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Parameter sensitivity and uncertainty analysis of the WetSpa model using PEST

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Abstract: The spatially distributed hydrologic model WetSpa is applied to the Torysa river basin (1297 km^2) located in Slovakia. Daily hydrometeorological data from 1991 to 2000, including precipitation data from 14 stations, temperature data from 2 stations and evaporation data measured at one station are used as input to the model. The spatial characteristic of the basin are described by three base maps, i.e. DEM, landuse and soil type, in GIS form using 100 m cell size. Results of the simulations show a good agreement between calculated and measured hydrographs at the outlet of the basin. The model predicts the daily discharge values with a good accuracy, i.e. about 73% according to the Nash-Sutcliff criterion. Sensitivity and uncertainty analysis of the model parameters is performed using a model-independent parameter estimator, PEST. It is found that the correction factor for calculating the actual evapotranspiration from potential evaporation has the highest relative sensitivity. Parameter uncertainty analysis gives an insight of a proper parameter set and parameter interval.

Key-Words: WetSpa model, PEST, Sensitivity analysis, Uncertainty, Flood prediction, Flow simulation, GIS-based hydrological modeling

1 Introduction

Distributed hydrological models are usually parameterized by deriving estimates of parameters from the topography and physical properties of the soils, aquifers and land use of the basin. The reliability of model predictions depends on how well the model structure is defined and how well the model is parameterized. However, estimation of model parameters is difficult due to the large uncertainties involved in determining the parameter values, which can not be directly measured in the field. Therefore model calibration is necessary to improve the model performance (Liu et al., 2005). Manual calibration and automatic calibration are two types of parameter estimation approaches. Automatic calibration involves the use of a search algorithm to determine best-fit parameters, and it offers a number of advantages over the manual approach. Automatic calibration is fast, it is less subjective, and since it makes an extensive search of the existing parameter possibilities, it is highly likely that results would be better than that which could be manually obtained. Unfortunately, model calibration does not guarantee reliability of model predictions. The parameter values obtained during calibration and the subsequent predictions made using the calibrated model are only as realistic as the validity of the model assumptions for the study watershed and the quality and quantity of actual watershed data used for calibration and simulation. Therefore, even after calibration, there is potentially a great deal of uncertainty in results that arises simply because it is unlikely to have error-free observational data (e.g. precipitation, streamflow, topography) and because no simulation model is an entirely true reflection of the physical process being modeled (Muleta and Nicklow, 2004). Sensitivity analyses are valuable tools for identifying important model parameters, testing the model conceptualization, and improving the model structure. They help to apply the model efficiently and to enable a focused planning of future research and field measurement (Siebera and Uhlenbrook, 2005). Due to spatial variability, budget constraints or access difficulties model input parameters always contain uncertainty to some extent. However, a model user has to assign values to each parameter. The model is then calibrated against measured data to adjust the parameter values according to certain criteria. This implies that the modeler has a clear understanding of all the parameters used as input to the model and of the processes represented in the model. Parameters that are not well understood may be left unchanged even though they are sensitive or are adjusted to implausible values. Not knowing the sensitivity of parameters can also result in time being uselessly spent on non-sensitive parameter optimization trials. Focus on sensitive parameters can lead to a better understanding and to better estimated values and thus reduced uncertainty (Lenhart et al., 2002). Therefore sensitivity analysis as an instrument for the assessment of the input parameters with respect to their impact on model output is useful not only for model development, but also for model validation and reduction of uncertainty (Hamby, 1994).

The WetSpa model used in this study is a grid-based distributed runoff and water balance simulation model that runs on an hourly or daily time step. It predicts hourly or daily overland flow occurring at any point in a watershed, and provides spatially distributed hydrologic characteristics in the basin. Inputs to the model include digital elevation data, soil type, land use data, precipitation and potential evaporation time series. Stream discharge data is optional for model calibration. In this paper, an application of the WetSpa model is presented for a rather large catchment located in Slovakia. Automatic calibration, and sensitivity and uncertainty analysis of the model parameters are performed using a model-independent parameter estimator, PEST.

2 WetSpa model

The WetSpa model was originally developed by Wang et al. (1997) and adapted for flood prediction by De Smedt et al. (2000) and Liu et al. (2003). The hydrological processes considered in the model are precipitation, interception, depression storage, surface runoff, infiltration, evapotranspiration, percolation, interflow, groundwater flow, and water balance in each layer. For each grid cell, four layers are considered in the vertical direction: a canopy layer, the root zone, a transmission zone and the groundwater reservoir. The total water balance for each raster cell is composed of a separate water balance for the vegetated, bare-soil, open water and impervious part of each cell. This allows to account for the non-uniformity of the land use per cell, which is dependent on the resolution of the grid. A mixture of physical and empirical relationships is used to describe the hydrological processes in the model. The model predicts peak discharges and hydrographs in any location of the channel network and the spatial distribution of hydrological characteristics in each cell. Hydrological processes in each grid cell are set in a cascading way, starting from a precipitation event. Incident rainfall first encounters the plant canopy, which intercepts all or part of the rainfall until the interception storage capacity is reached. Excess water reaches the soil surface and can infiltrate the soil zone, enter depression storage, or diverted as surface runoff. Depression storage is subject to evaporation and further infiltration. The sum of the interception and depression storage forms the initial losses at the beginning of a storm, and does not contribute to the storm flow. The surface runoff or rainfall excess is calculated using a moisture-related modified rational method with a potential runoff coefficient depending on the land cover, soil type, slope, the magnitude of rainfall, and the antecedent soil moisture. The values of potential runoff coefficient are taken from literature and a lookup table, linking values to slope, soil type and landuse classes (Liu, 2004). The difference between net precipitation and excess rainfall is the amount of infiltration into the soil. Evapotranspiration from the soil and vegetation is calculated as a function of potential evapotranspiration, vegetation type, stage of growth and soil moisture content. For the surface layer, actual evapotranspiration is computed as the area-weighted mean of the land use percentage, for which transpiration occurs from the vegetated parts and evaporation from the soil, while there is no evaporation from impervious areas. A portion of the remaining potential evapotranspiration is transpirated from the groundwater as a proportion of the groundwater storage. Finally, the total evapotranspiration is calculated as the sum of evaporation from interception storage, depression storage, and the evapotranspiration from soil and groundwater storage. For each grid cell, the root zone water balance is modeled continuously by equating inputs and outputs. The change of soil moisture content for each time interval is determined by subtracting the volume of initial abstraction (interception and depression), surface runoff, evapotranspitration, interflow, and percolation from the root zone. A fraction of the soil water percolates to the groundwater storage and some is diverted as interflow. The root zone is also subjected to evapotranspiration depending on the potential evapotranspiration rate and the available soil moisture. Groundwater discharges to the nearest channel proportional to the groundwater storage and the recession coefficient. Evapotranspiration from groundwater storage is also accounted for. Total runoff from a grid cell is the summation of surface runoff, interflow and groundwater discharge. Percolation and interflow are assumed to be gravity driven. The percolation out of the root zone is equated as the hydraulic conductivity depending on the moisture content as a function of the soil pore size distribution index. Interflow is assumed to occur in the root zone after percolation and becomes significant only when the soil moisture is higher than field capacity. Darcy's law and a kinematic wave approximation are used to determine the amount of interflow generated from each cell, in function of hydraulic conductivity, the moisture content, slope angle, and the root depth. The routing of overland flow and channel flow is implemented by the method of the diffusive wave approximation (Liu et al., 2003). An approximate solution using a two-parameter response function, termed average flow time and the standard deviation of the flow time, is used to route water from each grid cell to the basin outlet or a selected convergent point in the basin. The flow time and its variance are determined by the local slope, surface roughness and the hydraulic radius for each grid cell. The flow path response function at the outlet of the basin or any other down stream convergent point is calculated by convoluting the responses of all cells located within the drainage area in the form of the probability density function. This routing response serves as an instantaneous unit hydrograph and the total discharge is obtained by convolution of the flow responses from all spatially distributed precipitation excesses generated in the grid cells (De Smedt et al., 2005).

Because, groundwater movement is much slower than the movement of water in the surface and near surface water system, groundwater flow is simplified as a lumped linear reservoir on small GIS derived subcatchment scale. Considering the river damping effect for all flow components, overland flow and interflow are routed firstly from each grid cell to the main channel, and joined with groundwater flow at the subcatchment outlet. Then the total hydrograph is routed to the basin outlet by the channel response function. The total discharge is the sum of overland flow, interflow and groundwater flow, and is obtained by convolution of the flow responses from all grid cells. An advantage of this approach is that it allows the spatially distributed runoff and hydrological parameters of the basin to be used as inputs to the model. Inputs to the model include digital elevation data, soil type, land use data, and measured climatologic data. Stream discharge data is optional for model calibration. All hydrological processes are simulated within a GIS framework.

Since, a large part of the annual precipitation is in the form of snow, the conceptual temperature index or degree-day method (Martinec et al., 1983) is used to simulate snow melt. The degree-day method is simple but nevertheless has a strong physical foundation. The method replaces the full energy balance with a term linked to air temperature. It is physically sound in the absence of shortwave radiation when much of the energy supplied to the snow pack is atmospheric long wave radiation.

The WetSpa distributed model potentially involves a large number of model parameters to be specified during the model setup. Most of these parameters can be assessed from the field data, e.g. hydrometeorological observations, maps of topography, soil types, and land use, etc. However, comprehensive field data are seldom available to fully support specification of all model parameters. In addition, some model parameters are of a more conceptual nature and cannot be directly assessed. In the process of WetSpa model parameterization, the spatial patterns of the parameter values are defined using the available filed data to describe the most significant variations. This is done by using a data base and defining appropriate parameter classes of topography, soil type, land use, etc. For each class, all parameters are assessed directly from the data base. This approach enables to apply the model with information that is available in a catchment. The model has been applied in several studies, e.g. Barebeek catchment in Belgium (De Smedt et al., 2000), Alzette river basin in Luxembourg (Liu et al., 2003) and Hornad watershed in Slovakia (Bahremand et al., 2005), with different success. Gradually, major correction factors were introduced to compensate for the lack of precise field data and particular condition that might be present in the catchment. This approach enables to apply automated calibration procedures to improve the model performance.

The major model parameters that can be calibrated are listed in Table 1. All other model parameters are automatically derived using GIS tools and are kept constant. The choice of parameters to calibrate is based on earlier studies of the WetSpa model (Liu et al. 2003; Liu 2004).

Table 1. The model global parameters.

Symbol	Parameter	Unit
K_i	interflow scaling factor	-
K_s	initial soil moisture	-
K_e	correction factor for PET	-
K_g	groundwater recession coefficient	d^{-1}
K_{gi}	initial active groundwater storage	mm
K_{gm}	maximum active groundwater storage	mm
K_m	moisture or surface runoff exponent	-
K_p	maximum rainfall intensity	mm d^{-1}

Scaling factor for interflow computation, K_i, considers the effects of organic matter and root system on hydraulic conductivity used in interflow calculation. Initial soil moisture, K_s, is a ratio against field capacity defined in the input parameter file for setting up the initial soil moisture conditions. Soil moisture content is a key element in the model controlling the hydrological processes of surface runoff production, evapotranspiration, percolation and interflow. A proper initial soil moisture condition may provide a much more realistic starting point for predictions. However, for a long-term flow simulation in a watershed, the initial soil moisture condition is less important, as it affects the hydrological processes only in the initial part of the simulation. If the model is used for short-term flow simulation or event-based flood prediction, the antecedent moisture condition becomes one of the most important factors in runoff production as well as its distribution. Correction factor for potential evapotranspiration (PET), K_e, controls the actual evaporatranspiration from soil and the groundwater storage based on the measured evaporation data input to the model. The PET data used in the model are obtained from pan measurement or calculated by Pemman-Monteith or other equations using available weather data. These reference evapotranspiration rates refer to water surface or a grass cover in large fields. Actual reference or PET rates, however, may depend on local factors that are not addressed by these methods. For instance, the land use, elevation, as well as the micro-meteorological conditions for the grid to be simulated may be different from those prevailing at the site of the meteorological station whose data are being used. To account for these effects, a correction factor is required in the computed PET. The correction factor is normally close to 1, and can be calibrated by the model through a long-term water balance simulation. Specifically, when modelling in a mountainous catchment, the evapotranspiration stations are usually very sparse and are located in the river valley. To account for the effect of elevation, the correction factor for PET may be much lower in this case. Groundwater recession coefficient, K_g, is the proportionality constant used by the model to compute the groundwater flow from the groundwater storage. K_{gi} and K_{gm} are initial and maximum active groundwater storage in depth (mm). In the WetSpa model, groundwater balance is maintained on subcatchment scale and for the active groundwater storage, which is that part of storage in perched or shallow aquifers that contribute to the surface stream flow. Water percolating from the root zone storage may flow to active groundwater storage or may be lost by deep percolation. Active groundwater eventually reappears as baseflow, but deep percolation is considered lost from the simulated system. A value of initial groundwater storage is set up in the input parameter file for all subcatchment. This value can be adjusted during calibration by comparing the computed and observed low flows for the initial phase. The maximum active groundwater storage (K_{gm}) controls the amount of evapotranspiration from the groundwater. The parameters K_m and K_p are combined to modify the potential runoff coefficient based on soil moisture and rainfall intensity.

3 Application

3.1 Study area

The Torysa river is a tributary of the Hornad river located in Slovakia. Figure 1 shows the Torysa basin as a subcatchment of the Hornad basin, with topography, and location of precipitation and flow stations indicated in the figure. The watershed has an area of 1297 km^2 up to Kosicke Olsany station. The river joins the Hornad river at Zdana which is located about 17 km at downstream of Kosicke Olsany. The Torysa basin is mountainous, with elevations ranging from 189 to 1261 m. The mean elevation of the catchment is 509 m, and the mean slope about 14.4%.

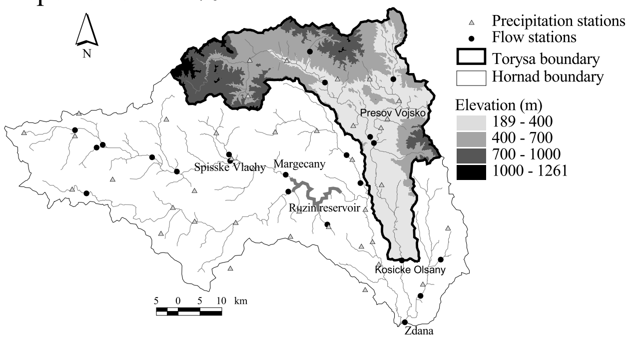

Fig.1. Hydrologic network of Hornad catchment, topography of Torysa subcatchment, and location of gauging stations.

A digital elevation model (DEM) for the river basin was obtained from the Slovak Hydrometeorological Institute (SHMU), and converted to a 100 m grid size, from which the drainage system and area were determined as shown in Figure 1. Land cover data were obtained from 30 m Landsat-7 Enhanced Thematic Mapper (ETM) satellite data, acquired on August 20th, 2000. The final landuse map for this study has 100 m cell size, and is composed of 6 different types of land cover: 41.3% of the basin is covered by forest (9.6% coniferous forest and 31.7% mixed & deciduous forest), 28.1% grassland and pasture, 27.5% agriculture areas, 3.1% urban area and about 0.05% water surfaces which are mainly reservoirs. The soil types were obtained from the Water Research Institute of Slovakia (VUVH).

There are 10 different soil textures in the catchment. The dominant soil texture is silt loam, which covers about 44.5% of the basin, followed by loam 20.3% and sandy loam 15.6%. The basin has a northern temperate climate with four distinct seasons. January is the coldest month and July is the warmest month of the year. The highest amount of precipitation occurs in the period from May to August while in January and February there is usually only snow. The mean annual precipitation of the watershed based on 10 years data of 14 stations within the basin is 630 mm, ranging from about 600 mm in the valley to more than 900 mm in the mountains. The mean temperature of the catchment based on a 40-year period isothermal map is about 6.7^{o}C. The annual potential evapotranspiration based on 10 years data of 1 station (Presov Vojsko) is about 588 mm. For this study, precipitation, temperature and discharge data were obtained from SHMU, whereas the potential evapotranspiration (PET) data were obtained from the Water Research Institute of Slovakia. The sets include daily precipitation of 14 stations, temperature of 2 stations, PET at 1 station, and daily discharge data at 6 gauging stations. All these data are available for a 10 year period from 1991 to 2000. Daily discharge data at 6 locations are available inside the catchment, but only the station Kosicke Olsany is used for model calibration (Bahremand et al., 2005).

3.2 Model simulation

Once the required data are collected and processed for use in the WetSpa modeling platform, identification of spatial model parameters is undertaken. Terrain features in each grid cell including elevation, flow direction, flow accumulation, stream network, stream link, stream order, slope, and hydraulic radius are first extracted from the DEM. The threshold for delineating the stream network is set to 10, i.e. a cell is considered being drained by streams when the upstream drained area becomes greater than 0.1 km^2. The threshold value for determining subcatchments is set to 1000, by which 65 subcatchments are identified with an average subcatchment area of 20 km^2. The grid of hydraulic radius is generated using a power law relationship, which relates hydraulic radius to the drained area (Liu et al., 2003), with an exceeding frequency of 0.5 (2-year return period) resulting in an average hydraulic radius of 0.005 m for the upland cells and 1.5 m at the outlet of the main river channel. Next, the grids of soil hydraulic conductivity, porosity, field capacity, residual moisture, pore size distribution index, and plant wilting point are reclassified based on the soil texture grid by means of an attribute lookup table. Similarly, the grids of root depth, interception storage capacity, and Manning's roughness coefficient are reclassified from the land use grid. For the river channels the Manning's coefficient is linearly interpolated based on the stream order grid with 0.055 m$^{-1/3}$s for the lowest order and 0.025 m$^{-1/3}$s for the highest order. The grids of potential runoff coefficient and depression storage capacity are obtained by means of attribute tables combining the grids of elevation, soil and land use, for which the percentage of impervious area within an urban cell is set to 30%. The grids for precipitation, temperature and PET are created based on the geographical coordinates of each measuring station and the catchment boundary using the Thiessen polygon extension of the ArcView Spatial Analyst. Finally, the grids of flow velocity, travel time to the basin outlet, as well as the standard deviation are generated, which enables to calculate the IUH from each grid cell to the basin outlet. Flow time for the most remote area is around 55 hours. The mean travel time for the entire catchment is 23 hours.

4 Results and discussion

4.1 Model calibration

For the model calibration, PEST program was used in this study. PEST is a nonlinear parameter estimation and optimization package, and is one of the most recently developed systems offering model independent optimization routines (Doherty and Johnston, 2003). It applies a robust Gauss–Marquardt–Levenberg algorithm, which combines the advantages of the inverse Hessian method and the steep descent method and therefore provides faster and more efficient convergence towards the objective function minimum. The best set of parameters is selected from within reasonable ranges by adjusting the values until the discrepancies between the model generated values and those measured in the field is reduced to a minimum in the weighted least squares sense. Due to its model-independent characteristic, PEST can be used easily to estimate parameters in an existing computer model, and can estimate parameters for one or a series of models simultaneously. Since its development, PEST has gained extensive use in many different fields, for instance, the automated model calibration and data interpretation in the groundwater model MODFLOW/MT3D (Doherty and Johnston, 2003) and some other surface runoff and water quality models (Baginska et al., 2003;

Syvoloski et al., 2003). Liu et al. (2005) applied PEST for the WetSpa model auto-calibration.

By combining a powerful inversion engine, PEST communicates with WetSpa through the model's own input and output files. During automatic calibration, model parameters are adjusted automatically according to the PEST optimization objective functions. The process is repeated until the stopping criterion is satisfied, e.g. maximum number of iterations, convergence of the total objective function, or convergence of the parameter set. The specifications of the calibration algorithm include model parameterization, the selection of calibration parameters, defining feasible parameter variation range, assigning prior information to a parameter group, assigning weights to members of the observation group, etc.

The 10 years (1991-2000) measured daily precipitation, temperature, PET, and discharge data are used for model calibration. The calibration process is performed for the global model parameters only, whereas the spatial model parameters are kept as they are. Because autocalibration and sensitivity analysis can be affected by initial input parameters (more discussion about the setting effect of initial parameter values is given in the next section), therefore to diminish these effects, a primary manual calibration is done to obtain proper initial parameters. Initial global model parameters are specifically chosen according to the basin characteristics as discussed in the documentation and user manual of the model (Liu and De Smedt, 2004). The simulation results are then compared to the observed hydrograph at Kosicke Olsany both graphically and statistically. The groundwater flow recession coefficient (K_g) is adjusted by fitting the baseflow, which is separated from the observed hydrograph. The interflow scaling factor (K_i), which is sensitive for high flows, is adjusted for the recession part after flood peak. The two parameters controlling the amount of surface runoff, i.e. the surface runoff exponent for a near zero rainfall intensity (K_m) and the rainfall intensity corresponding to a surface runoff exponent of 1 (K_p), are adjusted mainly for small storms, for which the actual runoff coefficients are small due to the low rainfall intensity. Initial soil moisture (K_s) and active groundwater storage (K_{gi}) are adjusted by comparison of the hydrographs and water balance for the initial phase. The maximum active groundwater storage (K_{gm}) controls the amount of transpiration from the groundwater, and therefore can be adjusted by comparison of the flow volume during dry periods.

With the initial parameter values obtained from the manual calibration, the PEST program is applied to run the WetSpa model for a sufficient number of optimization iterations, i.e. 30 iterations. Setting a value of 20 to 30 as maximum number of optimization iterations is often appropriate (Doherty et al., 1994). PEST estimates the best values of the model parameters by minimizing the sum of squares of the differences between calculated and measured model results. Figures 2 gives a graphical comparison between observed and calculated daily flow at Kosicke Olsany for the year 1999, showing that both the spring and summer flood hydrographs are well reproduced by the model. The simulation of snowmelt flood is important in this study, as it not only contributes to the results of model evaluation, but also provides a reliable soil moisture estimation at the end of the snow melting period, which affects following rainfall runoff processes. The calibrated groundwater flow recession coefficient at Kosicke Olsany is 0.000075 d^{-1}, and gives a good estimation for all base flows. Peak discharges, concentration time, and flow volumes are well predicted. The model performance is satisfactory, the flow volume is well reproduced, and the model efficiency (Nash-Sutcliffe criterion) is 73%. This indicates that the model is able to consider the precipitation, antecedent moisture, and runoff-generating processes in a spatially realistic manner based on topography, land use and soil type, resulting in a fairly high accuracy for both high and low flows, and the general hydrological trends being well captured by the model. The model shows that 8.9% of the precipitation is intercepted by the plant canopy, 83.6% infiltrates to the soil, 73.0% evapotranspirates to the atmosphere, 18.5% recharges to the groundwater reservoir, and 26.9% becomes runoff, of which direct flow, interflow, and groundwater flow contribute 5.2%, 4.2% and 17.5% respectively. These values are reasonable in view of the catchment hydrological characteristics.

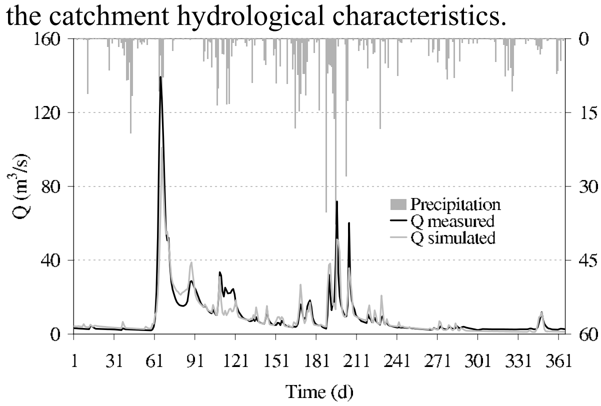

Fig.2. Graphical comparison between observed and calculated daily flow at Kosicke Olsany for the year 1999.

4.2 Sensitivity and uncertainty analysis

Sensitivity analysis can be used in the initial model parameterization process to investigate which parameters are sensitive with respect to the available observations, and which are insensitive and can be set to fixed values. PEST provides an independent sensitivity analysis module by adjusting model inputs, running the model, reading the outputs of interest, recording their values, and recommencing the computing cycle. However, the results of such an analysis should be carefully interpreted. The dimensionless, scaled sensitivities depends on the parameter values, and hence sensitivity statistics evaluated at some initial parameter values may be very different from the statistics obtained using other parameter sets (Hill, 1998). In addition, sensitivity statistics do not properly account for parameter correlations, implying that parameters that seem to be insensitive may have important correlations with other parameters that are essential for the model behavior (Madsen, 2002).

PEST uses a nonlinear estimation technique known as the Gauss-Marquardt-Levenberg method. The strength of this method lies in the fact that it can generally estimate parameters using fewer model runs than any other estimation method, a definite bonus for large models whose run times may be considerable. For nonlinear problems (most models fall into this category), parameter estimation is an iterative process. At the beginning of each iteration the relationship between model parameters and model-generated observations is linearised by formulating it as a Taylor expansion about the currently best parameter set; hence the derivatives of all observations with respect to all parameters must be calculated. This linearised problem is then solved for a better parameter set, and the new parameters tested by running the model again. By comparing parameter changes and objective function improvement achieved through the current iteration with those achieved in previous iterations; PEST can tell whether it is worth undertaking another optimization iteration; if so the whole process is repeated. The ability to calculate the derivatives of all observations with respect to all adjustable parameters is fundamental to the Gauss-Marquardt-Levenberg method of parameter estimation; these derivatives are stored as the elements of the Jacobian matrix used for sensitivity analysis. The composite sensitivity of each parameter is the normalized (with respect to the number of observations) magnitude of the column of the Jacobian matrix pertaining to that parameter. The Jacobian matrix comprised of m rows (one for each observation), and the n elements of each row are the derivatives of one particular observation with respect to each of the n parameters. The parameter sensitivity value is expressed by the relative composite sensitivity obtained by multiplying its composite sensitivity by the magnitude of the value of the parameter. The use of relative sensitivities in addition to normal sensitivities assists in comparing the effects that different parameters have on the parameter estimation process when these parameters are of different type, and possibly of very different magnitudes (Doherty et al., 1994).

The auto calibrated parameters and the result of parameter sensitivity analysis after the optimization process are presented in Table 2. As can be seen in the table, the relative sensitivity of the 8 calibration parameters varies within the range 0.005-0.308. Parameter K_e, which controls the actual evapotranspiration from soil and the groundwater storage, has the highest relative sensitivity. Parameter K_m, controlling the volume of surface runoff in the model, has the second highest sensitivity. Parameter K_{gm} has the least relative sensitivity. For this simulation K_s has the third place in the sensitivity ranking, but for a short period simulation this parameter has a more sensitive effect because the beginning of simulated hydrograph is always affected by the initial soil moisture condition.

PEST also gives a correlation matrix of the calibration parameters. This matrix shows that there are no significant correlations between parameters, except there is a rather high negative correlation between K_s and K_{gi} ($R = -0.74$), and a moderate positive correlation between K_e and K_{gm} ($R = 0.53$). Because sensitivities are calculated by changing the parameters one by one, they are not influenced by parameter correlations (van Griensven, 2002).

Table 2: Parameter values before and after automated calibration, and their relative sensitivities.

Parameter	Unit	Initial value	Auto calibration	Relative sensitivity	Rank
K_i	-	7.0	5.9	0.093	4
K_s	-	1	0.95	0.128	3
K_e	-	1	1.06	0.308	1
K_g	d^{-1}	4.1×10^{-5}	7.5×10^{-5}	0.025	5
K_{gi}	mm	63	34.5	0.013	7
K_{gm}	mm	630	1300	0.005	8
K_m	-	2.75	2.25	0.136	2
K_p	mm d^{-1}	250	660	0.015	6

After the parameter estimation process, PEST gives a list of the estimated parameters. The best estimates, which are point estimates, by themselves, do not portray the reliability or lack of reliability (variability) of these estimates. In this study, uncertainty or reliability of estimates is presented using interval estimates. The presentation of 95% confidence limits provides a useful means of comparing the certainty with which different parameter values are estimated by PEST. In addition to the best estimates, m, PEST also estimates the standard deviation, s, of the parameter estimates, so that significance intervals for each parameter are obtained as m ± $t_{\alpha,n}$s, where tα,n is student's t-distribution, with probability α and n degrees of freedom. In the present case n corresponds to the number of data minus the number of parameters that needs to be estimated, and for α usually 0.025 is chosen, so that each parameter is contained in the predicted interval with a probability of 1-2α, i.e. 95%. Table 3 gives the confidence intervals of the estimates that portray the uncertainty involved in the calibrated parameters. The table shows that Parameter K_{gm} is estimated with a large margin of uncertainty. It should be noted that the initial given value of this parameter is within its confidence interval which means that statistically there is no meaningful difference between the initial value of K_{gm} and its estimated value. This uncertainty could be because of the correlation between this parameter (as the least sensitive parameter) and parameter K_e (as the most sensitive parameter).

Table 3. The 95% confidence intervals of the calibrated parameters.

Para-meter	Initial value	Estimated value	Standard deviation	Lower limit	Upper limit
K_i	7.0	5.9	0.087	5.7	6.1
K_s	1	0.95	0.015	0.92	0.98
K_e	1	1.06	0.005	1.05	1.07
K_g	4.1 $\times10^{-5}$	7.5 $\times10^{-5}$	4.2 $\times10^{-6}$	6.7 $\times10^{-5}$	8.3 $\times10^{-5}$
K_{gi}	63	34.5	5.26	24.2	44.8
K_{gm}	630	1300	414	488	2112
K_m	2.75	2.25	0.023	2.21	2.30
K_p	250	660	58.6	545	775

It is found that the calibrated parameter set resulting from different initial values may differ considerably, and so does the evaluation results of the model performance. This is due to model nonlinearity, model uncertainty and high correlations between parameters, which makes the global minimum in the objective function difficult to find. The problem of nonlinearity is one of the major problems in the application of distributed modeling in hydrology particularly in large catchments. In the WetSpa model, the surface runoff is estimated by a modified rational method, the routing of flow is characterized by the linear transfer functions of the diffusive flood wave, and the groundwater flow is simplified by a linear reservoir method. This apparent linearity does not apply to the relationship between rainfall inputs and river discharge that is known to be a nonlinear function of antecedent conditions, rainfall volume, and the interacting surface and subsurface processes of runoff generation. As pointed out by Beven (2001), the use of pedotransfer functions to estimate a set of average model parameters at the element scale of a distributed hydrological model should not be expected to give accurate results. The problem of uncertainty arising from the modeling process is associated with the input data (temporal and spatial variability of parameters, initial and boundary conditions), the model assumptions and algorithms for describing the processes, and the measurements for model calibration and validation. The high uncertainty and correlations of the model parameters usually result in the non-uniqueness of parameter estimates and model predictions, making it difficult by the fact that the objective function may possess local minima, distinct from the global minimum.

To tackle this problem, it is always expected to supply an initial parameter set close to the true parameter set. This makes PEST optimization more efficiently, especially for highly nonlinear models or models with local objective function minima in the parameter space. Moreover, a suitable choice for the initial parameter set can also reduce the number of iterations necessary to minimize the objective function. For modeling in a large catchment or modeling with a high spatial and temporal resolution, this can mean considerable savings in computer time (Doherty et al., 1994). However, setting a proper initial parameter set is not an easy task. It needs a fully understanding of both the hydrological model and the physical characteristics of the study catchment. A trial with a number of different initial parameter set in PEST to find a more reliable parameter estimates is sometimes necessary. In this study, to assign a proper initial parameter set and to avoid the inefficiency caused by an unsuitable set, the final input parameters obtained from the manual calibration were used as the initial input parameters to the PEST.

From the experiences of this study, it is illustrated that PEST can be incorporated with a distributed hydrological model to estimate efficiently the model parameters. From practical and methodological points of view, the number of real calibration parameters should be kept low. This can be done by fixing the insensitive parameter values based on the PEST sensitivity analysis. Also, assigning different weights to the observations depending upon the data accuracy or the main target of the model may highly increase the efficiency of model calibration and the reliability of the parameter set.

4 Conclusion

In this paper an attempt is made to outline a method for estimating flood runoff in the Torysa basin by using detailed basin characteristics together with meteorological data as an input to the WetSpa spatially distributed model. To avoid the complexity inherent in estimating surface runoff, a simple but effective approach is presented where the whole basin is divided into grid cells, giving the possibility to simulate the hydrologic processes at reasonably small scale. The generation of runoff depends upon rainfall intensity and soil moisture and is calculated as the net precipitation times a runoff coefficient, which depends upon slope, land use and soil type. Overland flow is routed through the basin along flow paths determined by the topography using a diffusive wave transfer model, while interflow and groundwater recharge are simulated using Darcy's law and the kinematic approximation. Model parameters based on surface slope, land use, soil type and their combinations are collected from literature, which can be prepared easily using standard GIS techniques. The model is tested on the Torysa catchment in Slovakia with 10 years of observed daily rainfall and evaporation data. Good agreement with the measured hydrograph is achieved.

This paper also presents a strategy by incorporating a model-independent parameter estimator PEST for automatic calibration and sensitivity analysis. The results of this study demonstrate that the use of combining a GIS-based hydrological model with PEST can produce calibrated parameters that are physically sensible. The relative sensitivity of 8 lumped parameters is given using the PEST automated calibration scheme. It is found that the correction factor for calculating the actual evapotranspiration from PET has the highest relative sensitivity. The margin of uncertainty of each parameter is determined as they show e.g. the estimation of Parameter K_{gm} has the highest uncertainty. Parameter uncertainty analysis gives an insight of a proper parameter set and parameter interval.

Since the spatial distribution of hydrologic characteristics can be obtained from the model outputs at each time step, the model is especially useful to analyze the effects of topography, soil type, and landuse on the hydrologic behavior of a river basin.

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