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HYDROLOGICAL MODELLING OF THE KARST LJUBLJANICA RIVER CATCHMENT USING LUMPED CONCEPTUAL MODEL

HIDROLOŠKO MODELIRANJE KRAŠKEGA POREČJA LJUBLJANICE Z UPORABO ENOVITEGA KONCEPTUALNEGA MODELA

Cenk Sezen[1], Nejc Bezak[2], Mojca Šraj[2,*]

[1]Faculty of Engineering, Ondokuz Mayıs University, 55139, Samsun, Turkey

[2]Faculty of Civil and Geodetic Engineering, University of Ljubljana, Jamova 2, Ljubljana, Slovenia

Abstract

Modelling rainfall runoff is important for several human activities. For example, rainfall runoff models are needed for water resource planning and water system design. In this regard, the daily runoff was modelled using the Genie Rural, a 4-parameter Journalier (GR4J), Genie Rural, a 6-parameter Journalier (GR6J), and the CemaNeige GR6J lumped conceptual models that were developed by the IRSTEA Hydrology Group. The main difference among the tested models is in the complexity and processes that are considered in the various model versions. As a case study, the non-homogeneous mostly karst Ljubljanica River catchment down to the Moste discharge gauging station was selected. Models were evaluated using various efficiency criteria. For example, base flow index (BFI) was calculated for the results of all tested models and observed discharges in order to compare low flow simulation performance. Based on the presented results we can conclude that in case of the non-homogeneous and karst Ljubljanica catchment the CemaNeige GR6J yields better modelling results compared to the GR4J and GR6J models. Compared to the GR6J and GR4J model versions, the CemaNeige CR6J also includes the snow module and improved methodology for the low-flow simulations that are also included in the GR6J model version.

Keywords: lumped conceptual model, rainfall-runoff modelling, Ljubljanica River, calibration, validation.

Izvleček

Modeliranje površinskega odtoka kot posledice padavin je pomembno za različne človeške dejavnosti. Tako lahko hidrološke modele uporabimo za načrtovanje uporabe vodnih virov in vodnogospodarskih sistemov. V prispevku je prikazana uporaba različnih konceptualnih modelov (Génie Rural à 4 paramètres Journalier (GR4J), Génie Rural à 6 paramètres Journalier (GR6J) in CemaNeige GR6J), ki so bili razviti v sklopu hidrološkega dela raziskovalnega inštituta IRSTEA. Glavna razlika med modeli je v kompleksnosti ter obravnavanih procesih. Kot študijo primera smo izbrali nehomogeno, večinoma kraško porečje reke Ljubljanice do vodomerne postaje Moste. Rezultate uporabljenih modelov smo primerjali z uporabo različnih kriterijev ustreznosti. Kot enega izmed kriterijev smo uporabili tudi indeks baznega odtoka (BFI), ki smo ga izračunali za modelirane in izmerjene vrednosti pretokov. Na podlagi predstavljenih rezultatov

* Stik / *Correspondence*: mojca.sraj@fgg.uni-lj.si

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lahko zaključimo, da je za nehomogeno in kraško porečje različica modela CemaNeige GR6J izkazala boljše rezultate v primerjavi z GR4J in GR6J. Ta različica modela (CemaNeige GR6J) v primerjavi z različico GR4J vključuje tudi snežni modul in izboljšano metodologijo za modeliranje nizkih pretokov, ki je že vključena tudi v verzijo GR6J.

Ključne besede: enovit konceptualni model, model padavine–odtok, Ljubljanica, umerjanje, validacija.

1. Introduction

Hydrological modelling is a crucial part of water resource management. Forecasting and estimating hydro-meteorological variables like discharge is also a significant input to the design of water structures. In this regard, various hydrological models such as lumped, conceptual, distributed, physically-based, and data mining models have been used for hydrological modelling in recent years (e.g., Perrin et al., 2003; Anctil et al., 2004; Sedki et al., 2009; Humphrey et al., 2016). More specifically, Demirel et al. (2009) used the Artificial Neural Network (ANN) Model and Soil and Water Assessment Tool (SWAT) for the daily runoff modelling in the Pracana basin in Portugal. They showed that the ANN model performs better compared to the SWAT model, especially for the prediction of peak flows. Furthermore, Kurtulus and Razack (2007) investigated the performance of the ANN model for rainfall-runoff modelling in a karstic area in southwestern France. They concluded that the ANN model can model runoff in karstic areas. However, one should bear in mind that these kinds of models (i.e. black-box model types) often have shortcomings in terms of the modeller's ability to interpret the hydrological characteristics of modelled catchment through model structure (e.g., number of nodes in a decision tree model, the number of hidden layers in the ANN model). De Vos and Rientjes (2007) examined the performance of the ANN and conceptual Hydrologiska Byråns Vattenbalansavdelning (HBV) model for discharge modelling. The authors of this study showed that the ANN model yields better performance compared to the HBV model for one-hour-ahead forecasting, whereas the HBV model performs better than the ANN model for six-hour-ahead forecasting. In other words, the performance of these two models changes according to their different lead times. Besides the HBV model there are also other conceptual, lumped, distributed or physically based models available. One such model was introduced by Perrin et al. (2003), who developed the Genie Rural, a 4-parameter Journalier (GR4J) lumped conceptual model for daily rainfall-runoff modelling based on the data from 429 catchments that have diverse characteristics (i.e. located in different climate conditions, from semi-arid to tropical humid and temperate). The goal was to construct a robust model with a low number of parameters. Thus, the GR4J model uses only 4 model parameters to calculate discharge based on rainfall and evapotranspiration. Perrin et al. (2003) indicate that the GR4J model can be utilized for daily rainfall-runoff modelling in various cases. The model performance is performed to several other hydrological models and the GR4J performance is among the best ones (Perrin et al., 2003). Pushpalatha et al. (2011) proposed the Genie Rural, a 6-parameter Journalier (GR6J) lumped conceptual model for daily rainfall-runoff modelling. The aim was to improve the low flow simulation by adding one parameter to the Genie Rural, a 5-parameter Journalier (GR5J) model version that was developed as an improvement of the GR4J model version. Pushpalatha et al. (2011) compared the performance of the GR5J and GR6J models for runoff simulation. Accordingly, they showed that the GR6J model yields better results compared to the GR5J model for low flow simulation. The GR6J model was developed using data from a set of 1000 catchments in France. Pushpalatha et al. (2011) also used some karst catchments despite the fact that these kinds of catchments are more difficult to model. Moreover, the CemaNeige GR6J additionally uses a snow module to account for the snow accumulation in the catchment (Valéry et al. 2014a; Valéry et al. 2014b). This model version has two additional snow parameters, which means that in total eight parameters are used. In addition, CemaNeige model version was tested on a large data set; more specifically 380 catchments located in France, Sweden, Canada, and Switzerland were used (Valéry et al. 2014a). Catchments covered a wide range of altitudes and climate characteristics (i.e. snow types). The performance of the tested model was adequate for the investigated catchments. However, there are also other models available for rainfall-runoff modelling. For example, Rimmer and Salingar (2006) investigated the rainfall-runoff relation using the Hydrological Model for Karst Environment (HYMKE) in karstic catchments in Israel. In this respect, they described HYMKE model as a grey box model and they concluded that the HYMKE model can be used for runoff modelling in karst areas. Daliakopoulos and Tsanis (2016) compared the performance of the Sacramento soil moisture accounting model (SAC-SMA), which is a conceptual model, and the input delay neural network (IDNN) model for monthly rainfall-runoff modelling in southern Greece. They pointed out that IDNN model performs better than the SAC-SMA conceptual model especially for the high flow simulation, whereas the performance of IDNN model is not very good for simulating low flow.

In the study, we examined the performance of the GR4J, GR6J, and CemaNeige GR6J lumped daily conceptual models for rainfall-runoff modelling of the Ljubljanica River catchment in Slovenia. Thus, the main aim of the paper was to test various model versions for rainfall-runoff modelling in the case of a non-homogeneous karst catchment. In order to compare the performance of models the root mean square error (RMSE), Nash Sutcliff Efficiency (NS), and Kling Gupta efficiency (KGE) criteria were used. In addition, the Base Flow Index (BFI) was calculated for each model output and observed flow in order to reveal the low flow simulation performance.

2. Study Area and Data

2.1 Study Area

In order to compare the performance of the GR4J, GR6J, and CemaNeige-GR6J lumped conceptual models, the non-homogeneous (in terms of geology) Ljubljanica catchment in Slovenia was selected. The Ljubljanica River drains into the Sava River, which is part of the Danube River basin. Its catchment area covers 1778 km^2. The prevailing land use types are forest and semi natural areas. The majority of the catchment area is Dinaric karst, whereas a minor part of the region consists of pre-Alpine karst. The exact percentage of area covered by karst cannot be determined since the Ljubljanica River's geological structure is very complex and the exact catchment area of some of the karst rivers is not yet known. However, dinaric karst covers about 75% of the area and about 15% of the area is covered by pre-Alpine karst (Habič and Kos, 1987). The rest of the Ljubljanica River catchment does not have karst characteristics and flash floods are common for its tributaries (e.g. Gradaščica, Šujica) in the northern part of its catchment. Although flash floods can also occur in some parts of the karst area. Many studies regarding hydrological modelling have already be conducted for non-karst part of the Ljubljanica River catchment (e.g., Šraj et al., 2010; Pestotnik et al., 2012; Bezak et al., 2013; Šraj et al., 2016; Bezak et al., 2017; Kovačec and Šraj, 2017; Bezak et al., 2018). However, the major part of the Ljubljanica River catchment, which has significant karst characteristics and includes various karst springs such as Stržen, Pivka, Malenščica, Unica (Kovačič and Ravbar, 2016), demonstrates a complex hydrological behaviour, which makes modelling much more difficult. The Ljubljanica River catchment area and daily discharge values from the Moste gauging station are shown in Figure 1 and Figure 2, respectively.

Table 1: *Considered rainfall, evapotranspiration, and discharge gauging stations in the study.*

Preglednica 1: *Upoštevane postaje, kjer so se merile naslednje spremenljivke: padavine, evapotranspiracija, pretok.*

Name of the River	Rainfall gauging stations (elevation above sea level)	Evapotranspiration gauging stations	Discharge gauging station
Ljubljanica	Ljubljana (299), Topol pri Medvodah (662), Črni vrh nad PG (827), Lučine (639), Rovte (700), Črna vas (288), Želimlje (309), Hotedrščica (550), Logatec (485), Hrušica (872), Pokojišče (716), Cerknica (576), Postojna (533), Razdrto (577), Nova vas na Blokah (720), Šmarata (580), Hrib (827), Juršče (703)	Postojna and Ljubljana	Moste

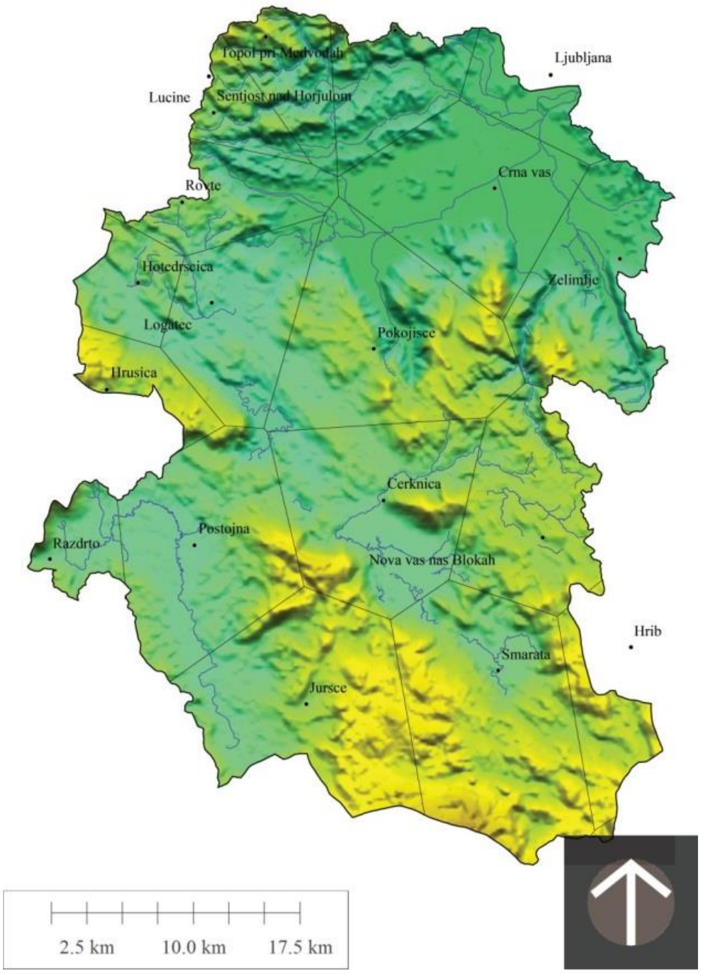

Figure 1: *Ljubljanica River catchment up to the Moste gauging station with considered rainfall stations and Thiessen polygons.*

Slika 1: *Porečje reke Ljubljanice do vodomerne postaje Moste z upoštevanimi padavinskimi postajami ter Thiessenovimi poligoni.*

Table 2: *Basic properties of measured data (P, E and Q) that were used for the hydrological modelling for the selected period (2000–2016).*

Preglednica 2: *Osnovne značilnosti obravnavanih merjenih spremenljivk (P, E in Q), ki so bile uporabljene pri hidrološkem modeliranju (obdobje 2000–2016).*

Variable	Mean [mm]	Standard deviation [mm]	Skewness	Maximum [mm]
Precipitation *(P)*	4.2	9.3	3.8	120.6
Evapotranspiration *(E)*	2.2	1.7	0.6	6.8
Discharge *(Q)*	2.5	2.5	1.7	17.01

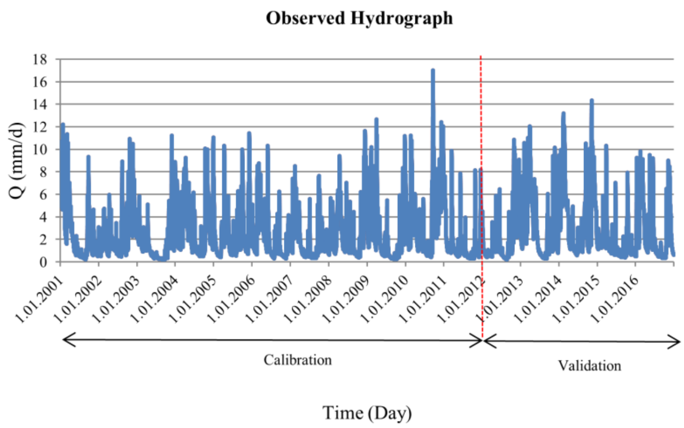

Figure 2: *Measured discharge values at the Moste gauging station for the selected period from 2001 until 2016. The red line divide the selected calibration and validation model period.*

Slika 2: *Merjeni pretoki na vodomerni postaji Moste za izbrano obdobje analiz od leta 2001 do 2016. Rdeča črta deli izbrano obdobje umerjanja in validacije modela.*

2.2. Background data and methodology

To model the runoff using the GR4J, GR6J, and CemaNeige-GR6J lumped conceptual models, daily discharge (*Q*), rainfall (*P*), and evapotranspiration (*E*) data were used. Accordingly, the daily data covers the period between 2001-2011 (4017 days) for the calibration period and 2012-2016 (1827 days) for the validation period. For the rainfall-runoff modelling in the Ljubljanica River catchment we considered discharge, rainfall, and evapotranspiration at the gauging stations that are presented in Table 1. The Thiessen polygons method was used to calculate the areal rainfall data for the Ljubljanica River catchment. The derived Thiessen polygons are shown in Figure 1. The discharge data used for the rainfall-runoff modelling was gathered at the location of the Moste gauging station, which is located few km before the confluence of the Ljubljanica and Sava Rivers. The areal evapotranspiration was calculated as an average of the evapotranspiration data from the Postojna and Ljubljana meteorological stations. These two stations were the only one with *E* data available. In this paper we used reference evapotranspiration values calculated using Penman-Montheith equation (Allen et al., 1998; Maček et al., 2018) because it was very similar to the potential evapotranspiration calculated using Oudin et al. (2005) equation. Basic statistical properties of *Q*, *P* and *E* are shown in Table 2.

2.3. GR4J Model

The GR4J model is a lumped conceptual model (Perrin et al., 2003) that is used for daily rainfall runoff modelling. P and E are used as input variables in this model. The GR4J conceptual model has four parameters (i.e. x_1, x_2, x_3, *and* x_4). Accordingly, x_1 stands for the maximum capacity of the production store (mm); x_2 for the groundwater exchange coefficient (mm); x_3 for the one day ahead maximum capacity of the routing store (mm); and x_4 for the time span of unit hydrograph (Perrin et al., 2003) In this study, the GR4J daily rainfall runoff was modelled out using the airGR package (Coron et al., 2017; Coron et al., 2018) in R software (R Development Core Team, 2015). For further information about GR4J model structure, one should refer to Perrin et al. (2003).

2.4. GR6J Model

The GR6J model is an improved daily lumped conceptual model that has six parameters (x_1, x_2, x_3, x_4, x_5, and x_6). The first four parameters are the same as by GR4J model. The additional two parameters (x_5 and x_6) represent the threshold for change in the F (ground water exchange term) sign and new routing store, respectively (Perrin et al., 2003; Pushpalatha et al., 2011). Pushpalatha et al. (2011) introduced the GR6J model in order to improve the low flow simulation performance as compared to GR4J and GR5J, particularly. The GR6J daily rainfall-runoff modelling in this study was also performed by using the airGR package (Coron et al., 2017; Coron et al., 2018) in R software (R Development Core Team, 2015). For further information about GR6J model structure, cf. Pushpalatha et al. (2011).

2.5. CemaNeige GR6J Model

The CemaNeige model (Valery et al., 2014b) is a Snow Accounting Routine (SAR) that has two parameters (i.e. snowmelt factor and cold-content factor). As inputs, the CemaNeige model uses daily liquid equivalent water depth of total precipitation, which comprises both rain and snowfall, and daily temperature (T) (Valery et al., 2014b). In this study, the CemaNeige-GR6J daily lumped model was applied, along with a combination of the Snow Accounting Routine (SAR) and the GR6J model with six full parameters (i.e. the CemaNeige GR6J uses 8 parameters), in order to observe whether there is any improvement in rainfall-runoff modelling results compared to the GR4J and GR6J models. Compared to the GR4J and GR6J models this model version also requires air temperature data and the catchment's hypsometric curve in order to model discharge. In our case the hypsometric curve of the catchment was determined using the digital terrain model of the catchment with a cell size of 100 m. The CemaNeige-GR6J model simulation was conducted by using airGR package (Coron et al., 2017; Coron et al., 2018) in R software (R Development Core Team, 2015). Cf. Valery et al. (2014a) and Valery et al. (2014b) for further information about the CemaNeige-GR6J model and other SAR models.

2.6 Assessment of Model Performance

To compare the models' performance, the correlation coefficient (R), Root Mean Square Error (RMSE), Nash-Sutcliffe (NS), and Kling-Gupta Efficiency (KGE) (Gupta et al., 2009) were used. The equations of these evaluation criteria are as follows:

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(Q_{sim,i} - Q_{obs,i}\right)^2} \qquad (1)$$

$$NS = 1 - \frac{\sum_{i=1}^{N}\left(Q_{obs,i} - Q_{sim,i}\right)^2}{\sum_{i=1}^{N}\left(Q_{obs,i} - \overline{Q_{obs}}\right)^2} \qquad (2)$$

$$KGE = 1 - \sqrt{(r-1)^2 + (\alpha-1)^2 + (\beta-1)^2} \qquad (3)$$

where N, $Q_{obs,i}$, $Q_{sim,i}$, stand for the sample size, the observed flow for the i-th time step, simulated flow for the i-th time step, respectively. $\overline{Q_{obs}}$ denotes mean of the observed flow, whereas r represents the correlation coefficient between observed and simulated flows, α symbolizes the ratio of standard deviation of observed and simulated flows, and β denotes the ratio of mean of observed and simulated flows.

Additionally, in order to observe the performance of models in the event of low flows, the Base Flow Index (BFI) analysis was implemented for the observed and simulated flows. BFI is the proportion of base flow volume (V_{base}) to the total flow volume (V_{total}) based on the hydrograph separation process (Gustard and Demuth, 2009):

$$BFI = V_{base}/V_{total} \tag{4}$$

Thus, the high values of BFI indicate a large continuous contribution of groundwater to river flow, which means that there is in all seasons a substantial flow in a stream in spite of long dry periods. One should refer to (Gustard and Demuth, 2009) to get more information about the BFI calculation steps.

3. Results and Discussion

The rainfall-runoff performance of the GR4J, GR6J, and CemaNeige GR6J lumped conceptual models is indicated in Table 3. The results show that the CemaNeige GR6J model yields better results than the GR4J and GR6J models in both calibration and validation periods, considering all of the applied performance criteria (R, RMSE, KGE and NS). The performance of the GR4J and GR6J models is very similar for the calibration period. On the other hand, the GR6J model outperforms the GR4J model for the validation period, as can be seen from Table 3.

Table 3: *Performance of different model versions based on several selected model selection criteria for the calibration and validation periods.*

Preglednica 3: *Rezultati modelov na podlagi različnih metod preverjanja učinkovitosti modela za obdobje umerjanja in validacije.*

Model	**GR4J**				**GR6J**				**CemaNeige GR6J**			
Criteria	R	NS	RMSE [mm]	KGE	R	NS	RMSE [mm]	KGE	R	NS	RMSE [mm]	KGE
Calibration period	0.88	0.77	1.1	0.80	0.88	0.77	1.1	0.80	0.91	0.85	1	0.85
Validation period	0.86	0.75	1.4	0.81	0.89	0.79	1.2	0.82	0.91	0.83	1.1	0.88

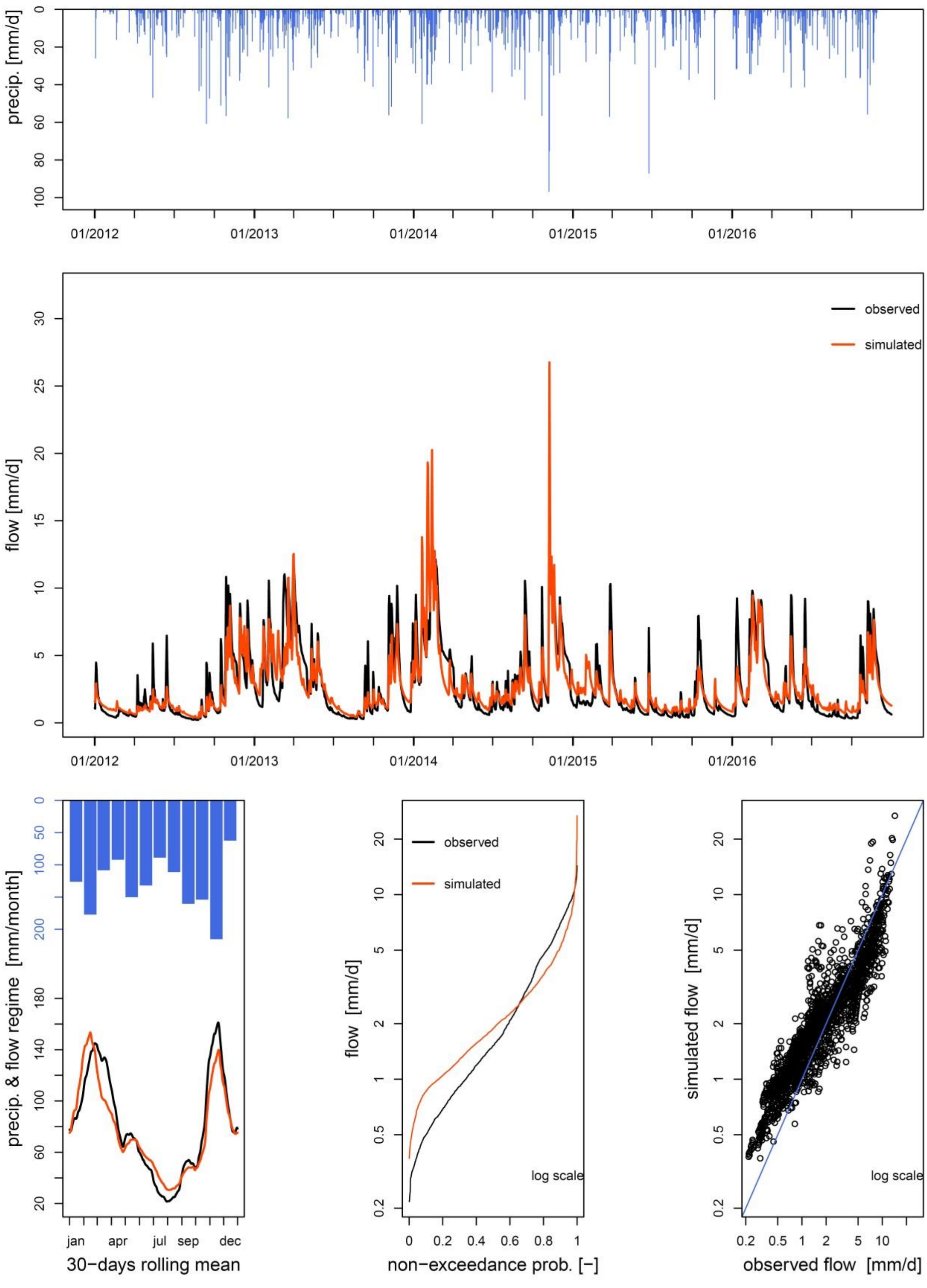

Figure 3: *Evaluation of the GR4J model results for the validation period. The comparison between modelled and observed daily discharge of the Ljubljanica River is shown using a daily hydrograph, 30-day rolling mean, flow duration curves, and a scatter plot in log-scale.*

Slika 3: *Prikaz rezultatov modeliranja z uporabo modela GR4J za obdobje validacije. Primerjava med modeliranimi in izmerjenimi vrednostmi pretokov reke Ljubljanice je prikazana s hidrogramom dnevnih vrednosti, hidrogramom 30-dnevnega drsečega povprečja, krivuljo trajanja in razsevnim diagramom v logaritemskem merilu.*

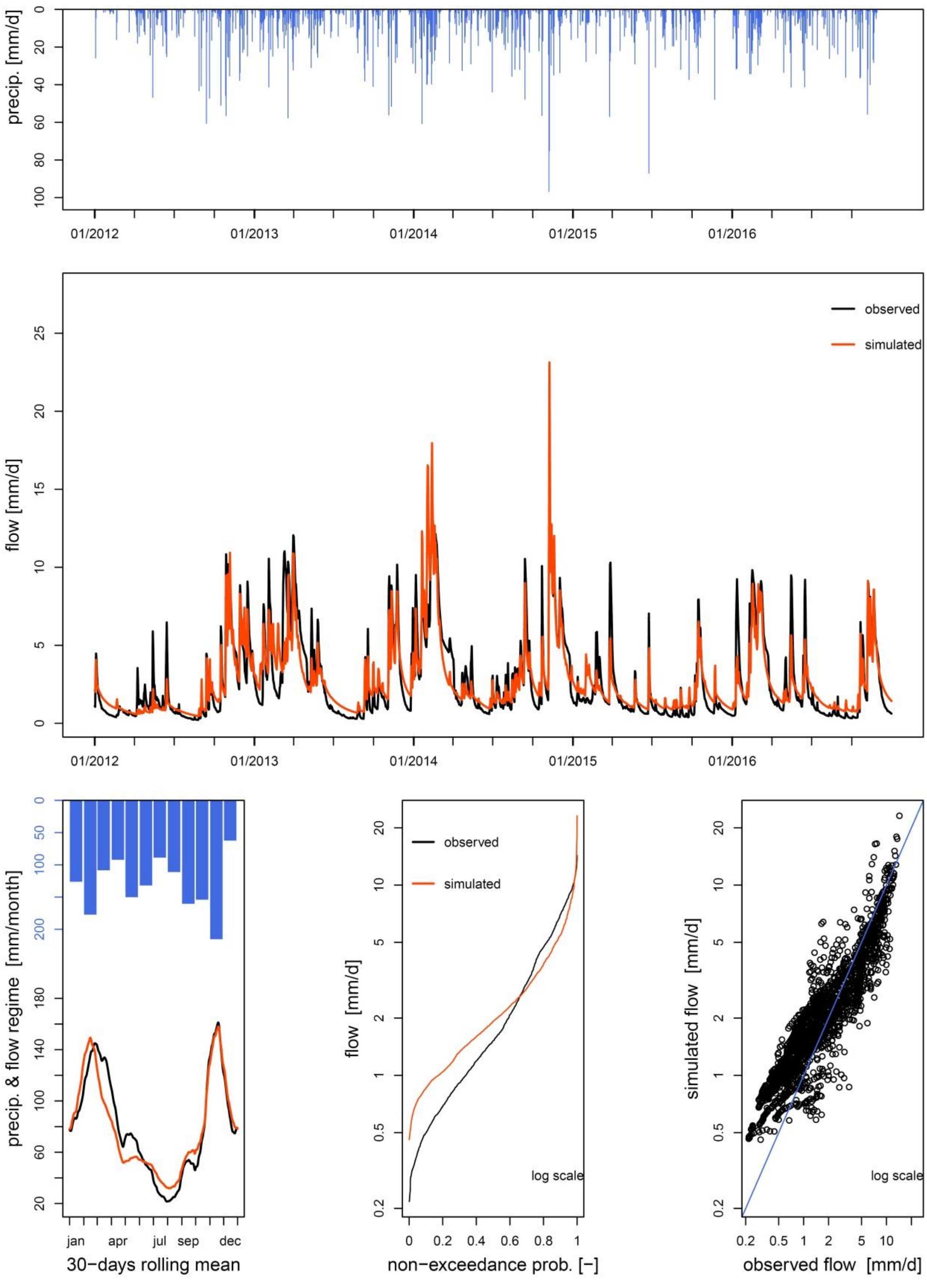

Figure 4: *Evaluation of the GR6J model results for the validation period. Comparison between the modelled and observed daily discharge of the Ljubljanica River is shown using a daily hydrograph, 30-day rolling mean, flow duration curves, and a scatter plot in log-scale.*

Slika 4: *Prikaz rezultatov modeliranja z uporabo modela GR6J za obdobje validacije. Primerjava med modeliranimi in izmerjenimi vrednostmi pretokov reke Ljubljanice je prikazana s hidrogramom dnevnih vrednosti, hidrogramom 30-dnevnega drsečega povprečja, krivuljo trajanja in razsevnim diagramom v logaritemskem merilu.*

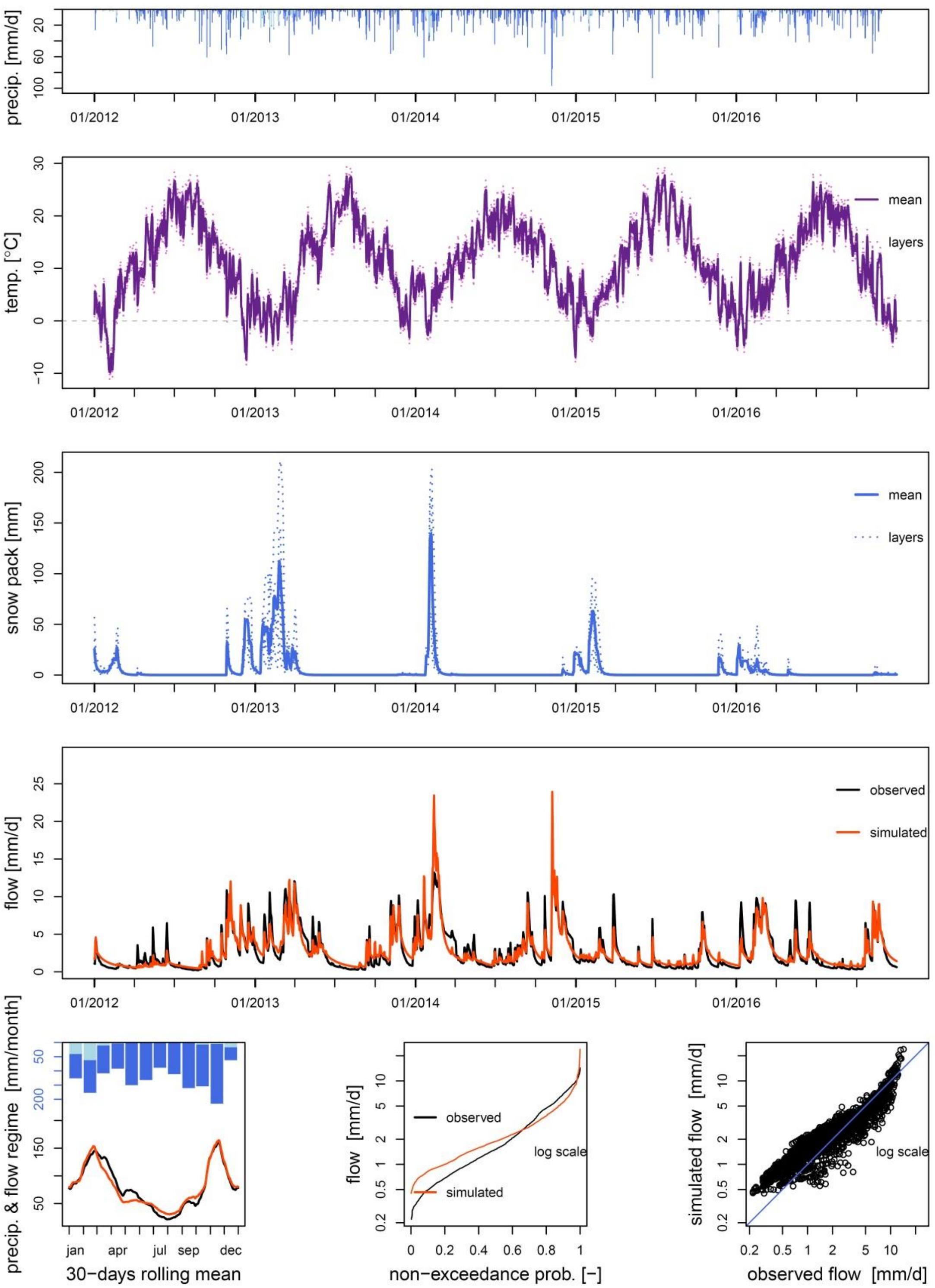

Figure 5: *Evaluation of the CemaNeige GR6J model results for the validation period. The comparison between the modelled and observed daily discharge of the Ljubljanica River is shown using a daily hydrograph, 30-day rolling mean, flow duration curves, and a scatter plot in log-scale.*

Slika 5: *Prikaz rezultatov modeliranja z uporabo modela CemaNeige GR6J za obdobje validacije. Primerjava med modeliranimi in izmerjenimi vrednostmi pretokov reke Ljubljanice je prikazana s hidrogramom dnevnih vrednosti, hidrogramom 30-dnevnega drsečega povprečja, krivuljo trajanja in razsevnim diagramom v logaritemskem merilu.*

According to the scatter diagrams of simulated and observed flows for the validation period shown in Figures 3-5, low flows are overestimated by the GR4J, GR6J, and CemaNeige GR6J models. On the other hand, the simulated high flows by the GR4J and GR6J models appear more scattered than the simulated high flows by the CemaNeige GR6J model for the validation period. However, all three considered models overestimate peak flows as can be seen from Figures 3-5. With regard to the 30-day rolling mean flow regime for each month, the CemaNeige GR6J model seems to give better results than the GR4J and GR6J models. Accordingly, the CemaNeige GR6J model yields relatively good model performance in terms of the 30-day rolling mean during the winter and autumn seasons, in particular. The simulation of runoff by the GR6J model is also more accurate during the autumn season, whereas the GR4J model results seems to be the worst among the examined models for all seasons. The non-exceedance probability graphs in Figures 3-5 also indicate that the CemaNeige GR6J model performs slightly better than the other two investigated models. Furthermore, the GR6J model performs slightly better than the GR4J model, a fact that is also demonstrated in Table 3.

BFI values were calculated (Table 4) to examine the low flow simulation performance of the models. It should be noted that hydrological models are often insufficient in modelling low flows. Therefore, we plotted modelled and observed discharge data on a log-scale, where low-flow model performance can be easily detected. Furthermore, we also evaluated several performance criteria, since some of them are better in detecting high flow performance. The calculated value of BFI for observed flows is 0.6 and the values for simulated flows using different model versions range from 0.68 to 0.72. The results show that the BFI values for the simulated flows by the GR4J and CemaNeige GR6J models are equal to each other and very close to the BFI values for the observed flows for the validation period. On the other hand, the low flow simulation performance of GR6J is weaker than in the case of the other two investigated models according to BFI analysis. The relationship between the base flow hydrograph and total flow hydrograph for the simulated runoff by the CemaNeige GR6J model is shown in Figure 6 as an example. In order to improve the performance of the GR4J model, improved versions of the GR4J model such as the GR5J (Le Moine, 2008) and the GR6J (Pushpalatha et al., 2011) models were developed. Pushpalatha et al., 2011 demonstrated that the GR6J model outperforms the GR5J model and thus the GR4J model, particularly for low-flow simulation. The results of our study demonstrate that the GR6J model's performance was slightly better than that of the GR4J model only for the validation period, whereas the performance of both models was similar for the calibration period, which is indicated in Table 3. On the other hand, BFI analysis showed that GR6J model did not perform better than GR4J model in terms of the low flow simulation for the karst Ljubljanica River catchment. For the selected Ljubljanica case study, one could therefore suggest using the GR4J model version instead of the GR6J since it uses fewer model parameters and performs similarly. In terms of model complexity and their application to real case study, both models have similar characteristics since both are implemented using the software R, namely in the airGR package.

The CemaNeige GR6J model (a combination of the Snow Accounting Routine (SAR) and the GR6J model) improved the performance for the GR6J model. When all the performance analyses in our study are taken into account, we can conclude that the CemaNeige GR6J model performs better than both other considered models, namely the GR4J and GR6J models. This verifies the findings of Valery et al. (2014a) and Valery et al. (2014b) with regard to the outperformance of daily lumped conceptual model combined with SAR compared to the daily lumped conceptual model without SAR. Moreover, the CemaNeige GR6J model requires slightly more input data but the use of this model with the airGR package is similar than for the GR4J and GR6J model versions.

Table 4: *BFI values for different model versions results and observed discharge values.*

Preglednica 4: *Vrednosti BFI za različne modelne rezultate in merjene vrednosti pretokov.*

Base Flow Index (BFI)			
GR4J	GR6J	CemaNeige GR6J	Observed flow
0.68	0.72	0.68	0.60

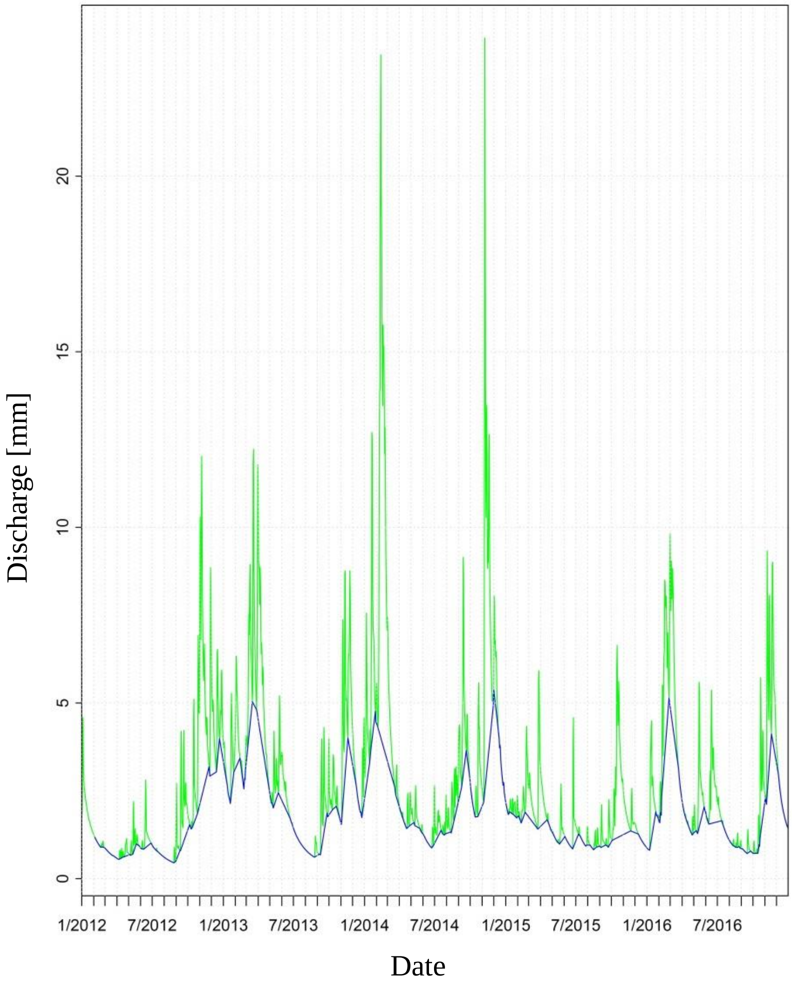

Figure 6: *Baseflow separation result for modelled discharge values using the CemaNeige GR6J model version. Baseflow is indicated with blue line. Surface runoff is defined as the difference between green (measured discharge) and blue lines.*

Slika 6: *Prikaz izločanja baznega odtoka na primeru modeliranih vrednosti modela CemaNeige GR6J. Bazni odtok je označen z modro črto. Površinski odtok predstavlja razliko med zeleno (merjeni pretok) in modro črto.*

The results indicate that for the Ljubljanica River catchment snow-related processes are important and have significant impact on rainfall-runoff modelling results because better model performance is obtained when the snow routine is also applied in the model (i.e. application of the CemaNeige GR6J model version). This is somehow expected since the Javorniki and Snežnik karst plateaus are important orographic barriers with relatively large annual rainfall amounts (i.e.

Javorniki mountain more than 2000 mm/year and Snežnik mountain more than 3000 mm/year).

4. Conclusion

Modelling runoff is crucial for water resource planning and management. In this respect, we compared the performance of the GR4J, GR6J, and CemaNeige GR6J conceptual models for daily rainfall-runoff modelling in the Ljubljanica River catchment in presented study. Thus, the findings of the study can be summarised as follows:

- The CemaNeige GR6J model yielded better results than the GR4J and GR6J models for rainfall-runoff modelling in the nonhomogeneous Ljubljanica River catchment with prevailing karst characteristics in both the calibration and validation period.

- Although the GR6J model slightly outperformed the GR4J model for the validation period, their performance was relatively similar for the calibration period.

- Overall, all three considered models slightly overestimate low and peak flows of the Ljubljanica River.

- BFI analysis was performed in order to compare the low flow simulation performance of the GR4J, GR6J, and CemaNeige GR6J models. Considering the BFI values for the observed flows the CemaNeige GR6J and GR4J models performed better than the GR6J for the low flow simulation of mostly karst catchment.

- The CemaNeige GR6J model seems to be more efficient for forecasting peak flows in comparison to the GR4J and GR6J models, since simulated high flows by the GR4J and GR6J models were more scattered than the simulated high flows by the CemaNeige GR6J model (Figures 3-5).

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