IOP Conference Series: Earth and Environmental Science

PAPER • **OPEN ACCESS**

Soil Moisture Simulation in Selected Austrian Catchements With Use of the Tuw Conceptual Semi-Distributed Rainfall Runoff Model

To cite this article: Martin Kubáň and Adam Brziak 2020 *IOP Conf. Ser.: Earth Environ. Sci.* **609** 012031

IOP Conf. Series: Earth and Environmental Science **609** (2020) 012031 doi:10.1088/1755-1315/609/1/012031

Soil Moisture Simulation in Selected Austrian Catchements With Use of the Tuw Conceptual Semi-Distributed Rainfall Runoff Model

Martin Kubáň, Adam Brziak

Department of Land and Water Resources Management, Slovak University of Technology Slovakia

martin.kuban@stuba.sk

Abstract. Nowadays, hydrological rainfall-runoff models are routinely used for modelling hydrological balances, the generation of floods, or droughts. For decades numerous rainfall-runoff models have been tested with many calibration procedures and different model structures. However, for rainfall-runoff, it is challenging to find a particular model structure and parameter set that can correctly describe the complicated flow formation processes in diverse physiographic conditions. Improvements to existing rainfall-runoff modelling concepts and data assimilation are therefore continuously being tested. In recent years, remote sensing has played an increasing role in the surveying of hydrological phenomena. Remote sensing of soil moisture data can be very helpful because soil moisture measurements in field conditions are not always straightforward. The quality of remotely sensed data is rising; nowadays, we can routinely start using data with proper spatial and temporal resolutions. In this paper, we have focused on an evaluation of the parametrisation of the soil moisture submodel of the TUW rainfall-runoff model by remotely sensed soil moisture data. We calibrated the TUW model for three selected catchments in Austria with flat hypsometric characteristics using discharges as a criterion. For the calibration, we used both the lumped and semi-distributed model versions of the model and compared the quality of the soil moisture of both versions. Both the lumped and semi-distributed versions performed well in the discharge simulation. In the case of the soil moisture simulation, we achieved slightly better results with the semi-distributed version of the model. Difficulties with accessing the data from the remote sensing are discussed since remote sensing sensors still have problems when clouds and snow cover the catchments.

1. Introduction

If we can promptly react to hydrological changes in a catchment, we can prevent the devastating effects of floods and droughts and make water resources management more effective. Hydrological rainfall-runoff (rainfall-runoff) models are a standard tool that is frequently used in such contexts in the hydrological and environmental sciences. One of the main problems in rainfall-runoff modelling is that most of the runoff formation processes exist below the surface of the earth. Even with all the modern technologies available, we not can precisely monitor and, as a consequence, correctly simulate how water moves below the surface of the earth. As a result, the rainfall-runoff modelling discipline can not disregard the many competing model structures and their respective parametrisations that have arisen to solve the problem in the past. Teams of scientists are still working on new model concepts. Therefore we have a choice of several rainfall-runoff models that give us reliable results, among which are these several derivatives of the HBV model [1]. These models are useable only if we have sufficient measured input data for the model´s calibration and validation (e.g., for seven years). No matter which rainfall-runoff model we use, it is necessary to calibrate, and subsequently validate, the performance of rainfall-runoff models against measurements of runoff and other auxiliary variables. However, there are always some problems connected with a model´s structure and the calibration setup concerning the specific type of catchment, etc.. Many authors have recently reported concerns about these problems [2-5].

Improvements to existing modelling concepts are therefore continuously being tested.

In recent years, remote sensing has played an increasing role in the surveying of hydrological phenomena. Soil moisture plays a fundamental role in the transformation of a rainfall to a discharge, and it drives the severity of droughts, floods, and other hydrological processes such as transpiration and evaporation. Estimating soil moisture is therefore crucial for all segments of water resources management. Measuring soil moisture in field conditions is problematic; moreover, upscaling point measurements to catchment scales is an uncertain process. Remote sensing of soil moisture data can therefore be helpful because it directly yields spatial estimates of the soil moisture in field conditions.The quality of remotely sensed data is continually improving; nowadays, we can use data with proper spatial and temporal resolutions.

In this paper, we are focusing on the parametrisation of the soil moisture component of the HBV-type (Technische Universität Wien) TUW rainfall-runoff model. Parajka [5] and Ceola [6] have discussed the acceptable ranges of all the parameters of the TUW model based on calibrations and validations using a one-day computational time step. They have recommended parameter ranges for practical use in Austria, which we used as the starting values for the parameter optimisation in this paper. With the same ranges of parameters, Sleziak et al. [1] tested the TUW rainfall-runoff model on 213 Austrian catchments, which they divided into two groups, i.e., catchments with prevailing rain and with prevailing snow regimes. They found that catchments with a rain regimes show better results of soil moisture simulations in general than catchments with snow regimes. In this paper, we are focusing on catchments with prevailing rain-driven runoff formation in order to test the quality of the discharge simulation of the soil moisture parametrisation in the TUW model using soil moisture data from remote sensing.

2. Methodology

For the calibration and the validation exercises in this paper, the conceptual lumped and semi-distributed version of the TUW rainfall-runoff model was selected [6]. This HBV-type model was developed as an extension of the original at the Technical University of Vienna. We tested two calibration strategies for the model in three lowland catchments in Austria with two structural types of the model,i.e., the lumped and the semi-distributed versions; we intended to find out simultaneously which model structure performs better in both discharge and soil moisture simulations.

The semi-distributed version of the model has spatially distributed input data that has been divided into 200 m hypsometric zones. The inputs were interpolated from the same measurement stations that we used as inputs for the lumped version of the model. Therefore, we can judge not only the effect of the model´s structure on the results, but also evaluate the effect of the input interpolation method on the model´s efficiency.

In the first step, we calibrated both versions of the TUW rainfall-runoff model using discharges as the criteria for quality. Subsequently, we used the parameters from this calibration period for the simulation of the soil moisture and the discharges in the testing period. Finally, we compared the simulation results with the data measured from the remote sensing and discharges measured. The degree of agreement between the simulated and measured discharges was evaluated using the Nash-Sutcliffe coefficient. The correlation between the simulated and remotely sensed soil moisture was chosen as the metric for the assessment of the quality of the soil moisture estimates.

3. The pilot area

We selected three catchments from the northern lowlands of Austria (Figure 1). To exclude the effect of physiography on the efficiency of the remote sensing of the soil moisture, we selected catchments with a typical lowland hypsometric profile as pilots for the comparison, since the remote sensing sensors of soil moisture are more efficient in lowland areas in general. Each of the three selected catchments is located in the same lowland region. The Waldzell catchment, which is the smallest (Identification Number 204685), is located along the Waldzell Ache river with an area of 24 km^2 and is spread over two hypsometric zones from 400 to 800 m a.s.l.. The Haging catchment (ID 204750) is located on the Antiesen river with an area of 164.9 km^2. It is distributed over two hypsometric zones from 400 to 800 m a.s.l.. The Mamling catchment is the largest (ID 204719) and is located on the Ach river. The area is 314.9 km^2 and comprises three hypsometric zones from 200 to 800 m a.s.l..

The meteorological and hydrological input data were available from the period 1961-2010. Data from the remote sensing (labelled as S1-ASCAT), which are a combination of the Sentinel 1 (1x1km) and "Advanced Scatterometer" ASCAT (level 2 with three spatial resolution 25 km × 25 km, 12.5 km × 12.5 km, and 1 km × 1 km), were available from the period 2007-2014. The S1-ASCAT data were interpolated into altitudinal zones of 200 meters.

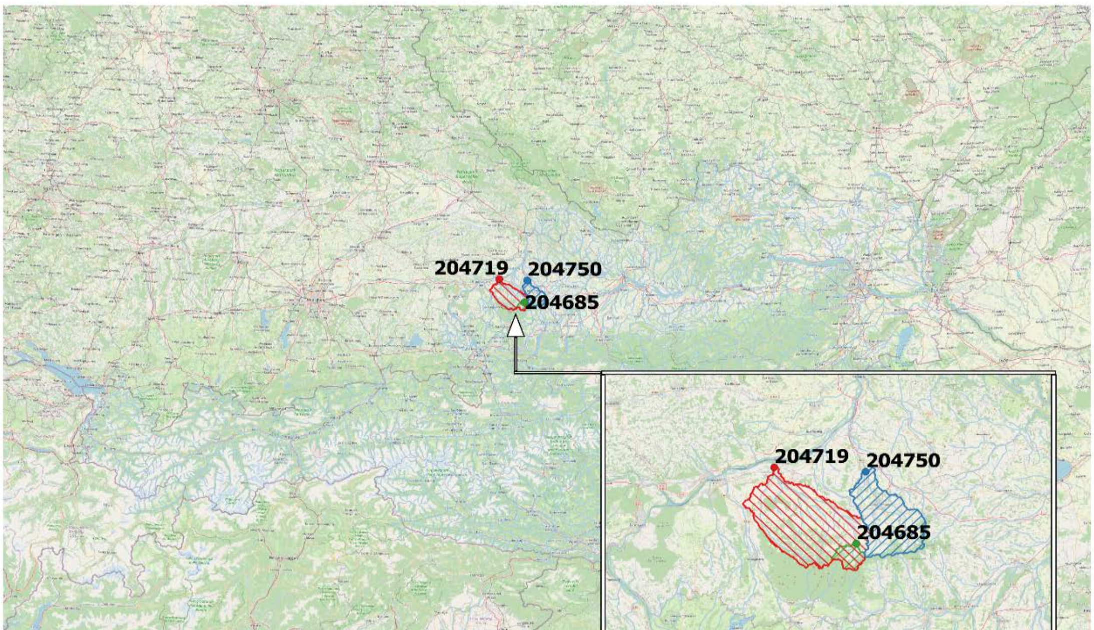

Figure 1. Location of the selected Austrian catchments: red hatching - Manling, blue hatching – Haging and green hatching – Waldzell catchments, respectively

4. Calibration and validation of the TUW model

The TUW model consists of three submodels: the snow, soil, and runoff generation submodels. In this paper, we mainly focused on the performance of the soil moisture and runoff generation submodels.The soil submodel simulates and controls processes that occur under the earth's surface in the upper soil moisture zone reservoir. This sub-model contains the following parameters: the limit for potential evapotranspiration (Lprat), field capacity (FC), and subsurface runoff formation (BETA). The snow submodel is controlled by the following parameters: snow correction coefficient (SCF), degree-day factor (DDF), and the threshold temperatures for rain, melting snow, and freezing (Tr, Tm, and Ts). The runoff submodel has the following parameters: surface and underground surface (k1, k2, and k3), the maximum base at low flows (Bmax), the threshold storage state (it drives the fast flow response), and runoff routing (Croute). The semi-distributed version has spatially distributed inputs divided into altitudinal groups with the distances of 200 vertical meters and the same number of parameters as the lumped model in each zone.

First, we calibrated the model by optimising its performance for discharge simulation using data from the years 1980-1990.

The calibrations were performed with 15 parameters with the ranges given in [7].The model´s performance was optimised by a linear combination of the Nash-Sutcliffe (NSE) and logarithmic Nash-Sutcliffe (log NSE) coefficients. For the automatic calibration, we used DEoptim [8] differential evolution algorithms.The NSE and Log NSE were also used as an indicator of the model efficiencies; we used the function $\frac{\mathrm{NSE+logNSE}}{2}$ for improving the model efficiencies.

Subsequently, we used the model parameters from the calibration period for the simulation of the soil moisture and discharges in the years 2007-2010 (the measured data from the remote sensing started in 2007). The lumped version of the model computed the average model states and discharge outputs for the whole catchment. The semi-distributed model computed the different states and outputs for each zone (one zone comprises 200 vertical meters).

The soil moisture simulations were confronted with data from the remote sensing. We detected missing values (mainly in the winter season) in the measured satellite data, which could be caused by the presence of snow cover or by cloudy days. We removed those days from the correlations.

We estimated the correlation between the simulated and measured data for each elevation zone separately and for the whole catchment.

In the correlation between the lumped and remotely sensed soild moisture data, we compared the average of the remotely sensed soil moisture with the model state for the whole catchment. For the distributed version, the model states for each hypsometric zone were confronted with the data from the remote sensing.

The results in Table 1 show that the semi-distributed version of the TUW model performed slightly better in the correlation than the lumped version of the model. However, as we can also see in the graphic comparison (Figure 2-4), the differences were minimal, and both versions of the model gave reliable results.

Table 1. Correlation between simulated soil moisture and estimated by remote sensing (S1-ASCAT) (period 2007-2010)

	Elevation zone (m a.s.l.)	200 - 400	400 - 600	600 - 800
204685	**Correlation - lumped model**		0.8	0.78
	Correlation - distributed model		**0.83**	**0.79**
204750	**Correlation - lumped model**		0.76	0.75

	Correlation - distributed model	**0.81**	**0.76**
204719	**Correlation - lumped model**	0.72	0.73
	Correlation - distributed model	**0.78**	**0.76**

Table 2. Runoff simulation efficiency (Nash-Suttcliffe (NSE) and logarithmic Nash-Sutcliffe (log NSE) in the calibration (1980-1990) and validation (2007-2010) periods

	TUW model	Calibration NSE (-)	Calibration log NSE (-)	Validation NSE (-)	Validation log NSE (-)
204685	**Lumped**	**0.69**	0.66	0,66	0,61
	Semi-distributed	**0.69**	**0.7**	**0,67**	**0,68**
204750	**Lumped**	0.68	**0.72**	0,65	0,66
	Semi-distributed	**0.72**	0.71	**0,69**	**0,74**
	TUW model	Calibration NSE (-)	Calibration log NSE (-)	Validation NSE (-)	Validation log NSE (-)
204719	**Lumped**	0.65	0.64	0,59	0,60
	Semi-distributed	**0.66**	**0.68**	**0,62**	**0,61**

In all three graphic comparisons (Figure 2, 3, and 4), we can see that the lumped version of the model simulates the broadest range of the soil moisture (differences between peaks and drops). The differences between simulations in different elevation zones are minimal and are attached.

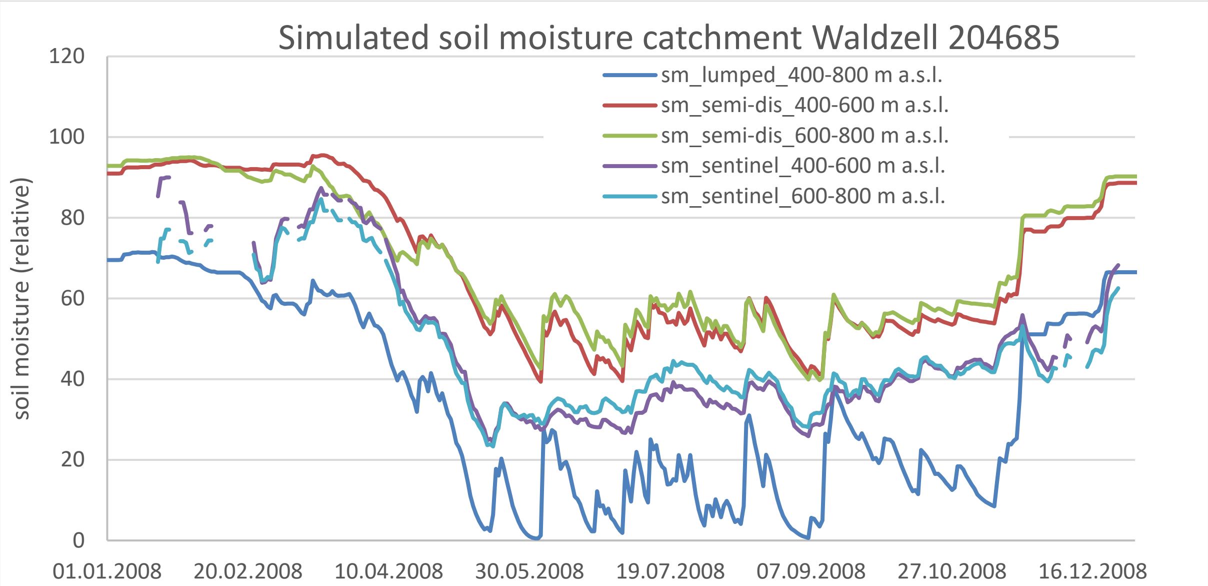

Figure 2. Simulated and measured relative root zone soil moisture (in percentage) for the catchment Waldzell (sm_lumped_400-800 m a.s.l. = average soil moisture simulated by TUW lumped model, sm_semi-dis_400-600 m a.s.l. = simulated soil moisture by TUW semi- distributed model for elevation zone 400-600 m a.s.l. etc.)

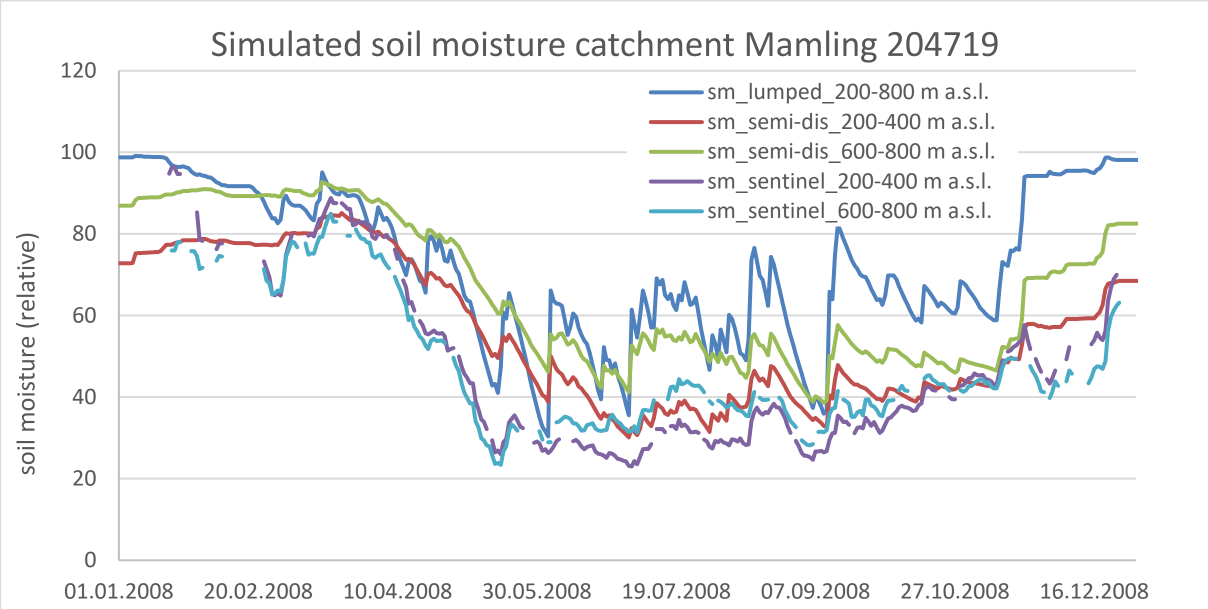

Figure 3. Simulated and measured relative root zone soil moisture (in percentage) for the catchment Mamling (sm_lumped_200-800 m a.s.l. = average soil moisture simulated by TUW lumped model, sm_semi-dis_400-600 m a.s.l. = simulated soil moisture by TUW semi- distributed model for elevation zone 400-600 m a.s.l. etc.)

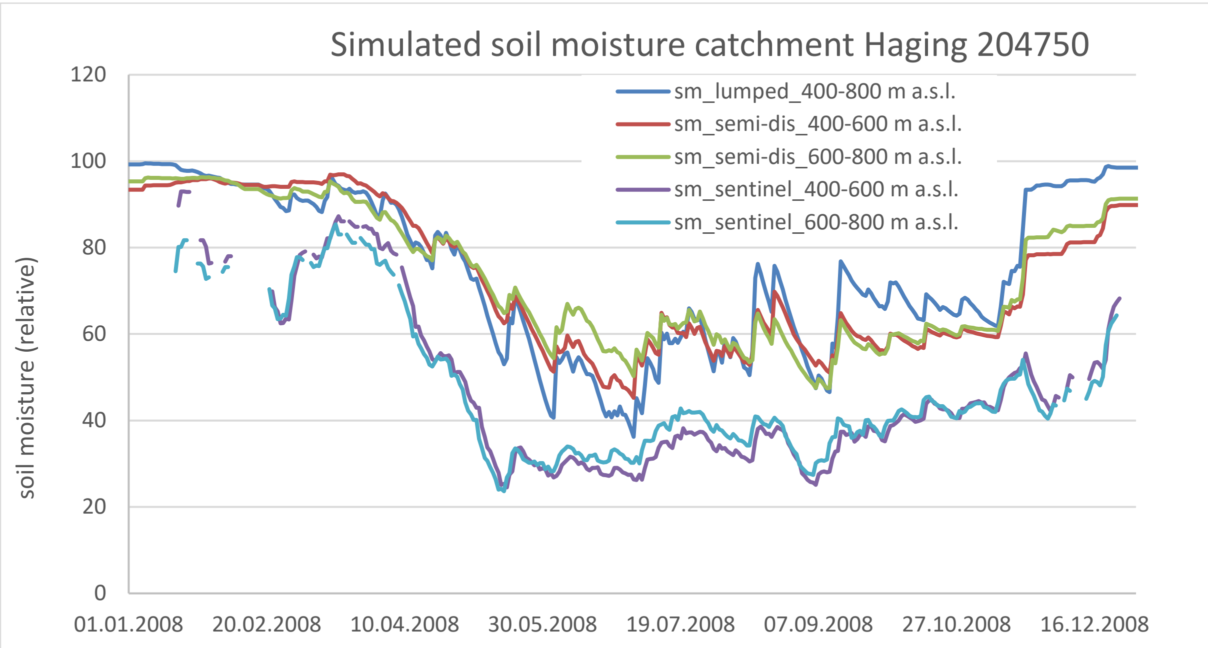

Figure 4. Simulated and measured relative root zone soil moisture (in percentage) for the Haging catchment (sm_lumped_400-800 m a.s.l. = average soil moisture simulated by TUW lumped model, sm_semi-dis_400-600 m a.s.l. = simulated soil moisture by TUW semi- distributed model for elevation zone 400-600 m a.s.l. etc.)

5. Conclusions

The discharge simulations showed that both model versions gave reliable results in the lowland region in the selected catchments. We can also conclude that both models delivered relatively reliable results in both the soil moisture and discharge simulations in the catchments with flat hypsometric characteristics. The semi-distributed version performed slightly better in the soil moisture correlation and also in the efficiency of the discharge simulation (see the R and NSE values in Table 1-2). These results also indicate that the interpolation of the spatially distributed model inputs from the station values of the air temperature and rainfall measurement station in the lowlands for the semi-distributed version reliably represented the natural spatial variability of these values. However, as many authors [6], [9], [10], have reported, we also detected problems with remotely sensed data from the winter season. There are missing data in the winter season, which we can find in the graphic comparison (Figures 2 to 4), too. These were removed from the correlation. The problems were most probably caused by the presence of snow cover or by cloudy days.

Acknowledgement
This work has been supported in the frame of the AlpCarp project under the bilateral program "Action Austria – Slovakia, Cooperation in Science and Education".This study was also supported by the Slovak Research and Development Agency under Contracts No. APVV: 19-0340, APVV -15-0497, and the VEGA Grant Agency No. 1/0632/19. The authors thank the agencies for their support.

References
[1] K. J. Beven, "Distributed models. In Anderson, M.G., and Burt, T.P. (eds.) Hydrological forecasting. John Wiley and Sons, Chichester, UK. Pp. 405-435. 1985.
[2] S. Ceola, et al., ” Virtual laboratories: new opportunities for collaborative water science”. Supplement of Hydrol. Earth Syst. Sci., 19, 2101–2117, DOI:10.5194/hess-19-2101-2015-supplement, 2015.
[3] L. Coron, V. Andréassian, C. Perrin, J. Lerat, J. Vaze, M. Bourqui, F. Hendrickx,” Crash testing hydrological models in contrasted climate conditions”: An experiment on 216 2012, 2012. Water Resources Research, vol. 48, w05552, DOI:10.1029/2011wr011721, 2012.
[4] R. Merz, J. Parajka, G. Blöschl, “ Time stability of catchment model parameters: Implications for climate impact analyses”. Water Resour. Res., 47,W02531, DOI: 10.1029/2010WR009505., 2011.
[5] J. Parajka, R. Merz, G. Blöschl,” Uncertainty and multiple calibrations in regional water balance modeling case study in 320 Austrian catchments”. Hydrol. Process, 21, 435 – 446, DOI: 10.1002/hyp. 2007.
[6] J. Parajka, V. Niemi, G. Blöschl, J. Komma, “Matching ERS scatterometer based soil moisture patterns with a simulation of a conceptual dual-layer hydrologic model over Austria”. Hydrol.Earth Syst. Sci. 13, 259-271, 2009.
[7] P. Sleziak, K. Hlavčová, J. Szolgay, J. Parajka, “ Dependence of the quality of runoff-simulation by a rainfall-runoff model on the differences in hydroclimatic conditions of calibration and validation period”. Acta Hydrologica Slovaca, Vol. 18, No. 1, 23 – 30. 2017.
[8] P. Sleziak, K. Hlavčová, J. Szolgay, J. Parajka, D. Duethman, M. Danko,” Factors controlling alterations in the performance of a runoff model in changing climate conditions”. J. Hydrol. Hydromech., 66, 4, 381-392. DOI:10.2478/johh-2018-0031. 2018.
[9] K.M. Mullen, D. Ardia, D. Gil, D. Windover, and J. Cline, DEoptim: An R Package for Global Optimisation by Differential Evolution. Journal of Statistical Software, 40(6), 1-26. 2011 [Online] Available at: http://www.jstatsoft.org/v40/i06/.
[10] L. Brocca. et.al, “ Soil moisture for hydrological applications: Open Questions and Opportunities. Water (2017). 9, 140, DOI: 10.3390/w9020140. 2017.