The role of land use and morphology representation in the setup and calibration of the conceptual TUW model

Martin Kubáň, Adam Brziak, Silvia Kohnová
Department of Land and Water Resources Management, Slovak University of Technology Slovakia

xkubanm@stuba.sk

Abstract. The processes of the transformation of rainfall to runoff are highly complicated, and the proper characterisation of these processes with conceptual hydrological models is a very challenging task. Morphology and land cover have a significant influence on a river basin's hydrologic response. Thus, catchment characteristics of the topography and land use play an essential role in parametrising the runoff concentration processes in hydrological models. In the study, our goal was to detect which characteristics and their spatial distribution influence the efficiency of a conceptual rainfall-runoff model efficiency most. The spatially lumped and semi-distributed versions of the TUW conceptual rainfall model, which is an HBV type model, were compared. Both models use the concept of lumped storages associated with the surface and subsurface, interconnected by thresholds and links to simulate the runoff transformation. We focused on two land-use characteristics, the percentage cover of the agricultural land and percentage cover of the forests, and the mean slope of the terrain as a topography characteristic. The differences between runoff model efficiencies both in the calibration and validation periods were evaluated. Based on which version of the model was more effective in the simulation of the runoff, it was detected which types of catchment land use, and morphology were better represented by using the lumped or semi-distributed version of the TUW model, respectively. The analysis aimed to improve the understanding of the influence of spatial representation morphology and land cover in conceptual models on model efficiency and may help to improve model setup and calibration.

1. Introduction
Recent extreme runoff events in Central Europe stimulate discussion how to efficiently model runoff processes describing them. In this respect, the regional understanding and modelling of catchment hydrological processes are becoming increasingly important for addressing water resources management questions [1]. Thus, there is a need to increase our understanding of the impacts of land use and management practices in the modelling on runoff processes. Rainfall-runoff modeling involves multiple steps, each of which can be associated with uncertainties in the calibration of the model. Three basic factors may affect the efficiency of hydrological models and the quality of the outputs modeled: the spatial representativeness of the input data, the structure of the model, and the uncertainties of the parameters [2-3]. The availability of additional and longer data series with finer temporal and spatial resolution are supporting the study and modelling of runoff hydrological regimes and contribute to better process parametrisation in deterministic models in diverse hydrological environments. Application of models using multiple datasets can improve the
characterization and predictions of changes in hydrological processes and climate change impacts on
the water cycle [4]. As the processes of the transformation of rainfall to runoff are highly complicated,
and the proper characterization of these processes with conceptual hydrological models is a very
challenging task. The confrontation of hydrological catchment models with new types of data and
process representation for distinct purposes enable testing the suitability of models in particular
environments. However, with the increasing number of hydrological models, there is an ongoing
problem concerning the right choice of the type of the model for the physiographic setting. Many authors
have discussed this problem, see (e.g. [5-9], etc.).

In the study, our aim was to detect which characteristics and their spatial distribution influence the
efficiency of a conceptual rainfall-runoff model most. The spatially lumped and semi-distributed
versions of the TUW conceptual rainfall-runoff model, which is an HBV type model, were compared.
Both models use the concept of lumped storages associated with the surface and subsurface,
interconnected by thresholds and links to simulate the runoff transformation. We focused on two land-
use characteristics, the percentage cover of the agricultural land and percentage cover of the forests,
and the mean slope of the terrain as a topography characteristic. The differences between runoff model
efficiencies both in the calibration and validation periods were evaluated. Based on which version of the
model was more effective in the simulation of the runoff, it was detected which types of catchment land
use, and morphology was better represented by using the lumped or semi-distributed version of the TUW
model, respectively. The analysis aimed to improve the understanding of the influence of spatial
representation morphology and land cover in conceptual models on model efficiency and may help to
improve the model setup and calibration.

2. TUW model
In this study, the HBV type rainfall-runoff model TUW was used in the lumped and semi-distributed
versions [10-11]. The model is based on the philosophy of the Swedish HBV model [9]. The lumped
version of the TUW model uses the averaged values of the air temperature, precipitation, and potential
evapotranspiration as inputs over the whole catchment. The semi-distributed version of the TUW model
considers spatially variable inputs by the catchments into 200 m elevation zones. The parameters of the
semi-distributed model were considered as lumped in this study. Both versions have extensively been
used for solving various hydrological problems (see e.g., [10]; [12]; [13]).

![Schematic structure of the lumped version of the TUW model](image)

---

**Figure 1.** Schematic structure of the lumped version of the TUW model, based on [14].
The TUW model consists of three sub-models: the snow sub-model, the soil sub-model, and the runoff formation sub-model. Figure 1 represents the structure of the lumped version of the TUW model.

For calibrating the model in this study, the DEoptim differential evolution algorithm was used [14], and the warm-up period was set at one year. The objective function, which is described in Eq. 1, combined the well-established Nash-Sutcliffe efficiency (NSE) and the logarithmic Nash-Sutcliffe efficiency (log NSE). The NSE and logNSE coefficients range from -∞ to 1, where 1 indicates a perfect simulation, i.e., an absolute equality between the observed and simulated flows. While the NSE is considered more appropriate for high flows, the logNSE is more appropriate for low flows [15].

The following NSE and log NSE formulas were used:

\[
\text{NSE} = 1 - \frac{\sum_{i=1}^{n} (Q_{\text{sim},i} - Q_{\text{obs},i})^2}{\sum_{i=1}^{n} (Q_{\text{obs},i} - \bar{Q}_{\text{obs}})^2}
\]

\[
\text{logNSE} = 1 - \frac{\sum_{i=1}^{n} (\log(Q_{\text{sim},i}) - \log(Q_{\text{obs},i}))^2}{\sum_{i=1}^{n} (\log(Q_{\text{obs},i}) - \log(\bar{Q}_{\text{obs}}))^2}
\]

where

- \(Q_{\text{sim}}\) – simulated mean daily flow,
- \(Q_{\text{obs}}\) – observed mean daily flow,
- \(\bar{Q}_{\text{obs}}\) – average of the observed flows.

The objective function (RME) was defined as:

\[
RME = \frac{\text{NSE}}{2} + \frac{\text{logNSE}}{2}
\]

3. Input data

The calibration of the model was performed on data from 180 catchments, which are distributed throughout the whole territory of Austria. These data have also been extensively used in previous modeling studies, e.g., by [12] and [13]. The catchment areas varied from 14.2 km² to 6214 km². Before processing the data, quality flags, missing data, etc., were visually inspected, and the only catchments that were selected were those not affected by an anthropogenic influence, e.g., by dams, canals, or any other artificial runoff regime transformations. (Figure 2)
The input data (rainfall, runoff, potential evaporation and air temperature) in the daily time steps from the period 1.1.1991 to 31.12.2000 were interpolated for the lumped TUW model version from point measurements taken across the Austria territory from 1091 stations by the external drift kriging method [14]. The runoff data were collected from 180 gauging stations by the Austrian Hydrographical Service. The potential evaporation data were calculated with the Blaney-Criddle method [16]. For the semi-distributed version of the TUW, the rainfall and air temperature input data model were taken from the Spartacus database [17] and were interpolated into the hypsometric zones by 200 vertical meters. The potential evaporation was calculated with the Blaney-Criddle method in the same hypsometric zones. The morphologic data slope was derived from the digital elevation model, and land-use information was from Copernicus Land Monitoring Service.

4. Results

4.1. Calibration results

The two versions of the conceptual hydrological model TUW [10] the lumped and semi-distributed version were calibrated for 180 Austrian catchments [14] in this paper.

For the assumption of the role of land use and morphology in the calibration process, we decide to divide the 180 catchments into the 6 groups by the runoff model efficiency RME results (from the lowest RME to best RME), each group consisting of the 30 catchments. The results are presented in table 1. (Semi-distributed TUW model) and table 2. (Lumped TUW model).

In table 1, for calibration of the semi-distributed version, we detect that RME is closely connected with the SL and AP characteristics. For the catchments with low SL characteristic, that means catchments with flat terrain, model shows the low model efficiency RME in opposite to catchments with high SL, where the model has better RME efficiency. In the case of the AP, the catchments with higher AP shows the low RME and in opposite the catchments with lower AP show the best RME. For the characteristic FP, we detect that the group with the lowest FP shows the best RME results.

Table 1. RME of the TUW semi-distributed model for 180 Austrian catchments, divided into 6 groups by the RME range, with a median of the catchments characteristics: Slope of the terrain (SL), Forest cover percentage (FP), and Agricultural lands percentage (AP)

| RME - range | RME-median | SL-median | FP- median | AP -median |
|-------------|------------|-----------|------------|------------|
| 0.00-0.71   | 0.68       | 8.53      | 44.63      | 29.57      |
| 0.72-0.75   | 0.74       | 13.51     | 66.06      | 16.88      |
| 0.75-0.78   | 0.77       | 14.48     | 57.61      | 26.40      |
| 0.78-0.81   | 0.80       | 22.53     | 51.86      | 14.02      |
| 0.82-0.85   | 0.83       | 26.46     | 46.20      | 11.50      |
| 0.86-0.93   | 0.88       | 31.13     | 36.19      | 7.62       |

In the lumped model version calibration (table 2), we detect the little lower influence of the SL, FP, or AP but the result was the same as in the calibration in the semi-distributed version. However, in this case, we did not detect a clear dependency between RME and SL, FP, and AP as by the semi-distributed model version. The RME was also lower than in the semi-distributed version, for that reason we decide to run the validation for the semi-distributed version and try to detect the same dependency patterns as in calibration.
Table 2. RME of the TUW lumped model for 180 Austrian catchments, divided into 6 groups by the RME range, with a median of the catchments characteristics: Slope of the terrain (SL), Forest cover percentage (FP), and Agricultural lands percentage (AP)

| RME - range | RME-median | SL-median | FP-median | AP-median |
|-------------|------------|-----------|-----------|-----------|
| 0.00-0.51   | 0.36       | 18.19     | 54.69     | 14.19     |
| 0.52-0.61   | 0.57       | 21.82     | 52.73     | 21.45     |
| 0.61-0.65   | 0.63       | 18.58     | 45.81     | 20.28     |
| 0.65-0.69   | 0.67       | 18.02     | 50.19     | 15.37     |
| 0.69-0.74   | 0.71       | 23.77     | 47.70     | 9.84      |
| 0.74-0.88   | 0.77       | 28.26     | 42.14     | 10.74     |

4.2. Validation results
The validation results for the semi-distributed model show high dependency between RME and SL, FP and AP, then in the calibration (table 3). The highest dependency could be observed between RME and SL. The catchments with the steep slope of the terrain, low forest cover percentage, and low agricultural land percentage, are in our estimation the most suitable for the use with conceptual semi-distributed rainfall-runoff model TUW.

From the land-use characteristics, we find the stronger RME and AP dependency than in RME and FP, but in both cases, we detect that with a lower percentage of AP and FP we can expect better RME results. (Figure 3)

Table 3. Validation RME of the TUW semi-distributed model for 180 Austrian catchments, divided into 6 groups by the RME range, with a median of the catchments characteristics: Slope of the terrain (SL), Forest cover percentage (FP), and Agricultural lands percentage (AP)

| RME - range | RME-median | SL-median | FP- median | AP -median |
|-------------|------------|-----------|------------|------------|
| 0.32-0.59   | 0.52       | 6.67      | 49.34      | 42.66      |
| 0.60-0.65   | 0.62       | 18.50     | 63.31      | 19.70      |
| 0.65-0.70   | 0.68       | 18.07     | 50.93      | 26.67      |
| 0.70-0.77   | 0.73       | 19.86     | 47.78      | 12.15      |
| 0.78-0.83   | 0.8        | 26.85     | 45.25      | 9.47       |
| 0.83-0.94   | 0.88       | 34.60     | 32.59      | 6.47       |
Figure 3. Validation RME of the TUW semi-distributed model. Left: Relationships between characteristics of the catchments and validation RME for 180 Austrian catchments. Right: Boxplots for the groups by the RME (from lowest RME - blue to best RME - green) and characteristics of the catchments: where SL – is the slope of the terrain, FP – the percentage of the forest cover, AP – the percentage of the agricultural land. The boxplots consist of the median (in the middle and 0.25 lower quartile and 0.75 upper quartiles).

The validation results for the lumped model version are summarised in table 4 and Figure 4.

We can see no dependence between RME and the selected catchment characteristics. The values of RME are also lower in comparison to the semi-distributed model version. These results support the finding that the semi-distributed version could better represent the runoff processes than the lumped one.
Table 4. Validation RME of the TUW lumped model for 180 Austrian catchments, divided into 6 groups by the RME range, with a median of the catchments characteristics: Slope of the terrain (SL), Forest cover percentage (FP), and Agricultural lands percentage (AP)

| RME - range | RME-median | SL-median | FP- median | AP -median |
|----------------|-------------|------------|-------------|------------|
| 0.22-0.46 | 0.41 | 15.55 | 42.57 | 19.75 |
| 0.47-0.59 | 0.55 | 19.30 | 63.06 | 18.18 |
| 0.59-0.62 | 0.61 | 16.84 | 45.53 | 17.65 |
| 0.63-0.65 | 0.64 | 13.12 | 46.53 | 34.94 |
| 0.66-0.70 | 0.68 | 22.88 | 45.77 | 9.84 |
| 0.71-0.89 | 0.75 | 17.04 | 38.71 | 11.40 |

Figure 4. Validation RME of the TUW lumped model. Left: Relationships between characteristics of the catchments and validation RME for 180 Austrian catchments. Right: Boxplots for the groups by the
RME (from lowest RME - blue to best RME - green) and characteristics of the catchments: where SL - the slope of the terrain, FP – the percentage of the forest cover, AP – the percentage of the agricultural land. The boxplots consist of the median (in the middle and 0.25 lower quartile and 0.75 upper quartiles). for 180 Austrian catchments.

Figure 5. Dependency between selected catchments characteristics, for 180 Austrian catchments, SL-FP (top), FP-AP (middle), and AP-SL (bottom)

From the dependency between catchments characteristic, Figure 5 it is obvious that there is dependency between the slope of the terrain (SL) and forest percentage (FP), it has got two links of low forest percentage where we got catchments with low slopes with agricultural lands without forests and mountainous catchments with no forests in alpine areas; that is why there is not dependency between RME and forest percentage (FP). Also, there is a connection between FP and AP, and very strong relationship between AP and SL. These relationships are important for our study because from calibration results, we can see that the best RME results are from the catchments with higher SL and lower AP and FP. That also means the model performance is worse in flats agricultural lands where we can expect higher evapotranspiration and water storage in the deep soil system. On the other hand, the model has great efficiency in mountainous areas without forest cover with shallow soil bed, where the rainfall contributed to the surface runoff or runoff from shallow soil bed.

5. Conclusion
In this paper, we try to find the connection between catchment characteristics like morphology and land use and runoff model efficiency. For representing morphology, we select the slope of the terrain (SL), and for the land use, we select the percentage of the forest cover (FP), and the percentage of the agricultural lands (AP) [18]. For the calibration, we used the two versions of the conceptual rain-fall model TUW [10], the semi-distributed and lumped version. For the calibration and validation was
selected 180 catchments across Austria [14]. Firstly, we calibrated the TUW model with semi-distributed and lumped models. The runoff model efficiency was estimated with RME = (NSE + log NSE)/2 [14]. Secondly, we sort the RME data from the lowest to the highest value and split it into 6 groups (each group has 30 catchments), then we make the graphic and median comparison for each group characteristics SL, FP, and AP. The results show a clear dependency between selected characteristics and the RME in the semi-distributed version. The highest dependency was between RME and the SL. In both graphical comparisons of median characteristics, we detected that the groups of the catchments with higher slope of the terrain perform better in RME. The semi-distributed model has great efficiency in mountainous areas without high percentage of forest cover and shallow soil beds, where the rainfall contributed to the surface runoff or runoff from shallow soil bed.

In the case of the lumped version, there was no clear dependency between RME and catchments characteristics.

Acknowledgment(s)
This work was supported by the Slovak Research and Development Agency under Contract No. APVV-19-0340 and the VEGA Grant Agency No. 1/0632/19. This work has also been supported within the frame of the Alp Carp Project No. 2019-10-15-002 under the bilateral program "Action Austria – Slovakia, Cooperation in Science and Education". The authors thank the agencies for their research support.

References
[1] J. Szolgay, G. Blöschl, Z. Gribovszki, and J. Parajka. Hydrology of the Carpathian Basin: interactions of climatic drivers and hydrological processes on local and regional scales – HydroCarpath Research. In Journal of Hydrology and Hydromechanics 68 (2), pp. 128–133, 2020. DOI: 10.2478/johh-2020-0017.
[2] M. Osuch, R.J. Romanowicz, M.J. Booij. The influence of parametric uncertainty on the relationships between HBV model parameters and climatic characteristics. In Hydrological Sciences Journal 60 (7-8), pp. 1299–1316, 2015. DOI: 10.1080/02626667.2014.967694.
[3] J. Seibert, and J.J. McDonnell. Land-cover impacts on streamflow: a change-detection modelling approach that incorporates parameter uncertainty. In Hydrological Sciences Journal 55 (3), pp. 316–332, 2010. DOI: 10.1080/02626661003683264.
[4] D. Finger, M. Vis, M. Huss, and J. Seibert. The value of multiple data set calibration versus model complexity for improving the performance of hydrological models in mountain catchments. In Water Resour. Res. 51 (4), pp. 1939–1958, 2015. DOI: 10.1002/2014WR015712.
[5] M. Jeniček. Apliation of the NASIM model for the simulation of the rainfall-runoff conditions in Čierna vody catchment. Diploma thesis in Charles University, Praha, 2005.
[6] K.J. Beven, and J. Freer. Equifinality, data assimilation, and uncertainty estimation in mechanistic modelling of complex environmental systems. Journal of Hydrology 249: 11–29, 2001. DOI: 10D1016/S0022–1694(01)00421-8.
[7] J. Buchtele, M. Buchtelova, and Y. Cisse. Investigation of changes in rainfall-runoff process in a hilly basin using different modelling tools, J.Hydrol. Hydromech., Vol. 50, No. 3, p. 185 Scientific Paper, English Language, 2002.
[8] Z. Kulhavý, and P. Kovář. Using of the hydrological balance for small catchments. VÚMOP, Praha, 2002.
[9] S. Bergström. The HBV model. Computers models of watershed hydrology, edited by V.P. Sing. Water. Resour. Publ, pp. 443-476, 1995.
[10] J. Parajka, R. Merz, and G. Blöschl. Uncertainty and multiple calibration in regional water balance modelling case study in 320 Austrian catchments, Hydrol. Process., 21, pp. 423-446, 2007. Doi: 10.1002/hyp.6253.
[11] J. Parajka, V. Naiemi, G. Blöschl, and J. Komma. Matching ERS scatterometer based soil moisture patterns with simulation of a conceptual dual layer hydrologic model over Austria Hydrol.Earth Syst. Sci. 13, 259-271, 2009.
[12] P. Sleziak, J. Szolgay, K. Hlavčová, and J. Parajka. The impact of the variability of precipitation and temperatures on the efficiency of a conceptual rainfall-runoff model. Slovak Journal of Civil Engineering, 24, 4, pp. 1-7, 2016. DOI: 10.1515/sjce-2016-0016.

[13] A. Viglione, J. Parajka, M. Rogger, J.L. Salinas, G. Laaha, M. Sivapalan, and G. Blöschl. Comparative assessment of predictions in ungauged basins – Part 3: Runoff signatures in Austria. Hydrol. Earth Syst. Sci., 17, pp. 2263–2279. doi:10.5194/hess-17-2263-2013.

[14] Sleziak, P., Hlavčová, K., Szolgay, J., Parajka, J. (2017): Závislosť kvality simulácie odtoku pomocou zrážko-vo-odtokového modelu od rozdielnosti hydroklimatických podmienok kalibračného a validačného obdobia. Acta Hydrologica Slovaca, 18(1), 23-30, 2013 (in Slovak).

[15] R. Merz, J. Parajka, and G. Blöschl. Time stability of catchment model parameters: Implications for climate impact analyses, Water Resour. Res., 47, W02531, 2011. doi: 10.1029/2010WR009505.

[16] J. Parajka, R. Merz, and G. Blöschl. Estimation of daily potential evapotranspiration for regional water balance modeling in Austria. In 11th International Poster Day and Institute of Hydrology Open Day “Transport of Water, Chemicals and Energy in the Soil–Crop Canopy–Atmosphere System”. Slovak Academy of Sciences: Bratislava; 299–306, 2003.

[17] J. Hiebl, and C. Frei. Daily precipitation grids for Austria since 1961, development and evaluation of spatial dataset for hydroclimatic monitoring and modeling. Theoretical and Applied Climatology 124, 161–178, 2016. doi:10.1007/s00704-015-1411-4.

[18] R. Tong, J. Parajka, A. Valentine, I. Pfeil, J. Komma, B. Széles, M. Kubáň, P. Valent, M. Vreugdenhil, W. Wagner, and G. Blöschl. The value of ASCAT soil moisture and MODIS snow cover data for calibrating a conceptual hydrologic model, Hydrol. Earth Syst. Sci. Discuss., https://doi.org/10.5194/hess-2020-436, in review, 2020.