Towards empirical knowledge as additional information in data-based flood forecasting techniques

Liersch, S., Volk, M.

Helmholtz Centre for Environmental Research – UFZ, Department of Landscape Ecology
Email: stefan.liersch@ufz.de

Keywords: *Flood forecasting, Flood risk assessment, GIS, Expert knowledge*

EXTENDED ABSTRACT

Floods are among the most frequent and costly natural disasters in terms of human hardship and economic loss. In recent years Europe suffered over 100 major damaging floods. Since 1998, floods have caused damages of some 700 facilities, the displacement of about half a million people and at least 25 billion Euro in insured economic losses. In the United States, about 90 percent of the damage caused by natural disasters is caused by floods and associated mud and debris flows. Reliable flood forecasting and adequate flood management could help to improve public safety and reduce economic losses. Performance of flood forecasting and flood risk management requires on the one hand technical prerequisites and on the other hand expert knowledge and experience. Thus, a functioning network of real-time climate and streamflow gauging stations, data transmitters, hydrodynamic models, inundation models, to name only a few, are representing the technical part. Water managers, scientists, decision makers etc. are representing the part of expert knowledge and experience sharing different tasks, such as, development of emergency plans, planning of flood protection infrastructure, hydrologic modelling, model development etc.

Often it seems that expert knowledge and experience is only used to operate and develop the technical part of the system and to make decisions, but is not taken into consideration to be more integrated in the flood forecasting or flood risk assessment procedure. Obviously, the reason behind is that it is difficult to integrate experience, provided by local experts, as "value" into the model based methods. Thus, it is necessary to develop methods or to use existing methods to combine expert knowledge and experience with technical flood forecasting and risk assessment approaches.

In order to make flood forecasting more reliable, particularly in data poor regions, it is necessary to make every piece of information available. Usually, the lack of data is more a lack of measured data, such as climate time series, than a lack of knowledge about system behaviour or cause and effect relations. Here we need strategies to make this kind of information more useful. Furthermore, modelling approaches have to be adapted to existing conditions, towards parsimonious models. Too often models are used only because they are well-known and based on sophisticated approaches, but require data that are usually not available.

In the course of the European NeWater project, where the authors are involved in, a prototype of a GIS-based monitoring and information system is under development. The focus is on integrating different types of information, such as "hard" (quantitative, measured) and "soft" (qualitative) information. In the context of flood risk assessment expert knowledge in form of thresholds and understanding of cause and effect relations between environmental processes and variables influencing the water regime can be considered as "soft" information to be integrated in the overall system. Therefore, two different methods, Bayesian belief networks, and a fuzzy logic approach, are taken into consideration to structure and to transform expert knowledge into information about flood risk level. Conceptual rainfall-runoff models, requiring only precipitation and temperature as input, are used to perform flood forecasting, based on short-term weather forecast data. The system is composed of five modules, based on freely available open source software where the core is a Geographic Information System (SAGA) with an interface to a relational database management system (PostgreSQL / PostGIS). It incorporates the lumped conceptual rainfall-runoff models IHACRES (***I**dentification of unit **H**ydrographs **a**nd **C**omponent flows from **R**ainfalls, **E**vaporation and **S**treamflow data*) and GR4J (*Modèles Hydrologiques du **G**énie **R**ural*) and an interface to integrate the expert knowledge-base. All data and information are stored in a centralized database and can be accessed and analyzed via the GIS user-interface.

1. INTRODUCTION

Floods are among the most frequent and costly natural disasters in terms of human hardship and economic loss. The catchment of the upper Tisza River is one of seven study areas of the European NeWater project, where the authors are participating. The catchment, situated in the geographical centre of Europe, is one of the river basins strongly affected by floods that are mostly generated in the Ukrainian part of the Carpathian Mountains in spring time. Natural extreme events like floods and droughts can occur almost simultaneously during one year. From the northwest to the southeast the river basin is surrounded by the Carpathian Mountains with elevations up to 2500 meters AMSL. Precipitation patterns are closely related to the altitudes with annual ranges from over 1700 mm in mountainous areas to below 500 mm in the lowlands (Jolánkai & Pataki, 2005). Dangerous floods can be triggered by abrupt snowmelt processes due to fast temperature increases or heavy rainfall events on the snow cover or the still frozen surface in mountainous areas. The regions mostly affected by floods in the Tisza river basin are the lowland areas in the Ukraine and Hungary. High water levels in the rivers draining the study area of the upper Tisza (~12,500 km^2), the Carpathian Mountains, can occur four to five times per year. The frequency is strongly related to the extent to which soils are saturated with water (ZFMP, 2006). Thus, the actual water content of the landscape is an important indicator for the level of flood danger. If at all, this parameter is not measured area-wide, but modelling could help to overcome this lack of information. A description of the used method is given in section 2.4.

Despite the fact, that the catchment is equipped with a number of automated climate stations, it can be considered as data poor. Data measured at these stations are precipitation, air temperature, discharge or water level, and water temperature. Current deficiencies in modelling for flood forecasting are on the one hand data quality and on the other hand data availability. From a modeller's point of view, available time series are usually too short and data quality is sometimes too low to calibrate the models in a sufficient way. Historical time series exists, but not always in digital format, or if in digital format, not in the necessary frequency, for instance, monthly means instead of daily values. The hydrodynamic model currently used by water managers for flood forecasting requires a lot of measured cross sections, that are not always available, as well as proper discharge time series. At several gauges water levels instead of discharge are measured, where water level data can only be used to calibrate hydrologic models if they are transformed to discharge via Q-h-relations. The rating curves used to convert water levels to discharge are sometimes old and thus are not representing the data properly.

As a complement to the current flood forecasting strategy, a simpler modelling approach, based on lumped conceptual rainfall-runoff models, could be helpful to overcome the problem of missing data, the lack of measured river cross sections for instance. This is the first step adapting the current flood forecasting strategy to the current situation. The second step is the development of an expert knowledge-base that contains rules of cause and effect relations derived from experience in order to support flood management. The knowledge-base is based on an analysis of flood pre-conditions resulting in a set of thresholds and causal relationships of environmental conditions that are most likely indicators for the probability of the occurrence of a forthcoming flood event. For instance, if precipitation in October and November exceeds a certain volume in combination with a quick temperature decrease in December, the water freezes in the soil, and thus the probability of a flood event will increase in the next spring. Where the rainfall-runoff models are used to perform streamflow forecast based on short-term weather forecast data, the rules defined in the expert knowledge-base are used to assess the level of flood risk. Two different methods, Bayesian belief networks, and a fuzzy logic approach, are taken into consideration to structure and to transform expert knowledge into information about flood risk level. A developing GIS-based monitoring and information system using real time climate data will automatically analyze the incoming data against the defined indicators and produce a warning message if necessary. The system is composed of five modules: a GIS, a database, a GIS-database interface, lumped conceptual rainfall-runoff models, and an expert knowledge-base.

2. METHOD

Concerning the GIS-based monitoring and information system, one objective is to make alternative sources of information available, where quantitative data are missing, basically in data-poor regions. Sources of alternative information can be diverse and data formats manifold, for instance information provided by surveys, a questionnaire, expert knowledge in form of interviews, reports, pictures, model results etc. Thus, the system, which is currently under development, must be able to deal with various data formats and types of information. The topic of flood forecasting will be supported by an integration of rainfall-runoff models and a knowledge-base, based on rules of cause and effects of environmental processes influencing the water regime. The system is composed of five modules fulfilling different tasks. Free available, platform independent, and open source software is used in all this. The components are described more detailed in the following.

2.1. GIS

Almost all data and information used in flood forecasting have a spatial reference, which requires the usage of GIS technology. Thus, the core of the system builds the open source Geographic Information System (GIS) SAGA (System for an Automated Geographical Analysis). It is implemented in an object oriented approach using the programming language C++ and the wxWidgets cross-platform toolkit to be platform independent. SAGA has been extended and adapted to the specific requirements and can be installed locally on any PC. In order to exchange data, such as tables and geographical data, between GIS and a web-database, an interface was developed. The interface is providing exchange functions as well as possibilities to analyse, visualize, and query data in the database in a user-friendly way. Furthermore, two lumped conceptual rainfall-runoff models have been implemented as modules and can be executed via the GIS user interface.

2.2. Database

The object-relational database management system (RDBMS) PostgreSQL is predominantly used to store environmental data, such as time series from a monitoring network. The extension PostGIS enables PostgreSQL to deal with geographical data in vector format implementing the OpenGIS Simple Feature Specification for SQL (OGC, 2005a, 2005b). Relevant geographic data in this context are for instance, point data (climate stations), line data (river network), and polygon data (catchment borders). Via look-up tables environmental time series data can spatially linked to their location in the real world and thus, easily accessed by the GIS interface. The database can be installed on a web-server allowing the user to access data via the internet from any location, providing all users with the same datasets. Sharing data with colleagues is much easier this way, and if time series are updated centrally, everyone has automatically access to the same new datasets – which is essential for decision makers at flood events. Furthermore, the database provides functions to analyse time series data as well as spatial data.

2.3. GIS-Database-Interface

The interface between GIS and database is implemented in the GIS environment. It provides comprehensive functions to access data in a PostgreSQL database installed on any server. SAGA can read geodata in the common ESRI Shapefile format, and export them to the database as OGC Simple Features. A new data object type, SimpleFeature, was implemented in SAGA in order to visualize and edit data in this format. Any SQL command, depending on the user's permissions, can be executed in the database via the interface and the results can be visualized in the GIS. The strength of SAGA is originally grid analysis. Using the spatial capabilities of PostGIS, the database interface extends the GIS towards advanced vector functionality. An important tool with regard to the usage of the integrated rainfall-runoff models is the pre-processing of relevant time series. Both models, described in the next section, require time series of precipitation, temperature / evapotranspiration, and discharge. The pre-processing tool enables the user to produce the necessary model input by selecting relevant climate and discharge gauges in a graphical user-interface. Weighting factors can be assigned to the selected stations, in order to increase or decrease the influence of a certain gauge. If the time series tables in the database are linked via look-up tables to the corresponding gauge point feature, the model input can be created with a few mouse clicks.

2.4. Rainfall-Runoff Models

Rainfall-runoff models play an important role in flood forecasting and thus have been implemented as modules in the monitoring and information system. The lumped conceptual rainfall-runoff models IHACRES (***I**dentification of unit **H**ydrographs **a**nd **C**omponent flows from **R**ainfalls, **E**vaporation and **S**treamflow data*) (Jakeman & Hornberger, 1993) and GR4J (*Modèles Hydrologiques du **G**énie **R**ural*) (Perrin et al., 2003) were chosen, because of their parsimonious data requirements. Only time series of precipitation, temperature, and discharge (for calibration) are necessary to run the models. These data are "theoretically" area-wide available in the Tisza study area. Both modules are equipped with a semi-automated calibration tool, based on the Monte-Carlo approach. IHACRES and GR4J have been successfully applied in a variety of different watersheds as presented by Jakeman & Hornberger (1993), Croke & Jakeman (2004), Croke et al.

(2004), Evans & Jakeman (1998), Perrin et al. (2003), Oudin et al. (2006). Additionally, both models have been tested in three German catchments by the author, because no data are not available yet from the study area in the Ukraine. In the German catchments, with mountain ranges up to 1300 meter AMSL, it became obvious that snowmelt processes are not represented sufficiently by the models. With regard to conditions in the Upper Tisza river, it is important to simulate snowmelt processes. Hence, a simple snowmelt module, based on the degree-day method (Singh & Singh, 2001) was implemented in both models, improving the streamflow simulations considerably in the cold seasons. Basically, which is important for flood forecasting, the peak flows are represented much better. Calibrated models can be used in forecast mode, using short-term weather forecast data (precipitation and temperature) to simulate streamflow in each sub-catchment. It is necessary to mention that the model output is a time series of discharge data Q in [m3/s]. To use these values in flood forecasting Q must be converted to water levels and critical water levels for each gauge must be known.

The model IHACRES is composed of two modules, a non-linear rainfall loss module and a linear storage module (Jakeman & Hornberger, 1993). In the non-linear module a time series of "excess" rainfall is estimated that is routed to the linear module. To calculate excess rainfall for each time step a catchment wetness index or antecedent precipitation index is calculated, representing the extent to which the catchment is saturated with water. This information is useful to assess flood risk. For instance, if saturation is high and forecasted precipitation is high, the flood risk might also be high. Thus, model results can support the flood risk assessment described in section 3.

The model GR4J simulated the streamflow in the German catchments, affected by snowmelt, slightly better than IHACRES. It belongs to the family of soil moisture accounting models, using only four calibration parameters (Perrin et al., 2003). The disadvantage is that it requires a time series of potential evapotranspiration instead of temperature. The probability, that potential evapotranspiration is available in a data poor region is quite low. For this reason a simple method (Hamon, 1961) was implemented, converting a temperature time series to evapotranspiration using only the latitude of the climate station in degrees as additional parameter. Accordingly, temperature or evapotranspiration values can be used to simulate streamflow with GR4J. Thus, the required model input is a daily time series of precipitation (P), potential evapotranspiration (ETp), and measured discharge to calibrate the model. The first step is the determination of net rainfall (Pn) and potential evapotranspiration. This is done by subtraction of ETp from P. If Pn is greater zero, a part of it (Ps) fills the production store that is important for low flow conditions. The other part of Pn (Pn-Ps) plus the water that is percolation leakage (Perc) from the production store is divided into two components. 90% of Pr (Pn-Ps + Perc) is routed by a unit hydrograph before it feeds a non-linear routing store. The remaining 10% of Pr are routed by a single unit hydrograph. The outflow of the routing store and the unit hydrograph, modified by a groundwater exchange function, are finally summarized to the simulated discharge. For a detailed model description see Perrin (2003).

2.5. Expert Knowledge-Base

The second part of the system is an expert knowledge-base (EKB) used to perform flood risk assessment. The EKB is a set of relationships of environmental conditions increasing or decreasing the flood risk level, based on an analysis of flood pre-conditions of the Tisza floods in 1998 and 2001 (ULRMC, 2006). In both cases the previous summer and autumn periods were extremely wet, leading to high soil moisture conditions and low water storage capacities of the landscape. Thus, the "wetness" of these seasons is the first indicator influencing the level of flood risk. If the winter period starts (temperatures below zero degrees), the water stored in the landscape starts freezing. Interesting for flood forecasting and risk assessment would be to know if the period between autumn and the period of freezing was dry and to which extent the soils are still saturated with water. This information could be provided by the landscape wetness index of the model IHACRES. Additionally or alternatively, the amount of water flowing out of the watershed during this time, in relation to the "wetness" of summer and autumn, is the second indicator influencing the flood risk level. The amount of snowfall during the winter is another factor and must be taken into account. A general indicator is a high water level in rivers that always increases flood risk. At last, thresholds of temperature and precipitation must be defined for the cold season with regard to significant snowmelt. If forecasted air temperature is increasing dramatically in a short period snowmelt starts immediately and in combination with precipitation in form of rainfall, the situation is very dangerous. Problematic is, that the occurrence of devastating floods are influenced dominantly by extreme weather conditions, such as extreme rainfall events and/or extreme increase of temperature during the cold season in a short time step. Often, landscape pre-conditions (land cover, saturation) are non-essential if an extreme rainfall event occurs. Thus, reliable weather forecast data are always necessary to predict floods. Nevertheless, monitoring and assessing the current state of a river basin is essentially important in order to assess a potential flood risk for not extreme weather conditions.

3. FLOOD RISK ASSESSMENT BASED ON EXPERT KNOWLDGE

The method to integrate the examples of expert knowledge, as explained in the above section, is not yet fixed. Currently, we propose two different potential methods.

3.1. Bayesian Belief Networks

One approach to incorporate the EKB is the usage of Bayesian belief networks (BBN), Jensen (1996). As illustrated in figure 1, the “child” variable *level of flood risk* is conditionally dependent on the states of the “parent” variables: *Wetness in Summer*, *Wetness in Autumn*, *Losses After Autumn*, *Snowfall Winter*, and the weather forecast data *Temperature Increase* and *Rainfall Winter*.

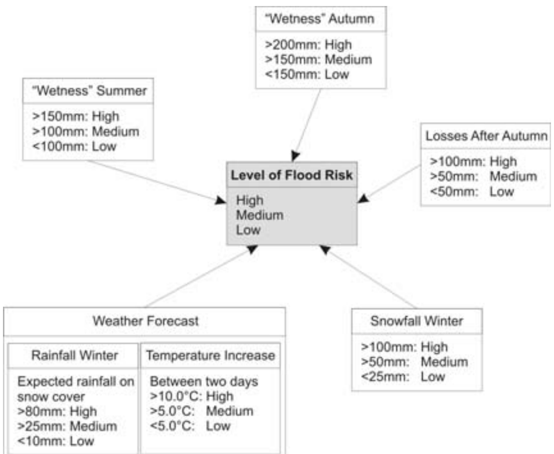

Figure 1. Factors influencing the level of flood risk

For each parent variable marginal distributions are defined which represents the probability of the occurrence of the states. Marginal distributions of *Wetness in Autumn* are for example: high = 15%, medium = 55%, and low = 30%. For each link between variables a conditional probability table must be created. An example of the relation between *Wetness in Autumn* and the *Flood Risk Level* is shown in table 1 below.

Table 1. Example of a conditional probability table between variable *Wetness Autumn* and *Level of Flood Risk*

		Wetness Autumn (B)		
		High (b_1)	Medium (b_2)	Low (b_3)
Flood Risk (A)	High (a_1)	0.7	0.4	0.05
	Medium (a_2)	0.25	0.5	0.5
	Low (a_3)	0.05	0.1	0.45

In the second step a “Joint Probability Table” must be developed for each link, where the sum of all values must be 1, as shown in table 2. Values are calculated based on the fundamental rule: $P(a_1|b_1)\ P(b_1) = P(a_1,b_1)$

Table 2. Example of a “Joint Probability Table”

		Wetness Autumn (B)				
		High (b_1)	Medium (b_2)	Low (b_3)		%
Flood Risk (A)	High (a_1)	0.105	0.22	0.015	=	0.34
	Medium (a_2)	0.0375	0.275	0.15	=	0.46
	Low (a_3)	0.075	0.055	0.135	=	0.20

To calculate the value of (a_1,b_1) 0.7 * 0.15 = 0.105.

According to Bayes’ Rule: $(P(B|A) = P(A|B)\ P(B))\ /\ P(A)$ table 3 was calculated. Where, for instance, $P(b_1|a_1) = (0.7 * 0.15 / 0.34) = 0.31$ meaning, that if the “Wetness in Autumn” is high, the probability of flood risk level “high” is 31%.

Table 3. Application of Bayes’ Rule

		Wetness Autumn (B)		
		High (b_1)	Medium (b_2)	Low (b_3)
Flood Risk (A)	High (a_1)	0.31	0.65	0.04
	Medium (a_2)	0.08	0.60	0.32
	Low (a_3)	0.04	0.28	0.68

Each variable that is added to the network is increasing the number of possible combinations. Number of Combinations = $(n_{states})^{n\ variables}$

3.2. Fuzzy Logic Approach

The second method to implement the rules of the EKB is based on a fuzzy logic approach. All variables, illustrated in figure 1, can be in the states *high*, *medium*, *low*. Increasing the number of possible states to *very high*, *high*, *medium*, *low*, *very low* could be considered for instance, without having the problem to increase the effort exponentially like in BBN. But in this example we use only three states arranged in a set (S) of ordered discrete terms. For example, $S = \{s_1 = \text{low}, s_2 = \text{medium}, s_3 = \text{high}\}$, where the position or the index of each term is the value used in calculations. The variables (V) influencing the flood risk level are: $V = \{v_1 = \text{Wetness in Summer},$

v_2 = Wetness in Autumn, v_3 = Losses after Autumn, v_4 = Snowfall in Winter, v_5 = Expected Temperature Increase, v_6 = Expected Rainfall}. To each variable a weight (ω) can be assigned, according to its importance of the contributions to flood risk. Where $\omega = (\omega_{v1}, \omega_{v2}, \ldots, \omega_{vn})$ and $\omega_i = \in |0,1|$, $\sum_{i=1}^{n} \omega_i = 1$.

An important question in this context is how these weights can be defined adequately. The first attempt to define appropriate weights could be based on a survey of expert knowledge in a discussion. Particularly local experts, working on flood management having a good system understanding, should be involved in this investigation. Thus, the assignment of weights is a subjective approximation based on the knowledge of system behaviour and processes relationships. The second approach to assess the weights is to derive the values from available historical data on the basis of probabilities. For instance, which state of a parameter was how often involved in flood pre-conditions that were leading to a flood? If there is a significant correlation between a certain state of a variable and a flood, the weight of this variable might be higher than weights of the other variables. The last approach is similar to the calibration of models and can be used to assess the weighting factors or to refine the settings of the approaches described before. In other words, it is a trial-and-error method where the weights are varied in a certain range and the result is the level of flood risk at a certain time. The overall objective is to obtain the flood risk level high before a "real" flood was occurring. Calculations based on the introduced fuzzy approach can be performed as shown in the following example:

Assuming ω = (0.05, 0.25, 0.05, 0.15, 0.2, 0.3) and:

Wetness summer (v_1)	low (1)
Wetness autumn (v_2)	high (3)
Losses after autumn (v_3)	medium (2)
Snowfall winter (v_4)	medium (2)
Expected temperature increase (v_5)	medium (2)
Expected rainfall (v_6)	high (3)

Flood Risk Level

$= (v_1)^{\omega 1} * (v_2)^{\omega 2} * (v_3)^{\omega 3} * (v_4)^{\omega 4} * (v_5)^{\omega 5}$

$= 1^{0.05} * 3^{0.25} * 2^{0.05} * 2^{0.15} * 2^{0.2} * 3^{0.3} = \underline{2.4}$

The result, a flood risk level of 2.4 is something between state *medium* and *high* and will be visualized in a map using a colour corresponding to the flood risk level. Instead of using discrete values, it can also be considered to use continuous variable states internally, derived from ranges defined by experts and current values calculated by the database.

4. RESULTS

This paper introduces an innovative data based flood forecasting system which integrates empirical knowledge as additional information, and is currently under development. Results in form of an application of the introduced monitoring and information system can not be given yet, because necessary data were still not provided to the authors by stakeholders of the NeWater Tisza case study.

The hydrologic models as well as the snowmelt module have been tested successfully in different German catchments and are ready to be applied in the Upper Tisza river basin. The actual state of the prototype of the GIS-based monitoring system is: The rainfall-runoff models IHACRES and GR4J are implemented as modules in the GIS environment, some improvements concerning different calibration methods and spatial assignment of model outputs to corresponding sub-catchments are still necessary. The interface between GIS and database provides currently the most important functionalities concerning data transfer and data analysis as well as pre-processing of time series for modelling. The expert knowledge-base must be developed together with stakeholders and local experts where threshold values and weighting factors must be assigned and investigated for each sub-catchment. Therefore, it is necessary to organize further meetings with stakeholders involved in the NeWater Tisza case study.

5. DISCUSSION

Since it is not possible to simulate or to predict floods accurately, every available piece of information that could support flood forecasting should be taken into consideration. Thus, the introduced monitoring and information system comprises methods to integrate alternative information in addition to conventional flood forecasting practices. It should be stressed here that the methods introduced to integrate the expert knowledge in order to assess the actual flood risk are usually not transferable to other conditions (watersheds) without modifications. The main reason is that the approach is based on basin immanent characteristics. Processes in one basin are not necessarily occurring in other watersheds, snowfall for example.

The reason for the implementation of two rainfall-runoff models is twofold. The model IHACRES simulates the current saturation of the catchment at each time step, that is an important indicator for flood risk, but the performance of streamflow simulation of the model GR4J was better in the German test areas than IHACRES simulations. Furthermore, it is useful to have the possibility to compare results from different models in order to better assess uncertainties in flood forecast simulations.

Comparing the methods to assess the flood risk level based on empirical knowledge, we favour the fuzzy logic approach, because of its simplicity and traceability. In opposition to the BBN approach it is not necessary to create complex tables representing all possible combinations. Moreover, increasing the number of possible states of a variable is not increasing the effort exponentially like in BBN. But, finally the application of both methods will show which approach will give more useful results.

6. CONCLUSION

Due to the fact that devastating floods occur frequently in many regions all over the world, it is necessary to improve existing flood forecasting strategies towards an integration of empirical knowledge and experience. Furthermore, it should be emphasized here that modelling approaches should always be adapted to local conditions, basically to the availability of data. Particularly in data poor regions it is necessary to develop new or to adapt existing methods to local conditions. Hence, further research is required to make local knowledge and experience available and applicable.

7. REFERENCES

Croke, B. F. W. & Jakeman, A. J., 2004. A catchment moisture deficit module for the IHACRES rainfall-runoff model. *Environmental Modelling & Software, 19*, 1-5

Croke, B. F. W.; Merritt, W. S. & Jakeman, A. J., 2004. A dynamic model for predicting hydrologic response to land cover changes in gauged and ungauged catchments. Journal Of Hydrology, 291, 115-131

Evans, J. P. & Jakeman, A. J., 1998. Development of a simple, catchment-scale, rainfall-evapotranspiration-runoff model. Environmental Modelling and Software, 13, 385

Hamon, W.R., 1961. Estimating potential evapotranspiration. In: Division, J.o.H. (Ed.), Proceedings of the American Society of Civil Engineers pp. 107-120

Jakeman, A. J. & Hornberger, G. M., 1993. How Much Complexity Is Warranted in a Rainfall-Runoff Model?. *Water Resources* Research, 29, 2637-2649

Jensen, F., 1996. An Introduction to Bayesian Networks. Springer-Verlag, New York.

Jolánkai, G. & Pataki, B., 2005. The Tisza River Project. Real-life scale integrated catchment models for supporting water- and environmental management decisions. Description of the "Tisza River Project" and its main results.

OGC, 2005a. OpenGIS Consortium, Inc. OpenGIS Implementation Specification for Geographic information - Simple feature access - Part 1: Common architecture Open Geospatial Consortium Inc.

OGC, 2005b. OpenGIS Consortium, Inc. OpenGIS Implementation Specification for Geographic information - Simple feature access - Part 2: SQL option Open Geospatial Consortium Inc.

Oudin, L.; Andreassian, V.; Mathevet, T.; Perrin, C. & Michel, C., 2006. Dynamic averaging of rainfall-runoff model simulations from complementary model parameterizations. Water Resources Research, 42

Perrin, C.; Michel, C. & Andreassian, V., 2003. Improvement of a parsimonious model for streamflow simulation. *Journal of Hydrology, 279*, 275-289

Singh, P. & Singh, V., 2001. Snow and Glacier Hydrology. Kluwer Academic Publishers

ULRMC, 2006. Ukrainian Land and Resource Management Center. Review of Flood Situation 1998/2001 and Recommendations on Flood Management.

ZFMP (Zakarpattia Flood Management Project), 2006. Flood Management in Zakarpattia Region. The European Union's TACIS Programme for Ukraine TACIS Programme.