# A two-stage time series model for monthly hydrological projections under climate change in the Lim River basin

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Climate change projections of precipitation and temperature suggest that Serbia could be one of the most affected regions in Southeast Europe. To prepare adaptation measures, the climate changes impact on water resources needs to be assessed. Pilot research is carried out for the Lim River basin to predict monthly flows under different climate scenarios. For estimation of future water availability, an alternative approach of developing a deterministic-stochastic time series model is chosen. The proposed two-stage time series model consists of several components: trend, long-term periodicity, seasonality and the stochastic component. The last one is based on a transfer function model with two input variables, precipitation and temperature, as climatic drivers. The Nash-Sutcliffe model efficiency for the observed period 1950-2012 is 0.829. The model is applied for the long-term hydrological prediction under the RCP emissions scenarios for the future time frame 2013-2070.

Keywords: two-stage deterministic-stochastic time series model; transfer function models; Lim River basin; Southeast Europe; climate change.

## Introduction

Water resources are particularly vulnerable to climate change (IPCC, 2013, Kundzewicz et al., 2008). Changing climate is causing long-term changes in hydrological cycle, affecting water resources with increasing evaporation, change in precipitation patterns and intensity, and affecting the processes involved in surface water storage (Simonovic, 2013).

Projected impacts of climate change on water resources distribution vary across Europe (Behrens et al. 2010, Forzieri, 2016). Rainfall-runoff models have been widely applied for the assessment of climate change impacts in Southeastern Europe (Haddeland, 2013; World Bank, 2015; World Bank 2017). The results of simulations with future climate scenarios predict temporal and spatial changes in the runoff pattern with more frequent extreme events, decrease in precipitation and increase in temperature in the lower Danube River basin (ICPDR, 2012; IPCC, 2013).

Development of rainfall-runoff models is a critical step for long-term flow projections under climate change scenarios. There are two commonly used approaches to obtain hydrological response under changing climate (Zeng et al. 2012). The first one uses physically based hydrological models (Simonovic, 2010; Sellami et al. 2016; Todorovic and Plavsic, 2016; Marchane et al. 2017; Joo et al. 2017), which describe the precipitation-runoff relationship with a set of physical laws and/or by conceptual methods. The alternative approach employs data-driven models that describe the relationship between the hydrological response and climate parameters in a basin (Hsu et al. 1995; Dibike and Coulibaly, 2005; Tisseuil et al. 2010; Zeng et al. 2012; Taver et al. 2015). Both approaches are conditioned on climate projections (typically precipitation and temperature) under different climate change scenarios. Climate change projections are either fed into the hydrological model or serve as the predictors in the empirical or statistical models to assess impacts on water resources. For this purpose, the climate projections from the Global Climate Models (GCMs), downscaled statistically or by means of the Regional Climate Models (RCMs), are used.

Long-term prediction of hydrological variables can also be obtained with the stochastic models (mainly time series models) developed from the observed hydrological time series (e.g. Pekarova et al. 2003; Pekarova and Pekar, 2006). They are used to identify the long-term hydrological pattern in terms of trend and/or multi-decadal cycles expressed as a function of time, which could be extrapolated in the future period for long-term hydrological predictions. This imposes uncertainty connected to the nature of multi-decadal flow variation that is referred to as “sudden shifts” (Sveinsson and Salas, 2003). This approach does not consider directly the projections of climatic drivers under a particular climate change scenario (or greenhouse gases emission pathways), but through proxy quantities (as precipitation and/or temperature). Consequently, the climate tendencies inherent in the climate scenarios cannot be explicitly recognized in predictions for the future by stochastic models.

The time series models based on transfer functions can be used to embed indirectly the influence of climatic drivers on variability of the hydrological time series. This idea was used by Stojković et al. (2017a) in developing a joint stochastic-deterministic approach to simulate the long-term sequences of the observed hydrological records. The proposed modelling scheme was comprised of deterministic components, such as the trend and low-frequency periodic components, seasonal periodic component and of the stochastic transfer function model with precipitation and temperatures as the input variables.

In this study, the methodology for developing stochastic long-term projections is developed with an assumption that future changes in climate variables are the major driver for the changes in hydrological response. The methodology is applied in two stages. In the first stage, a stochastic model of annual flows based on the transfer function model with precipitation and temperature projections as the input is applied for chosen climate scenarios. At this stage the framework proposed by Stojković et al. (2017a) is further developed to incorporate the outputs of the climate models and to derive the flow estimates taking into account the trend component, macro-periodic (low-frequency) component, and seasonal component for the future time frame. In this way, annual precipitation and temperature projections are transferred to the flow estimates by means of the annual transfer function model which is capable of deducing the long- and short-term flow persistence directly from the climate signal. The results of the first stage are then used in the second stage to identify the deterministic components of the deterministic-stochastic model for monthly flows (Stojković et al. 2017a), which in turn provides the long-term monthly hydrological projections instead of simply extrapolating the deterministic components into the future.

The objective of this study is to examine the climate change impact on hydrological regime of the Lim River basin in Serbia, which was identified as a basin affected by climate change (World Bank, 2015; World Bank 2017). Broader goal of the study is to provide a tool to support future water resources planning and management and the decision-making process.

## Methodology

### *General approach*

The stochastic models of hydrological variables are usually developed by decomposing the hydrological time series into a number of components, e.g. linear or nonlinear trend, jumps, periodic component, stochastic component and noise component (Yevjevich 1972). The model structure is determined primarily by the temporal discretisation scale. In addition to the components usually present in the models on the annual scale (trend, stochastic, noise components), the monthly models also incorporate the seasonal periodic component. The stochastic component is generally modelled with the time series models based on the Box-Jenkins approach (Box et al. 2008), while the remainder is the noise term.

Many observed hydrological series exhibit different trends (Stojkovic et al., 2017b), providing a motive to declare such series as non-stationary (Milly at al., 2008). Natural proxy records which reflect hydrological regime (e.g. tree ring chronologies) suggest that stationarity may never have existed, since the significant changes occurred at different points throughout history (Razavi et al., 2015). On the other hand, the hydrological series observations are generally too short to reject the stationarity hypothesis (Montanari and Koutsoyiannis, 2014). Longer hydrological series often exhibit long-term variability in a form of small amplitude and low frequency oscillations. Such behaviour, usually referred to as the long-term persistence, has been a constant subject of research since it was first studied by Hurst (1951). However, presence of the long-term persistence in a short series can be seen as a trend if the observed series covers only a part of a long-term cycle. Therefore, we don't have a proof of either stationarity or non-stationarity in the observed series.

It seems reasonable to assume that a hydrological time series model, which is to be developed on monthly scale with an aim of application over a long future time frame, should include not only a trend component but also a long-term periodic component describing the low frequency oscillations in the series. In addition, the trend component of a model designed for long-term projections cannot incorporate a simple linear trend (because extrapolating such a trend into future is not reliable). It has been shown that magnitude and direction of annual flow trend vary with the different time periods (Stojković et al. 2014). Therefore, a variable or moving trend would be a more convenient component for the long-term projections.

Moreover, a long-term hydrological projection model should consider changes of precipitation and temperature as the main runoff drivers. This can be achieved by employing transfer function models (Box at al. 2008). In the applied model, the transfer function model is embedded in the stochastic component.

With the above assumptions, the stochastic model for monthly flows comprises four elements: trend, long-term periodic and seasonal components, and also a stochastic component based on the transfer function model with precipitation and temperature as the input variables. The proposed methodology for long-term hydrological projections based on the climate input therefore consists of the following two stages:

- Stage 1. Creating annual hydrological projections with an application of the annual transfer function model with annual precipitation and temperature projections. This stage facilitates identification of the moving trend component and the long-term periodicity in the second stage.
- Stage 2. Creating projections on a monthly time scale with a compound stochastic model for monthly flows, which includes the trend, seasonal component and the transfer-function based stochastic component with monthly precipitation and temperature projections as the input variables.

In the remainder of this section, the monthly stochastic model is described first in detail, then the annual transfer function model, and finally the procedure for coupling two models into the two-stage methodology for the long-term hydrological projections.

***Model for monthly flows based on stochastic decomposition***

The monthly flow series model consists of the deterministic and the stochastic part. The deterministic part is composed of the following components: (i) trend component, (ii) macro-periodic (or low-frequency) component, and (iii) seasonal component. The remainder of the monthly series is the stochastic component, modelled as a function of monthly precipitation and temperature series as the independent time series. Such decomposition is formally expressed as follows (Stojković et al., 2017a):

$$\begin{aligned} Q(t) &= Q_{\mathrm{DET}}(t) + Q_{\mathrm{STOCH}}(t) + \varepsilon(t) = \\ &= [Q_T(t) + Q_P(t) + Q_S(t)] + Q_{\mathrm{STOCH}}(t) + \varepsilon(t), \quad t = 1, 2, \ldots, N \end{aligned} \tag{1}$$

where $Q(t)$ is monthly flow in month $t$, $Q_{\mathrm{DET}}(t)$ is deterministic part, $Q_{\mathrm{STOCH}}(t)$ is stochastic component, $\varepsilon(t)$ is the noise term (with mean $E(\varepsilon) = 0$, constant variance $\mathrm{Var}(\varepsilon) = \text{const}$, and covariance function $C_\tau = 0$ for all $\tau > 0$), and $N$ is the series length in months.

*Deterministic part*

The deterministic part of the monthly model consists of the trend component $Q_T(t)$, macro-periodic component $Q_P(t)$ and seasonal component $Q_S(t)$. The trend and the macro-periodic component are modelled at the annual time step, while the seasonal and stochastic components are modelled at the monthly time step.

The trend component $Q_T$ is a composite trend obtained by the linear moving window (LMW) procedure for trend assessment (Stojković et al., 2017b). In LMW, the time series is divided into sub-series of length $w = 30$ years. For each sub-series, the parametric linear trend is estimated from the condition of minimum residual variance for the trend slope. The result is a composite trend, calculated as the median of the linear trends of the sub-series at each yearly time step $u$:

$$Q_{Tw}(u) = \text{Median}\begin{cases} \left[Q_T(1,w),\ldots,Q_T(u,u+w-1)\right], & u = 1, w-1 \\ \left[Q_T(u-w+1,u),\ldots,Q_T(u,u+w-1)\right], & u = w, n-w+1 \\ \left[Q_T(u-w+1,u),\ldots,Q_T(n-w+1,n)\right], & u = n-w+2, n \end{cases} \quad (2)$$

where $n$ is number of years in the series (or $N$/12). The composite trend $Q_T$ is then removed from the annual flows series $Q$ to yield the first-order residuals:

$$Q'(u) = Q(u) - Q_{Tw}(u). \quad (3)$$

The first-order residuals $Q'(u)$ are smoothed by the LOESS (Locally Weighted Scatterplot Smoothing) method to facilitate identification of the long-term harmonics by spectral analysis. The significant low-frequency harmonics are identified from the relative cumulative periodogram as those outside the 95% confidence interval (Stojković et al., 2015). The macro-periodic component $Q_P$ is then obtained by summing the significant low frequency harmonics (Yevjevich, 1972):

$$Q_P(u) = \sum_{i=1}^{q} \left[ a_i \sin(2\pi f_i u) + b_i \cos(2\pi f_i u) \right] \tag{4}$$

where $a_i$ and $b_i$ are the Fourier coefficients, $f_i$ is frequency, $u$ is current time index for years, and $q$ is the number of significant harmonics.

To proceed to modelling of the seasonal component $Q_S(t)$, the annual deterministic components (trend $Q_{Tw}$ and macro-periodic $Q_P$) are first downscaled from annual to monthly time scale by using the low-pass filter and then removed from the monthly flow series to evaluate the monthly second-order residual series:

$$Q''(t) = Q(t) - \left[ Q_{Tw}(t) + Q_P(t) \right]. \tag{5}$$

where $t$ is the time index in months.

From the second-order residuals, the seasonal component $Q_S(t)$ is modelled on monthly scale by the spectral analysis, i.e. in the form of the Fourier series:

$$Q_S(t) = \sum_{i=1}^{q_S} \left[ a_{Si} \sin(2\pi f_{Si} t) + b_{Si} \cos(2\pi f_{Si} t) \right] \tag{6}$$

where $a_{Si}$ and $b_{Si}$ are the Fourier coefficients and $f_{Si}$ are significant frequencies of the seasonal cycle (≤12 months). In this step, it is assumed that the intra-annual cycle does not vary over time and that the seasonal periodic component is repeated each year. It should be noted that deterministic component can generally be eliminated from the second-order residual series $Q''(t)$ by seasonal differencing or seasonal standardisation (Moeeni et al. 2017). However, these methods don’t provide analytical solution of seasonal periodicity needed for modelling approach herein and, therefore, the spectral analysis is chosen as an appropriate tool for time series modelling.

*Stochastic transfer function component*

The stochastic component $Q_{\mathrm{STOCH}}(t)$ is modelled from the third-order residuals $Q'''$ computed by subtracting the whole deterministic part from the monthly flow series:

$$Q'''(t) = Q(t) - \left[Q_{Tw}(t) + Q_P(t) + Q_S(t)\right]. \tag{7}$$

The stochastic component $Q_{\mathrm{STOCH}}$ is described as a function of the meteorological drivers, namely monthly precipitation $X_1$ and temperature $X_2$. For this purpose, the Transfer Function (TF) time series model with two input time series is applied. The TF model identifies the relationship between the third-order residuals $Q'''$ and input meteorological time series. To comply to the assumptions of the TF model theory (Box et al., 2008), non-stationary input time series $X_1$ and $X_2$ are transformed into stationary ones. This is accomplished by first-order differencing of the input series, with resulting series denoted as $x_{1t}$ and $x_{2t}$. Similarly, the third-order residuals $Q'''$ are transformed by differencing into time series $y_t$. The TF model of the stochastic component is represented by the following expression (Box et al., 2008):

$$Q_{\mathrm{STOCH}}: \quad y_t = \frac{\omega_1(B)}{\delta_1(B)} x_{1t} + \frac{\omega_2(B)}{\delta_2(B)} x_{2t} + \frac{\theta(B)}{\phi(B)} a_t. \tag{8}$$

where $\omega_1(B)$, $\delta_1(B)$, $\omega_2(B)$ and $\delta_2(B)$ are TF model parameters related to the input series $x_{1t}$ and $x_{2t}$, respectively; $B$ is the lag operator or backward shift operator defined with $B^j X_t = X_{t-j}$. Equation (8) includes the noise term $a_t$ with its ARMA model parameters $\theta(B)$ and $\phi(B)$. Alternatively, the TF model with double input can be written as:

$$y_t = v_1(B)x_{1t} + v_2(B)x_{2t} + \psi(B)a_t. \tag{9}$$

where $v_1$ and $v_2$ are the impulse response weights in the TF model and $\psi(B)$ is an ARMA filter applied to the noise term if it exhibits any autocorrelation.

Identifying TF parameters is simple if the input time series are uncorrelated or come as white noise. If this is not the case, the input series $x_1$ and $x_2$ have to be prewhitened. The prewhitening procedure for identification of TF model is performed in the following steps (Box et al. 2008):

- Each input series $x_t$ is prewhitened by representing it as an ARMA($p$, $q$) model:

$$\phi_x(B)x_t = \theta_{\mathrm{x}}(B)\alpha_t, \tag{10}$$

  where $\alpha_t$ is the white noise, and $\phi_x$ and $\theta_x$ are the ARMA model parameters. Relation (10) gives the prewhitened series:

$$\alpha_t = \frac{\phi_x(B)}{\theta_{\mathrm{x}}(B)} x_t, \tag{11}$$

- The prewhitening model (11) is applied as a filter to the output time series $y_t$, resulting in the filtered random output series $\beta_t$:

$$\beta_t = \frac{\phi_x(B)}{\theta_{\mathrm{x}}(B)} y_t. \tag{12}$$

- Cross-correlation function $\hat{r}_{\alpha\beta}(k)$ between the random time series $\alpha_t$ and $\beta_t$ is computed for a range of lags $k$ and then used to estimate the impulse response weights $v_k$ as:

$$\hat{v}_k(k) = \frac{\hat{\sigma}_\beta}{\hat{\sigma}_\alpha}\hat{r}_{\alpha\beta}(k). \tag{13}$$

where $\hat{\sigma}_\beta$ and $\hat{\sigma}_\alpha$ are standard deviations of $\alpha_t$ and $\beta_t$, respectively.

Significance of the cross-correlation coefficients $\hat{r}_{\alpha\beta}(k)$ and the corresponding weights $\hat{v}_k$ is established by comparing them to the double standard error of the cross-correlation function.

Validation of the TF model adequacy is conducted by evaluating cross-correlation $r_{\alpha a}$ between the prewhitened input $\alpha_t$ and the noise term at in equations (8) and (11). For this purpose, the $S$ statistic proposed by Haugh (1976) is used:

$$S = N\sum_{k=-M}^{M}(r_{\alpha a}(k))^2, \tag{14}$$

Statistic $S$ is $\chi^2$-distributed with $2M + 1$ degrees of freedom (total number of lags in the cross-correlation function, where $M$ is the number of forward and backward lags). If $S$ is smaller than the critical value defined from the $\chi^2$ distribution for the chosen level of significance $\alpha$, the null hypothesis on the lack of cross-correlation cannot be rejected. Otherwise, the null hypothesis is rejected. Smaller cross-correlation between the prewhitened input variables and the residuals means that the TF model explains more variation between the input and output variables.

Additionally, the Box-Ljung test (Salas et al., 1980) is used to verify independence of the noise term $a_t$ of the TF model:

$$S_{BL} = N(N+2)\sum_{k=1}^{j}\frac{r_a^2(k)}{N-k}, \tag{15}$$

where $S_{BL}$ is the test statistic, and $r_a(k)$ is the autocorrelation function of the noise term.

The sum in eq. (15) is evaluated with autocorrelations up to lag $j$, which depends on the series length and the orders $p$ and $q$ of the ARMA filter $\psi(B)$ used for the noise term in eq. (9). The test statistics $S_{BL}$ is $\chi^2$-distributed with $j - p - q$ degrees of freedom. The null hypothesis that the model error is not autocorrelated is rejected at the level of significance $\alpha$ if $S_{BL} > \chi^2(1 - \alpha; j - p - q)$.

### *Transfer function model for annual flows*

The Annual Transfer Function Model (ATFM) is based on the methodology for modelling monthly stochastic component $Q_{\mathrm{STOCH}}$ in eq. (8), but is applied to the annual flow series. The differenced annual flow series $y_u$ are then modelled as follows:

$$y_u = \frac{\omega_1(B)}{\delta_1(B)} x_{1u} + \frac{\omega_2(B)}{\delta_2(B)} x_{2u} + \frac{\theta(B)}{\phi(B)} a_u . \tag{16}$$

where $u$ is yearly time index. The input time series in eq. (16) are the differenced annual precipitation $x_{1u}$ and temperature $x_{2u}$ in the river basin. Parameters in equation (16) are estimated for the observation period by the prewhitening method in the same fashion as for the monthly flows. Identification of ATFM involves the following steps: defining the observed input and output time series, standardizing and first-order differencing of inputs and outputs, estimating the parameters of TF by the prewhitening method, and verifying the model by means of the Haugh's statistic (eq. 14) and the Box-Ljung statistic (eq. 15).

### *Two-stage long-term prediction of monthly flows*

Long-term hydrological projections of monthly flows are obtained by applying the two-stage procedure with the annual and monthly time series models based on transfer functions, illustrated in Figure 1.

At stage 1, the ATFM is introduced with a role of providing initial projection of annual flows. The input for ATFM are the annual precipitation and temperature projections, which result from the climate modelling chain of global and/or regional climate models (GCM/RCM) fed by the climate change scenarios or pathways, and from the accompanying downscaling and correction procedures. Given these inputs, ATFM yields initial prediction of the annual flows in a future time frame.

At the second stage, hydrological predictions at both annual and monthly scale are considered. By using the annual flow projections from stage 1, the composite trend and long-term periodicity are identified at stage 2a with annual time step and then downscaled to monthly scale. At stage 2b the components with monthly time discretisation are assessed, including seasonal periodicity, stochastic component and noise component. Finally, the monthly flow projections for the given climate scenario are obtained as the sum of all components.

Having the initial annual flows in the future estimated, the long-term prediction of composite trend $Q_{Tw}$ and macro-periodic component $Q_P$ are established in accordance with eqs. (2) and (4). The remaining deterministic part is the seasonal component $Q_S$ expressed as a function of time by eq. (6). It is assumed that the seasonal component, which describes the intra-annual flow cycle, does not change during the historical period for which the model is identified (or baseline period in the climate impact studies). However, such an assumption may not be valid for the future. According to the climate change studies in the south-eastern Europe (World Bank 2015; World Bank 2017), the intra-annual precipitation pattern is expected to change significantly, even to a greater extent than the change in total annual precipitation. Also, the increasing temperatures suggested by climate modelling could also contribute to changing intra-annual flow patterns.

In the proposed model, it is assumed that the change in the intra-annual flow pattern follows the projected changes in the intra-annual precipitation pattern. This is done first by finding standardised average intra-annual flow and precipitation patterns, $k_Q$ and $k_{X1}$ respectively, for the baseline period:

$$k_Q(s) = (Q_S(s) - \bar{Q}_S)/\sigma_{Q_S}, \quad k_{X_1} = (X_1(s) - \bar{X}_1)/\sigma_{X_1}, \qquad s=1, 2,...,12 \qquad (17)$$

where $k_Q$ is obtained from the observed seasonal flow component $Q_S$ and $k_{X1}$ is obtained from mean monthly precipitation $X_1$ from GCM/RCM for the baseline period; $\bar{Q}_S, \bar{X}_1$ and $\sigma_{Q_S}, \sigma_{X_1}$ are the means and standard deviations of $Q_S$ and $X_1$ and $s$ is monthly time index. If the standardised intra-annual precipitation pattern for the future, devised from the precipitation projections, is denoted $k'_{X1}$, then the change ($k'_{X1} - k_{X1}$) between future and baseline period is applied to the standardised intra-annual flow pattern and the seasonal flow component $Q_S$ for the future is then expressed as:

$$Q_S(s) = \bar{Q}_S + \left[k_Q(s) - (k'_{X_1}(s) - k_{X_1}(s))\right] \cdot \sigma_{Q_S} = \bar{Q}_S + k'_Q(s) \cdot \sigma_{Q_S} \qquad s=1,2,...12 \, (18)$$

where $k'_Q$ now denotes future standardised intra-annual flow pattern.

The long-term projection of the stochastic component $Q_{STOCH}$ is obtained by using the monthly TF model (eq. 8) with future monthly precipitation and temperature projections from climate modelling as the input variables. The parameters of TFs are those estimated over the period of observations. Once all the considered components are estimated, the long term-projection of monthly flows $Q(t)$ are obtained by equation (1).

## Application to the Lim River basin

### *The Lim River basin*

The study is performed for the Lim River basin upstream of the Prijepolje hydrological station that covers area of 3160 km$^2$, located in southwest Serbia and northeast Montenegro (Figure 2a). The Lim River is 201.6 km long and represents the largest tributary to the Drina River. Three streams (the Vruja, the Gričar and the Dole) meet in Gusinje to create the Ljuča River. The Ljuča River flows into the Plav Lake, which represents the source of the Lim River. From the Plav Lake to its confluence with the Drina River, the Lim River runs in south-north direction through a relatively narrow valley. Among many tributaries, the most are small streams originating from springs in the karstic formations. The Uvac River is the major tributary of the Lim River in the territory of Serbia. The "Potpeć" dam and hydropower plant, with a reservoir having a storage volume of 44 million m$^3$, is located immediately downstream of the town of Prijepolje (World Bank, 2017).

The Lim River basin has heterogeneous physiographic, hydrological and climatic characteristics. It is a predominantly mountainous basin with approximately 65% of the area between altitudes of 750 and 1500 m a.s.l., 27% of the area above the altitude of 1500 m a.s.l. and only 7% of the area featuring hills at altitudes below 750 m a.s.l. (Kostić et al. 2016). The distribution of precipitation over the Lim River basin indicates a decreasing trend from south to north, with mean annual precipitation of 1150 mm at Andrijevica on the south to 800 mm at Priboj on the north. Mean annual temperature increases in the south-north direction from 7.6 °C at Plav on the south to 9.3 °C on the north. Northern parts of the Lim River basin receive the most precipitation in late spring, mainly in May and June, while the least precipitation occurs in March. The snow cover has an impact on dynamics of hydrological regime due to water accumulated in snow. For instance, snow depths at Plav and Bijelo Polje can be as high as 1.10 m and 0.87 m, respectively. The highest show depths in the Lim River basin occur from December to February, while the melting process occurs mainly in March. The floods in the Lim River basin occur between April and May; it therefore seems that the snowmelt runoff does not contribute significantly to the high flows.

Hydrological and meteorological records are available from 1950 to 2012. The time series of average precipitation and temperature over the Lim River basin to Prijepolje are estimated by the Thiessen polygons method. Six meteorological stations are used for this purpose (Figure 2b).

The sensitivity of seasonal and annual flows in the Lim River basin to variability of atmospheric drivers is addressed by using the simple linear least squares regression function (Bouwer et al. 2008). The sensitivity is expressed as linear regression coefficients estimated between observed watershed response and climate drivers. The seasonal and annual regression coefficients related to the precipitation and temperature averaged over the basin as the predictor variables, and flows at Prijepolje hydrological station as the response variable, are shown in Table 1. The results suggest that seasonal precipitation is the most important climate driver for seasonal flows, rather than seasonal temperature. The regression coefficients for precipitation are the highest in the winter and autumn seasons (0.588 and 0.606, respectively). Temperature has an impact on watershed response during the summer season, while substantially lower regression coefficients are obtained for the winter and spring temperatures (from -0.097 to 0.066) when high flows are expected. At the annual scale, precipitation is the most influential driver controlling the long-term variability of hydrological time series (Table 1). The annual regression coefficients related to precipitation and temperature are equal to 1.128 and -0.044, respectively.

***The climate projections data***

In this study, climate projections include precipitation and temperature under the scenarios of Representative Concentration Pathways (RCPs), proposed in the Fifth Assessment Report (IPCC, 2013). The moderate RCP 4.5 and a comparatively high greenhouse gas emissions option, particularly the RCP 8.5 scenario, are used in this study. The outputs from the Aladin 5.2 regional climate model (RCM) under the aforementioned climate scenarios are used for this study. The simulations cover the 2013-2070 time frame, while the baseline period is chosen to be 1961-1990 due to the availability of the observed data.

Statistical bias correction based on the empirical quantile mapping is applied to the RCM simulations at locations of the meteorological stations (Teutschbein and Seibert 2012). This method implies constructing cumulative probability functions for daily observed and simulated variable for each meteorological station during the baseline period. Consequently, a correction function is created for each month to transform the computed values to the observed ones with the same value of the cumulative probability function. Once the correction function is determined, it is applied to the climate datasets for the future time frame providing the bias-free daily precipitation and temperature.

The application of the bias correction method to the climate records for the meteorological stations within the Lim River basin is shown in Figure 3. Bias-free simulated precipitation and temperature are illustrated during the baseline period 1961-1990 alongside the observed values. For this purpose, precipitation and temperature during four seasons are used: winter season (January, February, March), spring season (April, May, June), summer season (July, August, September), and autumn season (October, November, December). The results suggest that the bias-corrected simulated temperatures agree well with the observed values (Figure 3b). The seasonal distribution of the corrected simulated precipitation mimics fairly the distribution of the observed precipitation (Figure 3a). The simulated precipitation is slightly overestimated during summer season and underestimated during winter.

The simulated climate for the Lim River Basin generally shows a decrease in annual precipitation for 2013-2070 relative to the baseline period 1961-1990. Under the RCP 4.5 and RCP 8.5 scenarios, this decrease ranges from 8.0% to 6.4%. Average air temperature shows an overall rise, which is similar for the two scenarios (1.8°C).

The climatic projections for the future time frame in the Lim River basin are also analysed for two 30-year time frames: 2013-2040 (near future) and 2041-2070 (mid-distant future). Relative changes in the median of annual precipitation and temperature with reference to the baseline period 1961-1990 are shown in Table 2. Both sets of climate scenarios suggest a moderate decrease in precipitation in both future periods (down to -10.9%). The RCP 4.5 scenario implies a slightly greater decrease in annual precipitation compared to the RCP 8.5 option. The climate modelling results also suggest a rapid rise in average temperatures over the two 30-year time frames.

The changes in seasonal distributions of precipitation and temperature within the Lim River basin are also noticeable. These changes are shown in Table 3 for the two 30-year time frames with reference to the baseline period 1960-1990. The character of the changes depends on the season, scenario and time frame. Winter precipitation is expected to increase slightly in the near future by 5.0% and 1.4% for RCP 4.5 and RCP 8.5, respectively. Similarly, winter precipitation is expected to increase slightly in the mid-distant future by 6.1% under RCP 4.5 and by 1.1% under RCP 8.5 scenario. The projected changes in spring precipitation are the most pronounced in the mid-distant future when precipitation is expected to decrease by 18.4% to 20.8% under the RCP 4.5

and 8.5 scenarios, respectively. The most significant reduction is suggested for summer precipitation in the mid-distant future, ranging from 30.4% to 33.0%. The autumn precipitation is expected to decrease more in the near future than in the mid-distant future.

Changes in the seasonal temperatures suggest an overall rise in all seasons. For the near future, it is most likely that seasonal temperatures would increase between 0.5°C and 1.5°C, whereas the most considerable increase is expected in the winter, spring and summer seasons over the mid-distant future (from 2.5°C to 2.8°C).

## ***Results***

### *Identification and verification of the monthly flows model*

The results of identification of the monthly flows model components for the Lim River basin are presented in Figure 4. The composite trend $Q_{Tw}$ shown in Figure 4a exhibits an oscillatory behaviour with a very low frequency and very small amplitude. The macro-periodic component $Q_P$ together with the trend component in Figure 4b shows alternating multi-decadal wet and dry periods in the Lim River basin. The seasonal component has the significant harmonic with the oscillation period of 12 months. However, the harmonics of 4 and 6 months are also significant at the 5% significance level. The seasonal component modelled with all significant seasonal harmonics using eq. (6) is added to the previous deterministic parts and shown in Figure 4c.

The stochastic component $Q_{\mathrm{STOCH}}$ is modelled with the TF model according to eq. (8) which uses monthly precipitation and temperatures in the Lim River basin as the input. The resulting component $Q_{\mathrm{STOCH}}$ is expressed at the monthly time scale as follows:

$$Q_{\mathrm{STOCH}}: \quad \hat{y}_t = \frac{(0.398 + 0.247B)x_{1t}}{1 + 0.434B + 0.352B^2} + (0.419 - 0.153B^2)x_{2t} + (1 + 0.008B)a_t. \quad (19)$$

where $\hat{y}_t$ is the output series, $x_{1t}$ and $x_{2t}$ are the inputs (differenced and standardised monthly precipitation and temperatures) and $a_t$ is the noise term.

Verification of the TF model in eq. (19) is conducted using the Haugh's statistic given in eq. (14). Its values for precipitation and temperature are $S(\alpha_1,a) = 120.7$ and $S(\alpha_2,a) = 124.6$, respectively. Both values are smaller than the critical value $S_{cr} = 125.5$ from the $\chi^2$ distribution for 101 degrees of freedom at the 5% significance level. It is concluded that the prewhitened input time series don't have significant cross-correlation with the residual term $a_t$. The Box-Ljung test is also used to check the independence of the TF model noise term. The value of Box-Ljung test statistic $S_{BL}(a) = 15.38$, which is smaller than the critical value $S_{BLcr}$=97.35 at the 5% significance level for 76 degrees of freedom, suggests that the noise term is the random series.

With all components identified, the modelled monthly flows are constructed according to eq. (1) and shown in Figure 4d. The Nash-Sutcliffe efficiency (NSE) measure is used as an indicator of model performance. The NSE = 0.829 suggests a very good agreement between the modelled and observed monthly flows according to classification proposed by Moriasi et al. (2007).

*Identification and verification of the annual transfer function model*

With standardised and differentiated annual precipitation and temperature series as the input for modelling annual flows $Q$ (as shown in Figure 1), estimated ATFM parameters are given by:

$$\hat{y}_u = \frac{(0.615 - 0.187B - 0.337B^2)x_{1u}}{1 + 0.482B + 0.318B^2} + (-0.418B + 0.120B^2)x_{2u} + (1 + 0.113B)a_t. \quad (20)$$

where $\hat{y}_u$ is differenced series of annual flows, $x_{1u}$ and $x_{2u}$ are differenced annual precipitation and temperature series and $a_t$ is a residual term. The Haugh's statistic is used again for verification of ATFM in eq. (20). Its values for precipitation and temperature are equal to $S(\alpha_1,a) = 67.6$ and $S(\alpha_2,a) = 47.7$, respectively. Both values are smaller than the critical value 72.6 at the 5% significance level for 51 degrees of freedom. Hence, the residual term $a_t$ does not exhibit significant cross-correlation with the input time series. In addition, the Box-Ljung test is applied to verify the noise term of ATFM. The value of the test statistics $S_{BL}(a)$ is equal to 5.65, and the critical value from the chi-squared distribution at the significance level of 5% for 5 degrees of freedom is 12.59. Therefore, the test statistic $S_{BL}$ has a lower-than-critical value, suggesting that the residual term is the independent series.

*Model application*

In the first application stage, the ATFM in eq. (20) is applied for the initial projection of future annual flows with the standardised and differentiated series of precipitation and temperature projections under climate scenarios for the future time frame as the input instead of the observed time series $x_{1u}$ and $x_{2u}$.

In the second application stage, the future composite trend $Q_{Tw}$ and macro-periodic component $Q_P$ are inferred from the annual flows estimated in the first stage. The obtained projections of annual flows under the RCP 4.5 and RCP 8.5 emission scenarios are shown in Figure 5. The future seasonal component $Q_S$ is defined using eq. (18) for two 30-year time frames: 2013-2040 (near future) and 2041-2070 (mid-distant future). It is assumed that the intra-annual pattern does not change within a 30-year time frame, but it differs for each of the two periods. By using observed seasonal flow and precipitation distribution, the relation given in eq. (18) is established based on precipitation projections under the RCP emission scenarios for the future time frame. In this way, the projected changes of precipitation from RCM are propagated into the projections of the seasonal flow components for two 30-year time frames. Note that a finer time scale (e.g. daily or sub-daily) is required to analyse the relationship between the snow-related processes and seasonal flow distribution. Therefore, the snow processes are not considered in this study due to a limitation regarding the coarse monthly time step used for the model development. The long-term projection of the stochastic component $Q_{\mathrm{STOCH}}$ is computed using TF model in eq. (19) with monthly precipitation and temperature projections from climate modelling as the input series.

Finally, the monthly flow predictions for the Lim River at Prijepolje are computed by downscaling annual deterministic components to monthly time scale and by summing all components as in eq. (1). Figure 6 presents the distributions of mean seasonal and annual flows for the two time periods under the RCP scenarios.

The long-term flow projections suggest gradually varying changes in the annual flows over the 2013-2070 time frame relative to the baseline period 1961-1990 (Figure 5). Median annual flow is expected to reduce by 8.7% and 5.7% under the RCP 4.5 and RCP 8.5 emission scenarios, respectively. For the near future, a reduction by 5.7% and 5.9% in median annual flows is suggested for the RCP 4.5 and 8.5, respectively (Figure 6 and Table 4). In the mid-distant future the annual flows could be somewhat more reduced by 11.7% and 5.4% for the RCP 4.5 and RCP 8.5 scenario, respectively.

The change in the intra-annual precipitation pattern and the general temperature rise in the future projected by the RCP emission scenarios are expected to introduce a significant change in the intra-annual flow distribution (Figure 6 and Table 4). A decrease in median summer and autumn flows is expected for the near future (2013-2070), followed by a more pronounced reduction in summer flows in the mid-distant future (2041-2070). The projections suggest an overall increase in median winter flows over both time frames, and a slight increase in median spring flows. For instance, spring flows during the near future will increase by 11.5% and 9.8% for the RCP 4.5 and RCP 8.5 scenarios, respectively. However, the changes in the spring flow medians are negligible for the mid-distant future. For the mid-distant future, a significant rise of winter flows is expected by 37.1% (RCP 4.5) and 26.6% (RCP 8.5). The reduced summer precipitation and temperature increase will affect greatly the summer flows in the mid-distant period by decreasing their medians by 62.6% and 73.9% under the RCP 4.5 and RCP 8.5 options, respectively.

## Discussion

Changing climate already has consequences in Serbia in increased variability of meteorological parameters, higher temperatures and changing precipitation patterns. Such changes lead to changes in the hydrological regime at both seasonal and annual scale (World Bank, 2009). Based on the results of climatic modelling under the A1B and A2 scenarios, Kržić at al. (2011) suggest an overall increase of temperature in Serbia ranging from 2°C to 4°C for the future frame 2071-2100 relative to the baseline period 1961-1990. They also expect that the temperature rise would be accompanied by a decrease in seasonal precipitation in the range from 10% to 20% for all seasons, except for the spring season.

The results of long-term projections for the Lim River basin imply that climate change could have considerable effects on the annual and seasonal flow pattern. The application of the presented methodology for long-term projections of the Lim River flows also suggests a decrease in annual flows towards the end of the 21st century relative to the baseline period 1961-1990. Previous studies indicate that the annual flows would reduce, and that seasonal flow distribution would change drastically (ICPDR, 2012; IPCC, 2013), while the macro-scale hydrological modelling for South-east Europe suggests a decrease in the annual flows in the range of 20-30% (Arnell, 2003).

The projections for the Sava River basin, a 96,000 km$^2$ basin to which the Lim River basin belongs, were developed in a study by the World Bank (2015) by means of the HEC-HMS deterministic hydrological model. The results from the World Bank study show that the change in mean annual flows over 2011-2070 under A1B scenario in the Lim River basin is negligible, with a more significant increase in winter flows and decrease in summer flows. The expected decrease in the Lim River annual flows in this study is more severe than in the study by the World Bank (2015). However, the seasonal change predicted by two studies is generally consistent except for the smaller change in winter flows in contrast to a more substantial increase in the study by the World Bank (2015).

Different local character of hydrological projections could be seen by comparing the predicted changes in flows for the Lim River, on one hand, and for the Kolubara and Toplica Rivers in Serbia, on the other hand (Haddeland, 2013). Hydrological projections for the latter two basins under the A1B emission scenario are obtained by applying the HBV hydrologicalal model. The impact of climate change on annual and seasonal flows of the aforementioned rivers under A1B scenario is significantly greater than for the Lim River, with a decrease by about 35% by the end of the 21$^{st}$ century.

Obviously, the range of changes obtained in different studies can be attributed not only to regional characteristics but also to a range of uncertainty sources, including each element within the hydroclimatic modelling chain. Uncertainty in the hydrological projections depend on the selection of GCMs and RCMs, the assumed initial and boundary conditions, choice of the bias correction method, the chosen greenhouse gas emission scenarios and scenarios of future socio-economic development (Kundzewicz et al. 2018). Also, there are uncertainties related to the hydrological modelling caused by a lack of reliable information needed for setting up the model structure and for model calibration. The largest uncertainty in the predicted flows is most likely due to the selection of the GCMs or RCMs, bias-correction methods and the internal variability of the climate system (Mandal and Simonovic 2017). It seems that the choice of emission scenarios introduces the least contribution in the watershed response compared to the selection of climate models and bias correction methods (Stojkovic and Simonovic 2019). Therefore, the decision-makers need to develop several hydrological scenarios for planning on based on an ensemble of GCM/RCMs while the use of a single GCM/RCM prevents capturing climate modelling uncertainty in the watershed response.

Hydrological prediction can generally be based on either rainfall-runoff modelling or the time-series (Box-Jenkins) approach. The former approach represents a standard tool to estimate the impacts of climate change on water resources over long time frames, such as the whole 21$^{st}$ century. The latter technique is based on the time series analysis utilised to assess the annual or seasonal streamflow predictions for much shorter time horizons, while the implementation of this concept for the long-term projections is limited due to the random nature of hydrological process (Stojković et al. 2017c). Therefore, uncertainty associated with the application of the time series concept increases with the length of the prediction time frame. In order to reduce this uncertainty when applying the time series approach for long-term projections, the transfer function time series model is included in the proposed modelling scheme with an aim to introduce the climate signal in the flow sequences. Given that the application of the proposed methodology to the Lim River basin has shown results that are comparable to those of other climate change impact studies in the region, it seems that the proposed approach can reconcile the two aforementioned concepts by being based on the time series analysis and by taking into account precipitation and temperature projections obtained from climate modelling.

The main advantage of the time-series based modelling scheme in comparison to the hydrological models is that it represents a more parsimonious approach (Augustin et al. 2008). The proposed modelling approach can preserve the main features of the hydrological processes characterised as the long- and short-term statistical dependence and use them to provide monthly flow estimates under climate change. Also, deriving the model structure and its parameters directly from the data reduces uncertainties related to the structure of a hydrological model. Using the climate inputs at a coarse (monthly) time scale brings benefits by avoiding high uncertainties associated with daily or sub-daily precipitation resulting from the RCMs. Derived flow estimates at monthly time scale under the future climate can be considered more reliable than those obtained by running hydrological models with daily or sub-daily climate input because in the latter case the high uncertainty about daily climate input stemming from climate modelling is propagated into streamflows. Therefore, it is more likely that the major source of uncertainty in the application of the proposed methodology to the Lim River basin stems from the climate models. The limited pool of climate modelling outputs for this study lead to a limited insight into the climate modelling uncertainties, which could be better characterised by using multiple climate simulations by a greater number of climate models. Moreover, the bias correction methods may have an influence on predicted flows, especially in terms of high flows. For this reason, the use of additional bias correction methods (e.g. parametric quantile mapping) could lead to explaining a portion of uncertainty in the predicted flows for the Lim River basin.

Potential weakness of the proposed model is in the representation of the seasonal model component, which is modelled by means of spectral analysis under the stationarity assumption, meaning that the seasonal component remains unchanged throughout the simulation period. Changing climate is expected to affect the intra-annual flow distribution in the studied region, and consequently the seasonal component would also be expected to evolve in time. This potential drawback of the proposed model can be improved by analysing the long observed hydrological series and climatic drivers such as precipitation, temperature, and evapotranspiration. For the river basins where snow dynamics plays a significant role, snow melt can be analysed implicitly by using temperature as a conditional variable, which can propagate the changes in the snow cover into the seasonal flow component. For finer time scales such as daily or sub-daily, the impact of the snow dynamics on hydrological regime needs to be analysed by means of the deterministic (rainfall-runoff) hydrological models.

**Conclusions**

In contrast to conventional climate change impact assessment based on the application of rainfall-runoff simulation models, this paper proposes an alternative procedure with which future precipitation and temperatures are used as the input to the two-stage deterministic-stochastic model based on the transfer functions for monthly hydrological projections. Model components based on the transfer functions allow introducing climatic drivers into a time series model in addition to the components that describe stochastic structure (serial correlation) of the hydrological time series, such as trend, long-term periodicity, and seasonality. The proposed model can capture both short-term and long-term statistical dependence of monthly flow series. This is provided by employing time series decomposition at annual and monthly time scale, which separates high-frequency (seasonal) and low-frequency (persistence) components.

Application of the proposed approach to the Lim River basin in Serbia over the historical period 1950-2012 has shown a very good agreement of the model results with the observed data, as measured by the Nash-Sutcliffe efficiency coefficient. The results of the model application for producing monthly flow projections under the RCP emission scenarios suggest that a decrease of annual and seasonal flows is expected in the future compared to the baseline period 1961-1990. Median annual flow for 2013-2070 is expected to decrease by 8.7% and 5.7 % for the RCP 4.5 and RCP 4.5 scenarios, respectively. The greatest reduction of annual flows by 11.7% under the RCP 4.5 scenarios is expected in the 2041-2070 time frame. The decrease of the annual flows would mainly be caused by a significant reduction in the summer and autumn flows. Although the model application was limited to a modest number of outputs from a single RCM, a part of uncertainties within the climate modelling chain was captured by including different emission scenarios (RCP 4.5 and RCP 8.5).

The results of the model application are comparable to the results of similar studies, which were based on the conventional approach based on the application of rainfall-runoff simulation models. As such, the proposed stochastic modelling approach can be used in the climate change impact studies and further considerations of the climate change adaptation strategies. The model can be utilized for different tasks such as evaluating the long-term water availability in terms of future wet and dry periods and preparing effective water management plans.

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# TABLES

Table 1. Seasonal and annual regression coefficients estimated between watershed response and atmospheric forcing (precipitation and temperature) within the Lim River basin. (WIN-December-February, SPR-March-May, SUM-June-August, AUT-September-November, ANN)

Table 2. Change in the median of annual precipitation and temperature for the Lim River basin relative to the baseline period 1961-1990.

Table 3. Change in the median of seasonal precipitation and temperature for the Lim River basin relative to the baseline period 1961-1990 (WIN-December-February, SPR-March-May, SUM-June-August, AUT-September-November, ANN)

Table 4. Change in the median seasonal and annual flows of the Lim River at Prijepolje relative to the baseline period 1961-1990 (WIN-December-February, SPR-March-May, SUM-June-August, AUT-September-November, ANN).

FIGURES

Figure 1. Illustration of the two-stage procedure for long-term hydrological projections with time series models based on transfer functions.

Figure 2. (a) Location of the Lim River basin (grey polygon); (b) The Lim River basin to Prijepolje hydrological station with locations of meteorological stations (m.s.).

Figure 3. Observed and bias corrected simulated climate variables for the meteorological stations located in the Lim River basin: (a) seasonal precipitation, (b) mean seasonal temperature. (WIN-December-February, SPR-March-May, SUM-June-August, AUT-September-November, ANN)

Figure 4. Modelling monthly flows of the Lim River at Prijepolje: $Q$ - observed monthly flows, $Q_{Tw}$ - composite trend, $Q_P$ - macro-periodic component, $Q_S$ - seasonal component, $Q_{STOCH}$ - stochastic component.

Figure 5. Projected annual flows of the Lim River at Prijepolje with the composite trend: RCP 4.5 and RCP 8.5 scenarios.

Figure 6. Distributions of the seasonal and annual flows for the Lim River at Prijepolje under RCP 4.5 and RCP 8.5 emission scenarios for baseline period 1961-1990, near future 2013-2040, mid-distant future 2041-2070. (WIN-December-February, SPR-March-May, SUM-June-August, AUT-September-November, ANN)