydrograph from rather dry conditions (rule 27 dominates) to intermediate (rule 16), wet (rule 11) and very wet conditions (rule 1 starts to be activated, meaning that even fast interflow on the steep hillslopes of the catchment may contribute to runoff) (Fig. 5a). On the falling limb the system shifts slowly from rule 11 over to 16 to 21. After four days without rain the probe B1 shows still wet conditions, indicating that still slow interflow is produced on the hillslopes (Fig. 5b).

Fig. 6 shows a completely different system behaviour: A convective rainfall of 20 mm switches the system state so that rules 27, 16, 3 and 2 are activated simultaneously (Fig 6a). This is only an intermediate to slightly wet system state without significant runoff contribution from the steep hillslopes (no fast interflow). But probe FH (Fig. 6b) indicates that partially infiltration excess flow ("Hortonian overland flow") can be expected.

The system state during the peak discharge for the second validation event (Fig. 7) lies between the ones of Fig. 5 and Fig. 6. Peak discharge is slightly overestimated that means the threshold between "dry" and "wet" for probe B1 seems not to be appropriate.

During all three events probe FF shows values above 80% relative saturation, this indicates that saturation excess flow from the plateau regions of the catchment is contributing to runoff (Fig. 5b, 6b, 7b). Probe FF shows the typical threshold behaviour often observed in hydrological systems: In our case, it acts as a switch between no runoff / runoff. Probe FH seems to represent the mean moisture state of the catchment. High values may be explained either by a short term infiltration excess flow (Fig. 6) or by a long lasting positive water balance (Fig. 7). Probe B2 indicates fast interflow and return flow during peak discharge (Fig. 5). Probe B1 shows a similar behaviour during peak discharge, but keeps high values if long lasting slow interflow production can be assumed (Fig. 5).

CONCLUSIONS

It has been possible to predict the system behaviour by an entirely data-driven fuzzy system only by using measured soil moisture and rainfall data. The determination of a mean moisture state (probe FF) is not sufficient. In order to fit the extremer events (peaks), it has been necessary to conduct measurements of soil moisture at additional selected locations, thus representing the dominant runoff generation processes within the basin (measurements at "representative locations").

This means:

(a) measurement locations have to represent all relevant runoff generation processes in order to capture the entire bandwidth of system dynamics.

(b) since our model is totally data driven, the time series of soil moisture used for calibration must contain all possible system states in order to enable the model to predict the catchment's runoff response on rainfall input based on characteristic moisture patterns.

The latter point is the largest disadvantage of the presented method. This means, that the system can not extrapolate, except with detailed expert knowledge about possible system states and corresponding runoff responses. However, the fuzzy logic method allows for using most of the information inherent in the time series about the correlation between soil moisture dynamics and runoff generation in the catchment. In addition the demand for measurement accuracy is not very high: fuzzy systems are per se error tolerant. The ability to implement (unsharp) expert knowledge into the fuzzy rules is another big advantage.

OUTLOOK

The fuzzy logic system presented in this study might also be designed as an online system, which derives the actual system state from online soil moisture measurements (Becker 2004; Schädel 2006). This system could be used e.g. as an online flood prediction system and, additionally, as a system which raises alarm independently when a certain system state is reached or conceivable.

At present, there is a study in progress, which investigates the possibilities of improving time series analysis in order to better determine the number of processes relevant for runoff production. Principal component analysis (PCA) and analysis using Self Organising Maps (SOM, Kohonen 2001) are currently tested as methods to reduce the dimensions of the input data (18 TDR probes in our example). These methods would also allow for detecting redundancies in the data. Furthermore, a better evaluation of the automatically determined weighting factors of the fuzzy variables become possible.

In the near future, the fuzzy logic system will be extended by implementing system state depending hydrographs in order to account for the dynamics in translation and retention time in the drainage system of the catchment (Fig. 4). In addition, automatic optimization will be introduced into the fuzzy system.

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TABLES

Table 1 Definition of fuzzy premises (there have been selected only the rules that were activated during the events shown in Figs 5 to 7).

No of rule	probe FF	probe FH	probe B1	probes B2
1	wet	wet	wet	wet
2	wet	wet	wet	intermediate
3	wet	wet	dry	intermediate
5	wet	intermediate	dry	dry
7	dry	wet	wet	intermediate
8	dry	wet	dry	dry
9	dry	intermediate	dry	dry
11	wet	intermediate	wet	wet
14	dry	wet	wet	wet
15	wet	wet	wet	dry
16	wet	intermediate	wet	intermediate
17	wet	intermediate	wet	dry
18	dry	intermediate	wet	wet
19	wet	intermediate	dry	wet
21	dry	intermediate	wet	intermediate
24	dry	wet	wet	dry
27	wet	intermediate	dry	intermediate
29	dry	wet	dry	intermediate
31	dry	intermediate	wet	dry
35	dry	intermediate	dry	intermediate

probe FF: installed in 20 cm depth, stagnic podsol, representative for saturation excess flow

probe FH: installed in 35 cm depth, sandy-loamy cambisol, representative for percolation

probe B1: installed in 7 cm depth, podzol with iron pan, representative for fast interflow

probes B2: mean of probes installed in 8 and 60 cm depth, sandy cambisol, return flow for extreme events

FIGURES

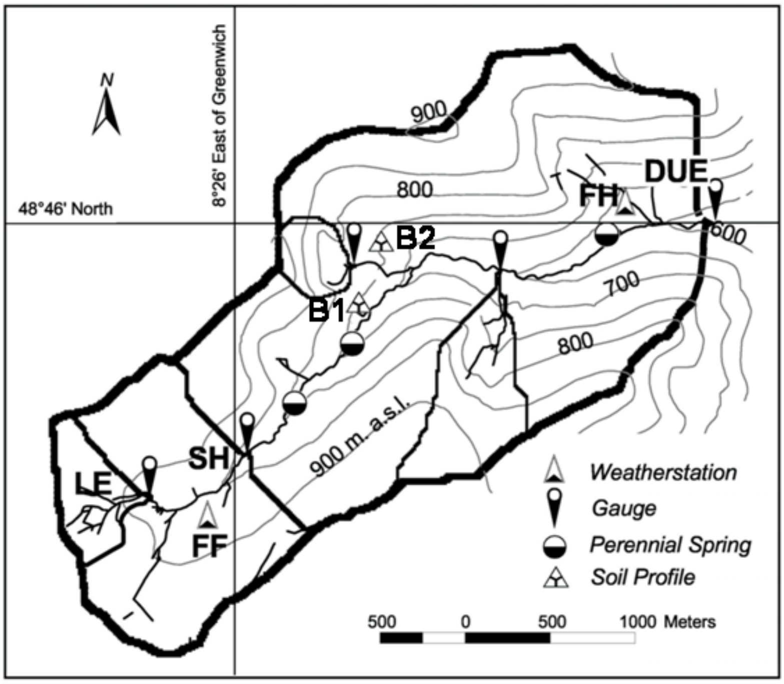


Fig. 1 Site map and instrumentation of the hydrological test site Duerreych

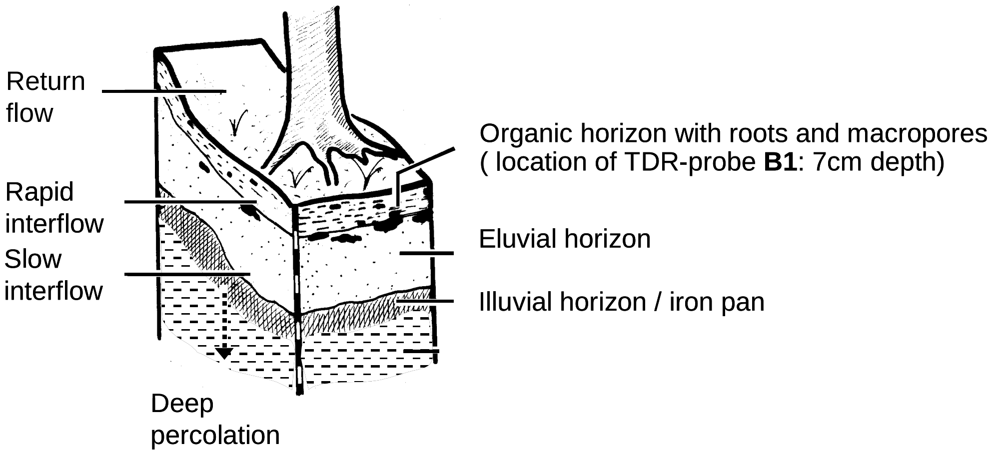
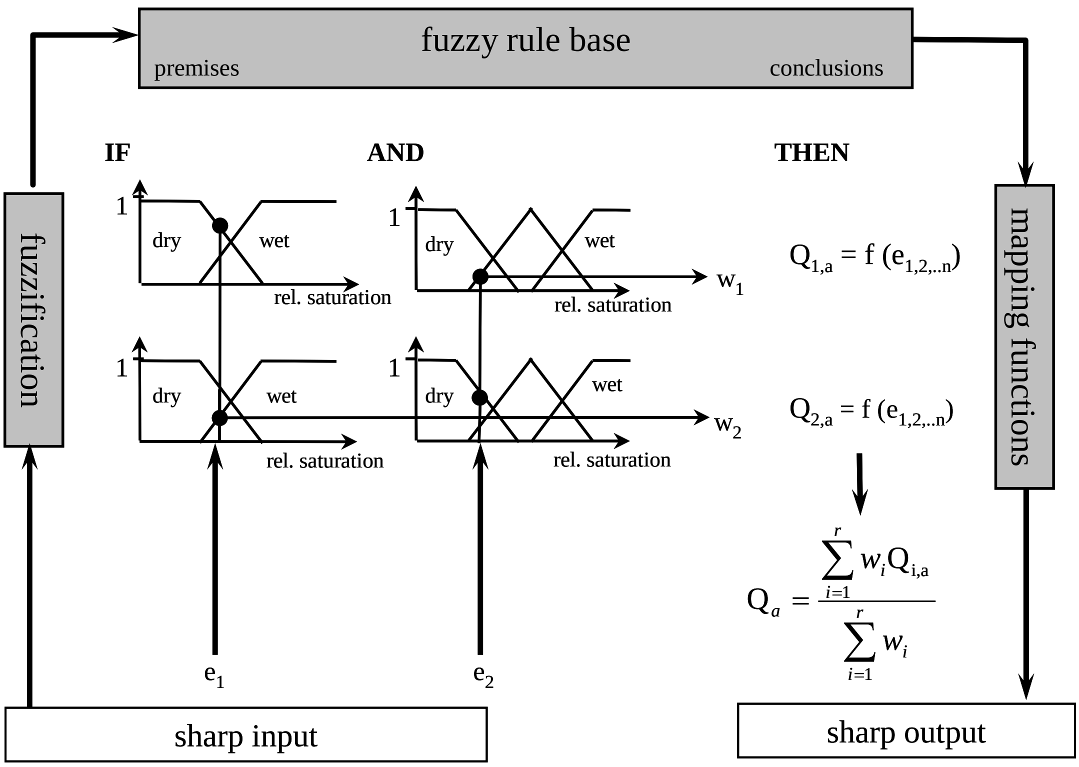


Fig. 2 Podzol slope section: Macropores and reduced permeability in the subsoil cause interflow (after Waldenmeyer 2003)



Legend: e_1, ... e_n: measured data of probe 1..n
w_1, ...w_n: degree of fulfilment for rule 1..n
$Q_{1,a}$, ... $Q_{i,a}$: discharge fraction for rule 1..n

Fig. 3 Fuzzy inference system: membership functions, fuzzyfication, aggregation of premises und TSK-mapping of rule consequence for two rules with two probes each.

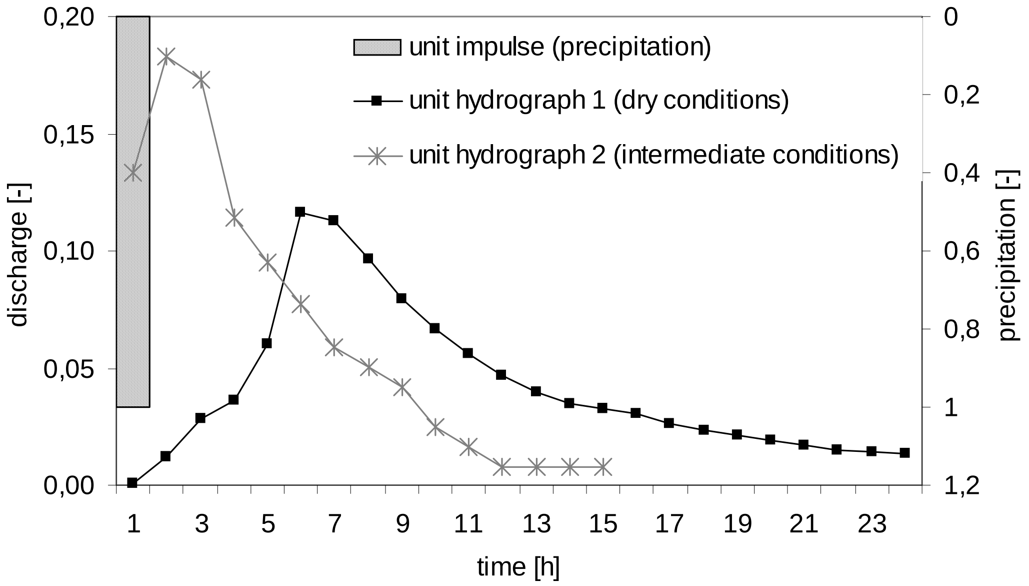


Fig 4 Unit hydrographs for the Duerreych basin derived from two different runoff events (unit hydrograph 1: event on 14 July 1999 with runoff coefficient about 0.06, unit hydrograph 2: event on 28 August 1999 with runoff coefficient about 0.17).

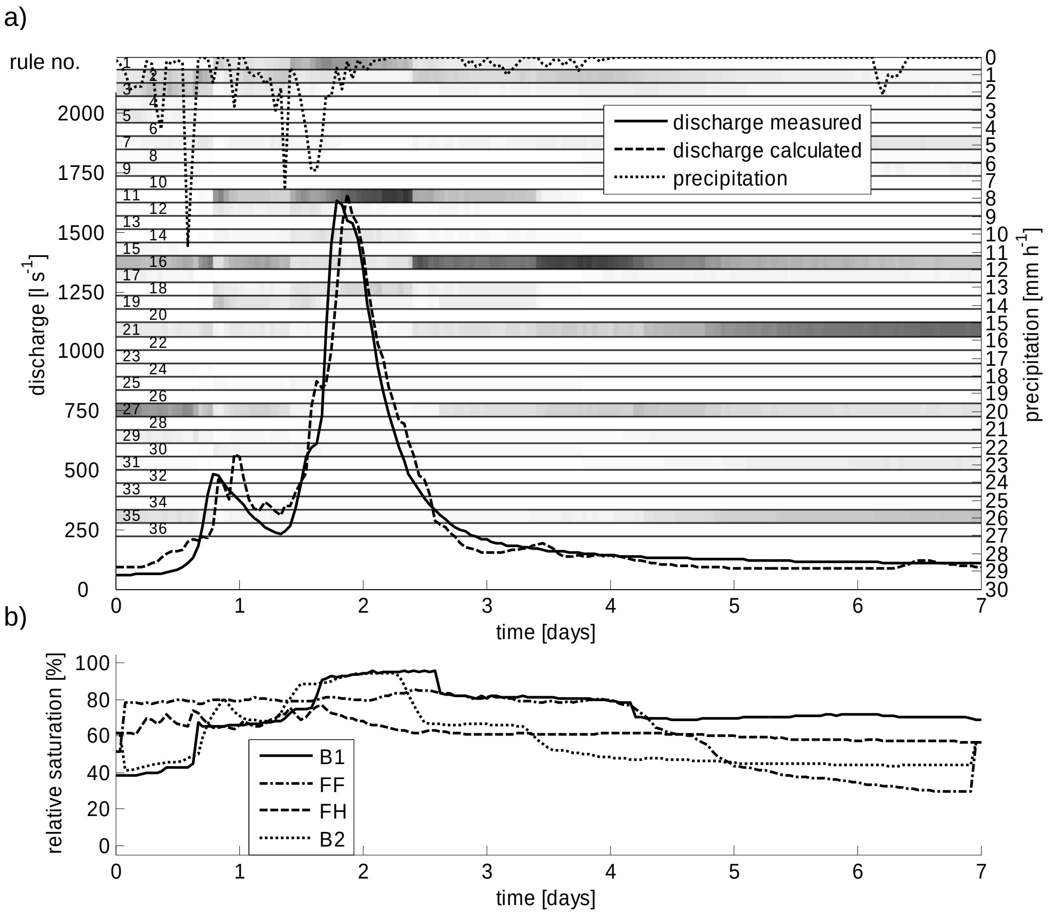


Fig 5 a) Calculated discharge for the calibration event in December 1997 and degree of fulfilment (grey shading) for the fuzzy rules no 1 to 36 (the darker the grey value the higher the degree of fulfilment).

b) Measured soil moisture at different sites

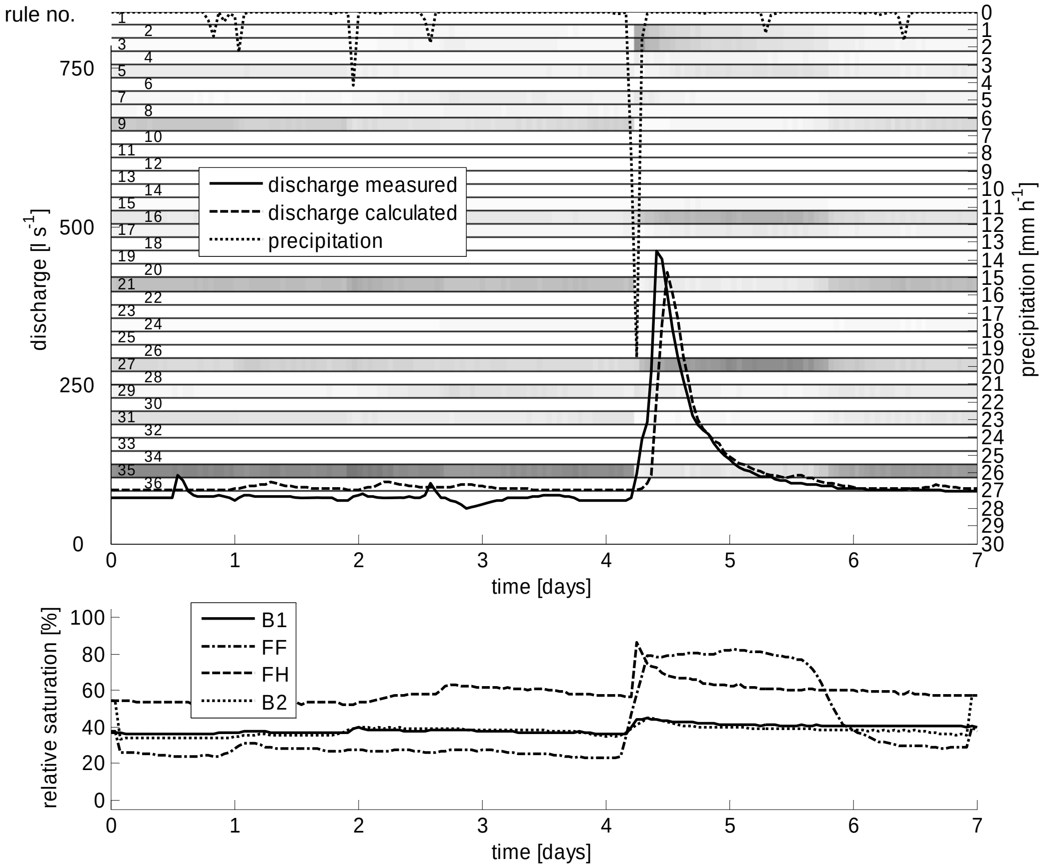


Fig 6 a) Calculated discharge for the validation event in July 1997 and degree of fulfilment (grey shading) for the fuzzy rules no 1 to 36 (the darker the grey value the higher the degree of fulfilment).

b) Measured soil moisture at different sites

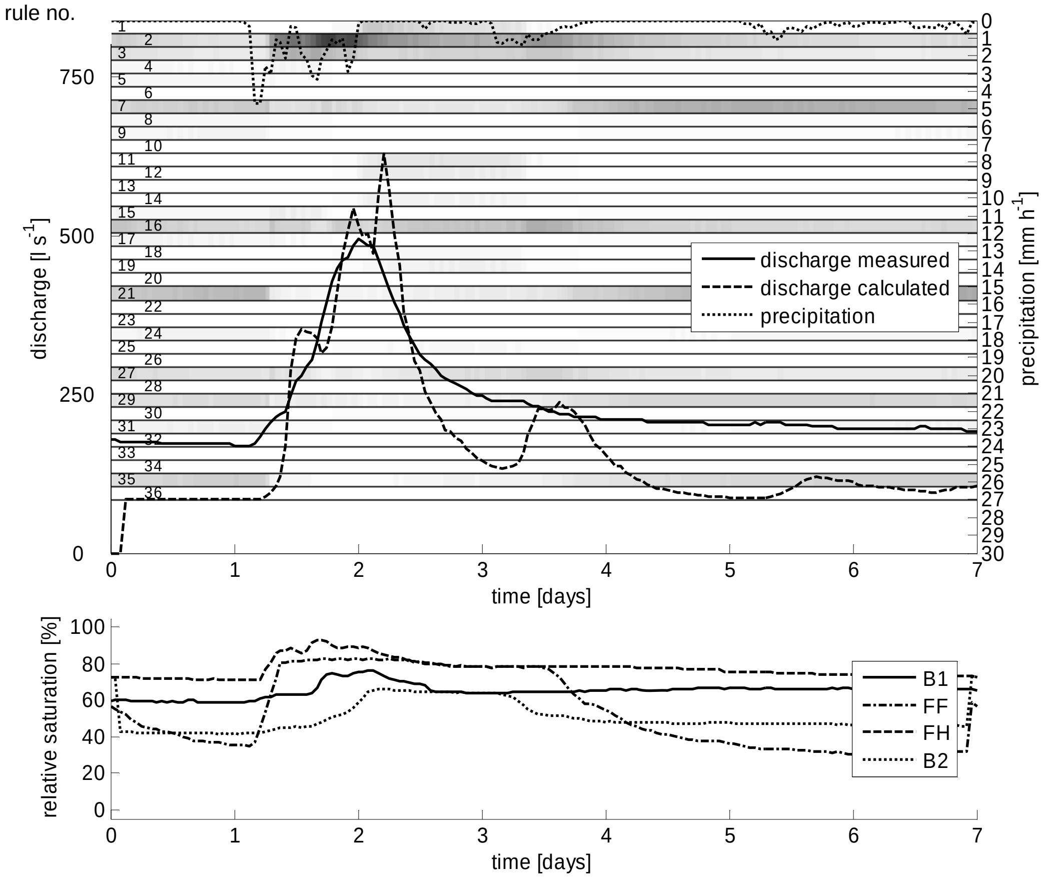


Fig 7 a) Calculated discharge for the validation event in January 1997 and degree of fulfilment (grey shading) for the fuzzy rules no 1 to 36 (the darker the grey value the higher the degree of fulfilment).

b) Measured soil moisture at different sites