

Uncertainty of annual runoff projections in Lithuanian rivers under a future climate

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ABSTRACT

Uncertainties of runoff projections arise from different sources of origin, such as climate scenarios (RCPs), global climate models (GCMs) and statistical downscaling (SD) methods. Assessment of uncertainties related to the mentioned sources was carried out for selected rivers of Lithuania (Minija, Nevėžis and Šventoji). These rivers reflect conditions of different hydrological regions (western, central and southeastern). Using HBV software, hydrological models were created for river runoff projections in the near (2021–2040) and far (2081–2100) future. The runoff projections according to three RCP scenarios, three GCMs and three SD methods were created. In the Western hydrological region represented by the Minija River, the GCMs were the most dominant uncertainty source (41.0–44.5%) in the runoff projections. Meanwhile, uncertainties of runoff projections from central (Nevėžis River) and southeastern (Šventoji River) regions of Lithuania were related to SD methods and the range of uncertainties fluctuates from 39.4% to 60.9%. In western Lithuania, the main source of rivers' supply is precipitation, where projections highly depend on selected GCMs. The rivers from central and southeastern regions are more sensitive to the SD methods, which not always precisely adjust the meteorological variables from a large grid cell of GCM into catchment scale.

Key words | climate change, GCM, RCP, statistical downscaling, uncertainty analysis

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INTRODUCTION

The accuracy of runoff projections highly depends on a wide range of factors related to climate change. Application of different climate scenarios and modelling tools for calculation of runoff projections increases the spread in the ensemble. When projecting river runoff, it is important to assess the uncertainties of selected tools and input data. Usually, the main sources of uncertainty are linked to global climate models (GCMs) and climate scenarios (RCPs). However, statistical downscaling (SD) methods can be regarded as an additional source of uncertainty as well. The GCM in combination with RCP provides the basis for

investigation of future climate change. On the other hand, they are also the primary sources of systematic errors.

There are large biases comparing GCM output data with historical observations. Therefore, SD methods are used for the reduction of mentioned biases. Latif (2011) maintains that the primary uncertainty of projections is caused by the variability of natural hydro-meteorological processes. It is difficult to estimate such natural variability; hence, the assessment of uncertainties of GCMs is very important. The uncertainty interpretation as the range of runoff projection was successfully applied in several studies (Dobler *et al.* 2012; Bosshard *et al.* 2013). These studies constitute a solid basis for the exploration of uncertainties in runoff projections. The mentioned studies were conducted in a variety of locations using different climate and hydrological

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models and considered many hydrological parameters. This diversity of results provides in-depth analyses but makes it difficult to compare them as well. Therefore, the discussion about uncertainties related to climate change focused on climate sensitivity, which highly depends on the chosen GCM (Ahlström *et al.* 2013). GCMs are limited by the inherent simplifications of some processes in Earth's climate system. Accordingly, the model outputs involve different kinds of biases when comparing them to the observed climate variables (Räty *et al.* 2014) and the combinations of GCMs and RCP scenarios became the primary sources of climate projection uncertainty.

Addor *et al.* (2014) considered and systematically analysed a large number of uncertainty sources, which were estimated from simulations of future runoff projections in different Swiss catchments. This study revealed that GCMs and RCMs are usually the main sources of uncertainty and the uncertainty originating from the hydrological models dominated in the catchments, where the feeding sources of snow and ice melt is substantial. The relative contributions of four uncertainty sources (emissions scenarios, GCMs, local adjustment methods and HBV parameterisation) in hydrological projections of four catchments in Norway were discussed by Lawrence & Haddeland (2011). The results demonstrated that all of these sources can significantly contribute to the dispersion of projections of the mean annual flood. The importance of individual factors varied between catchments. It has been demonstrated that the selection of a GCM largely determines the variability in runoff projections. To identify long-term runoff changes, it is important to assess the uncertainties of the GCM in the historical period (Chen *et al.* 2017; Shen *et al.* 2018). Kundzewicz *et al.* (2018) proposed four measures for uncertainty reduction: increase of data reliability, reduction of uncertainties of GCMs, integration of regional climate models and hydrological models as well as solutions to optimise hydrological modelling.

There have been many studies where SD methods were applied for corrections of climate model outputs using observation data, where biases of data series of air temperature and precipitation for future periods are generally reduced (Hagemann *et al.* 2011; Räty *et al.* 2014). The application of SD methods helps to correct projections of meteorological variables. This way, the projections of

surface runoff and river hydrological regime in impact assessment studies can be improved (Hagemann *et al.* 2011; Hundecha *et al.* 2016). Some studies also analysed the advantages and disadvantages of different SD approaches (Teutschbein & Seibert 2013; Maraun 2016). The mentioned scientific studies can be used for the selection of SD methods to improve GCM outputs for a fine temporal and spatial scale.

In Lithuania, uncertainty analysis of river runoff projections is not widely discussed. Kriauciūnienė *et al.* (2013) assessed uncertainties of runoff projections made according to GCMs (ECHAM5 and HadCM3), SRES group emission scenarios (A2, A1B and B1) and calibration parameters of HBV model and established that the largest uncertainties were related to emission scenarios. Keršytė *et al.* (2015) evaluated the output of 24 GCMs of CMIP5 project which were simulated under all RCP climate scenarios. According to GCM outputs, some GCMs (GFDL-CM3, HadGEM2-ES and NorESM1-M) were selected as the best fit to reflect the local climate conditions of Lithuania. According to the mentioned scenarios and GCMs, the projections of runoff of the selected catchments of the Nemunas River basin were modelled (Stonevičius *et al.* 2017; Šarauskienė *et al.* 2018). Also, there are two European-scale studies, where alternative downscaling methods for bias corrections of precipitation and runoff projections in 11 river catchments from nine countries of Europe (including one in Lithuania – the Merkys River catchment) were chosen and discussed (Sunyer *et al.* 2015; Hundecha *et al.* 2016). However, these previously mentioned studies did not take into account the accuracy of runoff projections related to the potential uncertainty sources. The potential impact of SD methods on the correction of biases of GCM output has not been sufficiently investigated as well. Therefore, this research focuses on the evaluation of uncertainties of runoff projections according to climate scenarios, GCMs and SD methods in Lithuanian rivers from different hydrological regions in the near and far future. The evaluation of the accuracy of runoff projections will help to identify the uncertainty sources which have the most significant influence on the final results. Respectively, it will provide an opportunity to select more precise GCMs, climate scenarios and downscaling methods for accurate projections of annual runoff.

STUDY AREA AND DATA

The Nemunas River is a major Lithuanian river. The total length of the Nemunas is 937 km, while the river's basin area covers 98,200 km². Seventy-two per cent of Lithuanian territory falls within the Nemunas River basin. Lithuania falls within one climate zone. When the climate is homogeneous, the physico-geographical conditions have a larger influence on the formation of the rivers' runoff. Accordingly, the division into hydrological regions is done by the existing local physico-geographical conditions (relief, lithology, soils, land use, etc.), which differently transform precipitation into the surface and subsurface runoff.

Three river catchments (Minija – 2,942 km², Nevėžis – 6,140 km² and Šventoji – 6,888 km²) were selected for this research. These catchments are from different hydrological regions of Lithuania (Western (LT-W), Central (LT-C) and Southeastern (LT-SE)) (Figure 1). The main source of runoff generation in western Lithuania is precipitation.

The type of runoff generation in central Lithuania is mixed (snowmelt and rainfall). In southeastern Lithuania, the main feeding source is groundwater. Due to the previously mentioned physico-geographical factors and runoff generation patterns, the Lithuanian rivers from the same hydrological region have synchronic relations of the runoff.

The selected rivers are represented by the water gauging stations (WGS) of Kartena WGS (Minija River), Dasiūnai WGS (Nevėžis River) and Ukmergė WGS (Šventoji River). Runoff projections of the mentioned rivers were carried out for the near and far future. Nine meteorological stations (MSs) were selected for hydrological modelling of selected rivers (Figure 1). The weight of each MS was determined using the Thiessen polygon method for hydrological modelling in selected catchments. The reference periods of 1986–2005 was used for calibration (1986–1995) and validation (1996–2005). Therefore, the daily observations of the average air temperature (T , °C) and daily precipitation amount (P , mm) of

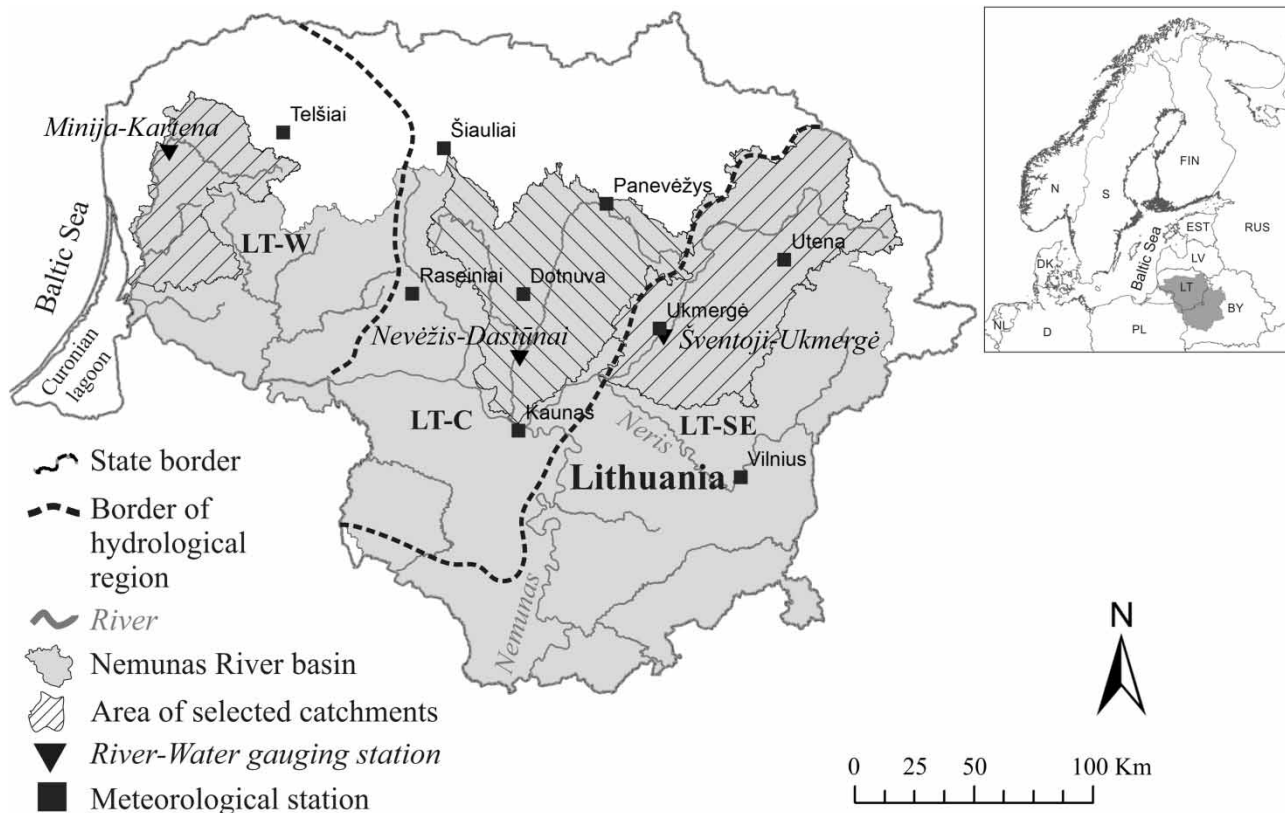


Figure 1 | The location of selected river catchments, water gauging stations, and MSS.

MSs, as well as daily discharge (Q , m^3/s) of selected WGSs, were used for this analysis.

The output (daily air temperature and daily precipitation amount) of three GCMs (GFDL-CM3, HadGEM2-ES and NorESM1-M) of the CMIP5 project generated by three RCP climate scenarios (RCP2.6, RCP4.5 and RCP8.5) were used for projecting the annual river runoff of the selected Lithuanian catchments in the 21st century. The raw data (air temperature and precipitation) of simulations of the reference period as well as projections (according to RCP2.6, RCP4.5 and RCP8.5) of the near future and far future have been taken from the NOAA (National Oceanic and Atmospheric Administration) GFDL (Geophysical Fluid Dynamics Laboratory) and WDC (World Data Center for Climate) CERA data portals. Three GCMs (GFDL-CM3, NorESM1-M and HadGEM2-ES) from the mentioned databases with different spatial resolution were selected (Table 1). These GCMs were selected as the best fit (according to the median and range of selected meteorological variables of raw GCM output data) for climatic conditions of Lithuania (Keršytė et al. 2015) and reflect the uncertainty of the selected ensemble.

MSs located in different grid cells of the GCM were selected (Figure 2). Respectively, all historical observations of MSs (which coincide with particular grid cells) were used for SD methods to correct the systematic biases of GCM output in the reference period as well as biases of projections in the future.

METHODS

For evaluation of possible patterns and uncertainties of projections of river runoff in the near and far future according to observation data and available geographic information,

Table 1 | The spatial resolution of selected GCMs

No.	GCM	Abbreviation	Grid resolution	
			Longitude	Latitude
1.	GFDL-CM3	GFDL	1.5°	2°
2.	HadGEM2-ES	Had	1.875°	1.25°
3.	NorESM1-M	Nor	2.5°	1.895°

hydrological models of the selected rivers were created (Figure 3). The general procedure used was as follows: the output data (T , P) of GCMs of GFDL-CM3, HadGEM2-ES and NorESM1-M according to RCP (2.6, 4.5 and 8.5) climate scenarios were adjusted to Lithuanian conditions by applying SD methods of bias correction (BC) with variable, change factor (CF) with variable and quantile mapping (QM). Applying the HBV software (Lindström et al. 1997), the resulting corrected data of T and P series were used to simulate projections of daily discharge in the near (2021–2040) and far future (2081–2100). The simulated values were compared to the values of the reference period (1986–2005) and the uncertainties of runoff projections were calculated according to the used uncertainty sources (RCPs, GCMs and SD methods). These steps in the procedure are described in detail in the following paragraphs.

In the periods of 2021–2040 (near future) and 2081–2100 (far future), projections of daily data of precipitation and temperature were adjusted using three different SD methods – BC, CF and QM. According to Sunyer et al. (2015), the selection of SD methods requires choosing the methods based on different underlying assumptions as well as including the change in mean and variance. Therefore, the well-known and widely applied SD methods were used in this research. Also, they can be flexibly used for adjustment of the several meteorological variables, such as precipitation and air temperature. The major idea of selected methods is to downscale data with low resolution to a fine spatial scale to reproduce the local conditions. All SD methods were trained with local observations for the reference period (1986–2005).

The BC method corrects the projected raw daily data of GCM outputs in mean and variance (Ho et al. 2012; Hawkins et al. 2013):

$$V_{BC}(t) = \overline{O_{REF}} + \frac{\sigma_{O,REF}}{\sigma_{V,REF}} (V_{RAW}(t) - \overline{V_{REF}}) \quad (1)$$

where V_{BC} is a corrected meteorological variable of GCM output, O_{REF} is observation in the historical reference period, V_{REF} is a meteorological variable of GCM output from the reference period, P_{RAW} is a meteorological variable of raw GCM output for the future period. The time mean is denoted by the bar above a symbol. Equation (1) was used to represent the relationship between distribution of O_{REF}

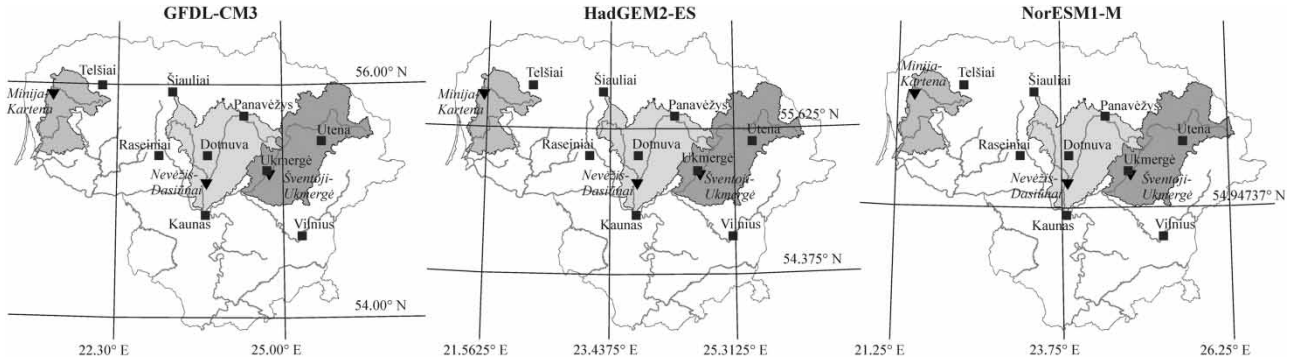


Figure 2 | Location of the MSS, selected river catchments, and spatial distribution of the grid cells of selected GCMs over Lithuania.

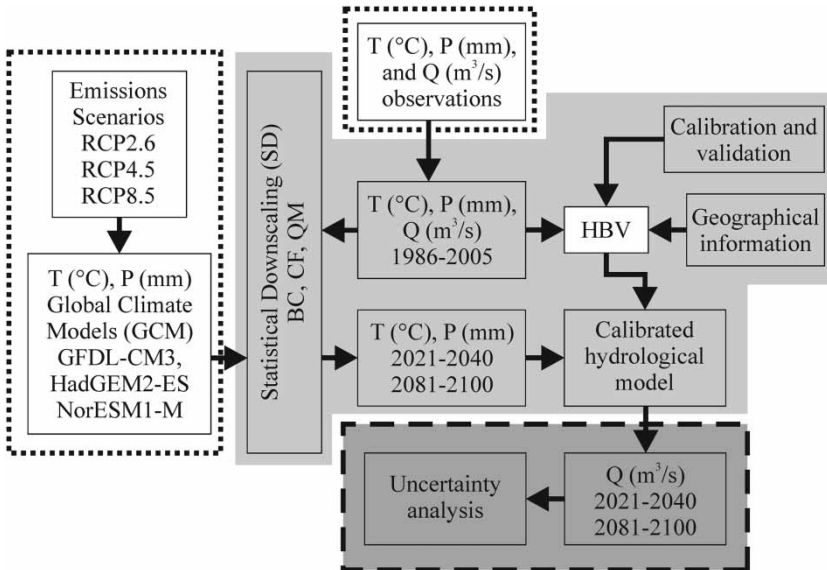


Figure 3 | The workflow of the uncertainty analysis of runoff projections related to selected uncertainty sources.

(observations in the reference period) and the distribution of V_{REF} (GCM simulations in the reference period), therefore $\sigma_{O,REF}$ and $\sigma_{V,REF}$ are standard deviations of daily observations and meteorological variable of GCM output in the reference period, respectively.

The CF method adjusts the observed variables according to the differences between projected variables of GCM output and simulated GCM output from the reference period. It is described by the following equation (Ho et al. 2012; Hawkins et al. 2013):

$$V_{CF}(t) = \overline{V_{RAW}} + \frac{\sigma_{V,RAW}}{\sigma_{V,REF}} (O_{REF}(t) - \overline{V_{REF}}) \quad (2)$$

which was used to represent the relationship between the distribution of V_{RAW} (GCM projection in the future) and the distribution of V_{REF} (GCM simulations in the reference period), therefore $\sigma_{V,RAW}$ and $\sigma_{V,REF}$ are the standard deviation of GCM output of the future projections and deviation of GCM output in the reference period, respectively.

The QM method (Gudmundsson et al. 2012) is based on the concept of transformation of the selected variable:

$$\begin{aligned} V_{Obs} &= h(V_{GCMREF}) \\ &= ECDF_{Obs-1}(ECDF_{GCMREF}(V_{GCMRAW})) \end{aligned} \quad (3)$$

where V_{Obs} is observed meteorological variable, $V_{GCM REF}$ is GCM output for the reference period, $V_{GCM RAW}$ is a meteorological variable, which is projected by GCM for the future period. $ECDF_{Obs-1}$ is an empirical cumulative distribution function for the observed period and $ECDF_{GCM REF}$ is empirical cumulative distribution function for the GCM reference period. First, all the probabilities in $ECDF_{Obs-1}$ and $ECDF_{GCM REF}$ are calculated at a fixed interval of 0.01. Then, h in each interval is estimated as the relative difference between the two different ECDFs. Interpolation

between the fixed values is based on a monotonic tricubic spline interpolation. The correction of the number of wet days was done using the empirical probability of non-zero values in V_{Obs} . After that, all GCM values below this threshold were set to zero (Sunyer et al. 2015). The method was implemented by Python software.

The HBV (*Hydrologiska Byråns Vattenbalansavdelning*) hydrological model created by SMHI (Swedish Meteorological and Hydrological Institute) is a rainfall-runoff model and describes hydrological processes in a river catchment scale (<https://www.smhi.se/en/research/research-departments/hydrology/hbv-1.90007>). The HBV model evaluates and calculates how in the river basin district, the atmospheric precipitation is transformed into river runoff taking into account temperature, evaporation, infiltration, accumulation in natural water bodies and the influence of the basin relief (Figure 4).

The periods of 1986–1995 and 1996–2005 were selected for calibration and validation of hydrological models, respectively. The hydrological model of each simulated river is calibrated in five stages using 16 basic calibration parameters, which depend on the local physical geographical characteristics and river basin attributes. During calibration steps, the models were evaluated by observed discharges, i.e., how simulated discharges coincide with measured discharges by changing values of calibration parameters. The simulated discharges of calibration and validation of the created hydrological models and the average rates (observed and simulated) of discharge for the used periods are presented in Table 2 as well as deviations (%) of simulated discharge from the observed values. The highest R^2 was obtained in the Miniija River for calibration (0.88) and validation (0.83). Also, Table 2 shows the comparison of discharges where differences between measured

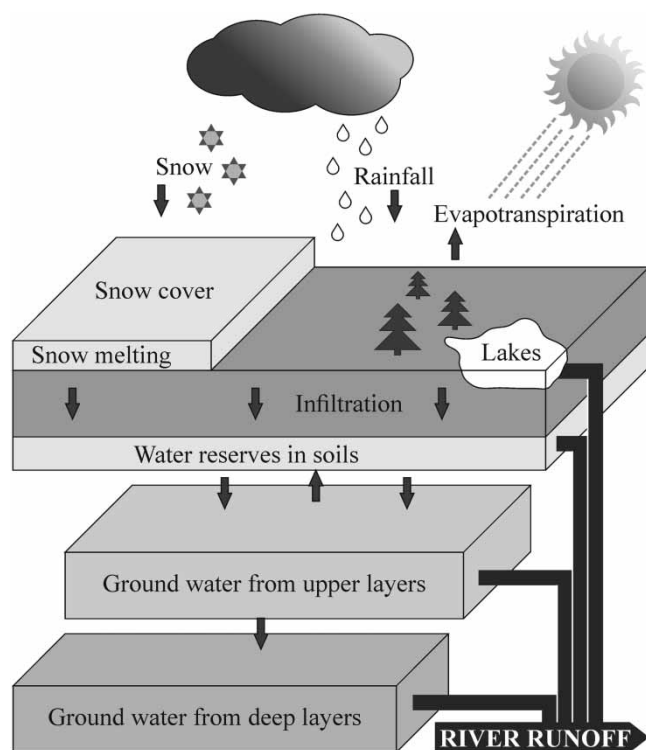


Figure 4 | Conceptual scheme and processes of the HBV model (prepared according to the Integrated Hydrological Modelling System 2005).

Table 2 | Statistics of calibration and validation of created hydrological models and deviation (%) of simulated discharge from the observed values

River-WGS	Calibration			Validation		
	R^2	Average Q (m ³ /s)		R^2	Average Q (m ³ /s)	
		Observed	Simulated (ΔQ , %)		Observed	Simulated (ΔQ , %)
Miniija-Kartena	0.88	17.7	18.4 (4.0)	0.83	16.8	16.6 (-1.2)
Nevėžis-Dasiūnai	0.86	38.9	34.6 (-11.1)	0.77	29.0	33.7 (16.2)
Šventoji-Ukmergė	0.75	46.5	44.5 (-4.3)	0.68	41.8	43.9 (5.0)

and simulated values are not high. The smallest deviation was in the Minija River (up to 4%) and the largest in the Nevėžis River (up to 16%). According to various studies, these discrepancies are small because in individual cases deviation errors of discharge measurement can reach 35% (Neff & Nicholas 2005). Taking into account the results of the calibration and validation of the model (Table 2) and the long data series used for these procedures, the created models are well prepared for projections of river runoff according to different climate scenarios in the future.

The evaluation of uncertainties associated with selected sources of uncertainties is necessary for projecting annual runoff changes in the future. In this study, the uncertainties of annual runoff projections consist of uncertainty sources as follows: climate scenarios (RCPs), GCMs and SD methods. In Lithuania, Kriaučiūnienė et al. (2013) evaluated the uncertainties of runoff projections using other sources of uncertainty (GCMs, SRES group climate scenarios and calibration parameters of HBV). Therefore, the uncertainty analysis of this research is based on a similar methodology. All possible combinations of uncertainty sources were made for evaluating the three sources of uncertainty (A, B, C) when each of them consists of three components ($A_1, A_2, A_3, B_1, \dots, C_3$). Accordingly, the 27 unique projections of runoff for each of the three catchments were created. The variable A represents the analysed source of uncertainty, while B and C are the remaining two sources of uncertainty. The same combinations of components ($B_1, B_2, B_3, \dots, C_3$) help to identify the uncertainties of A components (A_1, A_2, A_3). The uncertainties of source A were calculated by combining the same combinations of components B and C. The maximum value minus minimum value was estimated from the horizontal selections of A_1, A_2 and A_3 and the arithmetic average of the above-mentioned difference was calculated. The calculation of the contribution of each source to the spread in outcomes is based on the uncertainty caused by the three sources of uncertainty and calculates the percentage from other sources of uncertainty based on the average in difference.

RESULTS AND DISCUSSION

All deviations of annual runoff projections of the near and far future were calculated from their simulations in the

reference period according to the same combinations of GCM and applied SD methods. Depending on different GCMs and SD methods, the projections of RCP scenarios fluctuated in a wide range. The deviations of annual runoff projections of the rivers of Minija, Nevėžis and Šventoji in the near and far future are shown in Figure 5. The projected annual runoff according to selected RCPs decreased on average from 13.3% in the near future to 33.9% in the far future compared to the reference period. In the near future, the lowest changes in river runoff were projected by RCP4.5 scenario, while the largest deviations and their variations were obtained according to RCP2.6 scenario. Meanwhile, the differences between RCPs increased in the far future because, on average, the RCP2.6 scenario projected the smallest decrease of river runoff but the largest range of possible projections. The most dramatic changes (up to a 47.2% decrease) of river runoff were projected by RCP8.5 in the far future.

The projections of river runoff determined by different GCMs showed similar patterns of deviations between the selected rivers and periods. The largest decrease of annual runoff was obtained applying the output of the Had climate model in both analysed periods, while the projections of the Nor model were the closest to the reference period. The projections with the highest range of deviations were obtained according to the GFDL model, especially in the far future.

The effect of SD methods on the projections of annual runoff was significant in the near and far future as well. The projections based on the BC and CF methods showed similar deviations in runoff projections. According to the mentioned methods, the average decrease of runoff consisted of 11.3% and 9.7% in the near future, and 18.5% and 18.7% in the far future, respectively. In all analysed rivers, the smallest average deviation of runoff projections from the reference period was obtained using the QM method. The deviations varied from -4.4% in the near future to -5.5% in the far future. However, the QM method provided the largest range of projected changes in the rivers Minija and Šventoji.

The obtained results of this research coincide with European study, where 15 combinations of RCM/GCM and eight different SD methods were used (Hundechea et al. 2016), because the decrease of annual runoff in the river catchments of Nevėžis and Šventoji were determined. In the

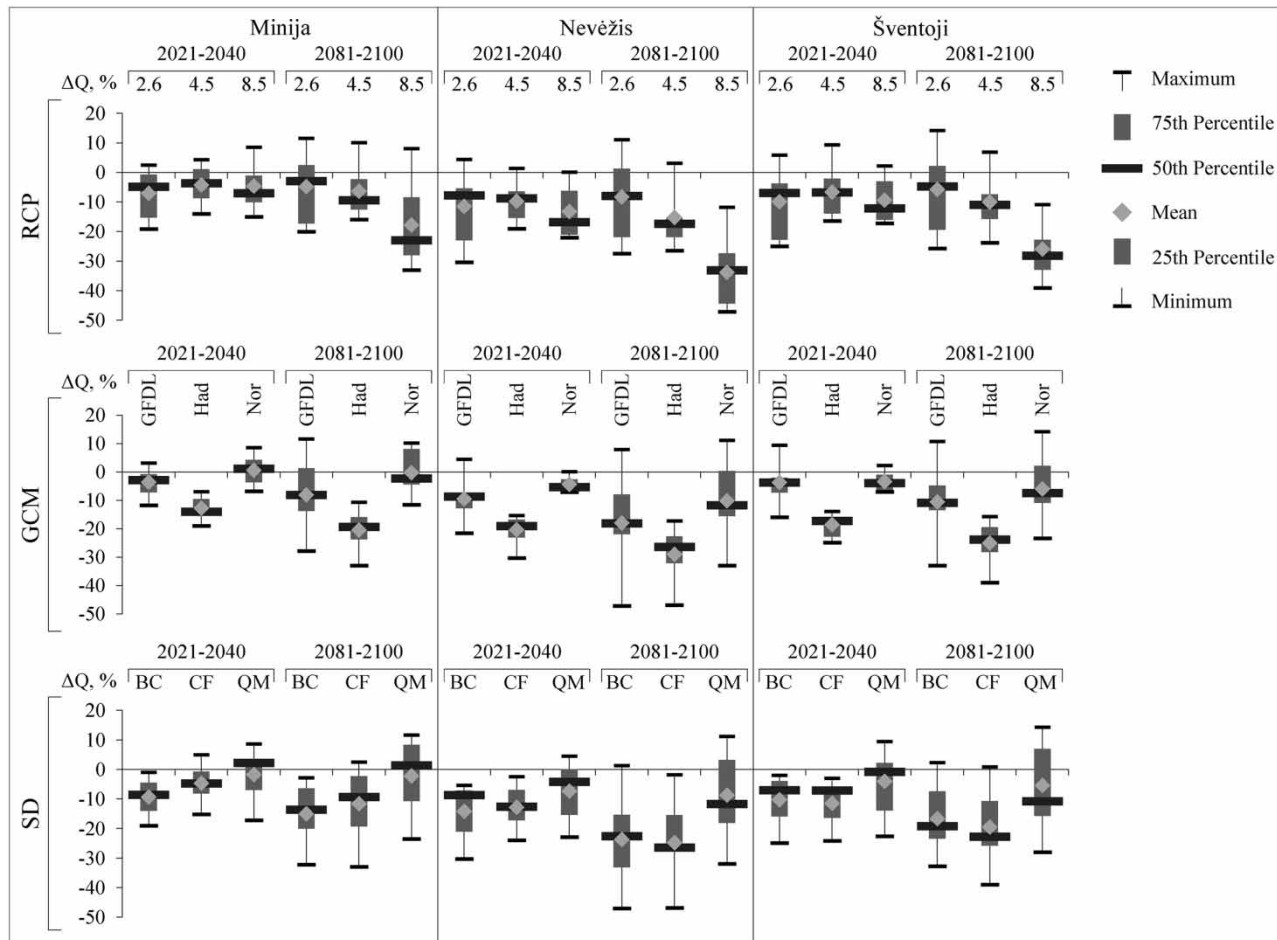


Figure 5 | Deviation of annual runoff projections from the simulations of the reference period in selected rivers according to RCP, GCM, and SD in the near and far future.

study of [Hundechea et al. \(2016\)](#), the general tendency of extreme flow projections tend to decrease in catchments where runoff generation from snowmelt is dominant; one of the selected case studies was from Lithuania – the Merkys River catchment, which falls within hydrological regions of southeastern Lithuania, where the Šventoji River is also located. Therefore, the established tendencies of runoff projections in the rivers (Šventoji and Nevėžis) of snowmelt-driven floods are linked to decrease as well as in the study of [Hundechea et al. \(2016\)](#).

The projection and assessment of tendencies of future river runoff are important for the identification of possible uncertainties regarding the selection of projection sources (RCP, GCM and SD). In this research, various combinations of these three sources provide wide range projections of river runoff. A high number of peaks (above reference

period values) in the annual runoff hydrograph of the Miniija River (Kartena WGS) ([Figure 6](#)) formed due to rainfall, which is the main feeding source of rivers in the western region of Lithuania, i.e., river runoff has a rapid reaction to heavy rainfall. The range of runoff projections in the Miniija River varies depending on the season and GCM ([Figure 6](#)). However, the largest peaks occur in the winter season. Meanwhile, models of GFDL and Nor provide a wide variation of projections for the autumn season. In the 21st century, the mentioned GCMs provide lower projections (below reference period) of runoff for the summer season, while the values of discharge projections of the Had model range from average to very low.

The runoff of Nevėžis River (Dasiūnai WGS) has a very sensitive response to different climate scenarios and SD methods. Accordingly, runoff projections for different

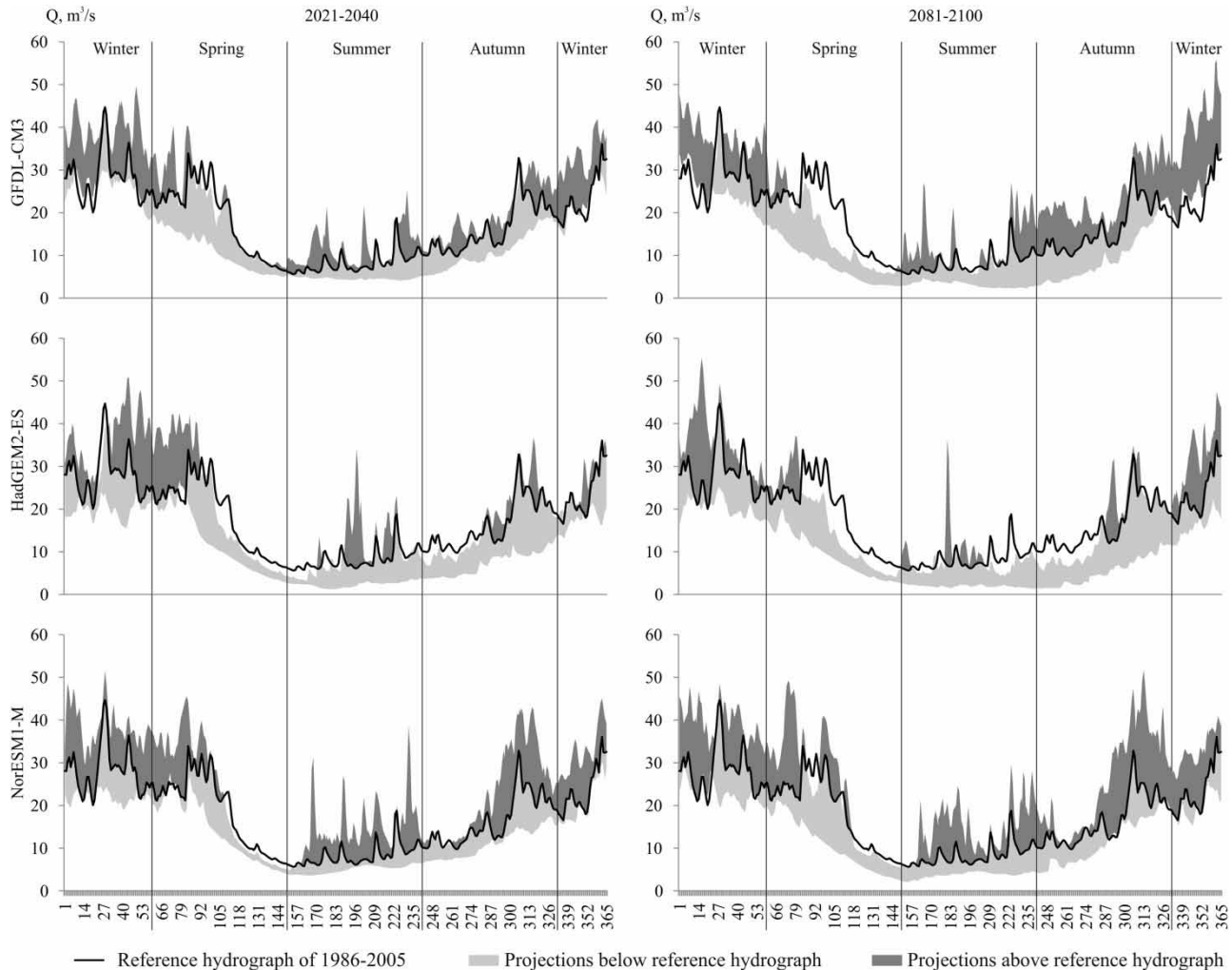


Figure 6 | Uncertainty of runoff projections of Minija River (Kartena WGS) according to GFDL-CM3, HadGEM2-ES, and NorESM1-M GCMs for the periods of 2021–2040 and 2081–2100.

seasons vary widely (Figure 7) as large seasonal differences in discharge are a prominent feature of rivers in central Lithuania. In the period 2021–2040, the annual runoff projections responsively reacted in winter and spring seasons. Therefore, their projections differed from extreme low values to values above the reference period for different scenarios. During the period 2081–2100, the projections for the mentioned seasons varied from very low discharges to values of the reference period. Only the Nor model projected higher values of the annual runoff in the seasons of winter and spring. The maximum range of possible changes in the Nevėžis River was expected in spring when runoff projections assumed very high uncertainties. This showed the vulnerability of spring floods to climate change

conditions. Rising air temperature influenced the period of snow accumulation. Therefore, a lower amount of water resources was accumulated in the river basin. Consequently, the size of the spring flood decreased.

The hydrograph of the reference period (1986–2005) of the Šventoji River (southeastern hydrological region) compared with the hydrographs of other rivers (Minija and Nevėžis) has the most stable distribution (Figure 8). This form of hydrograph is typical for rivers of the LT-SE region, where groundwater feeding is dominant. Due to sandy soils, a significant part of surface runoff from snow melting and precipitation supplies groundwater which feeds the rivers during summer. Hence, water resources in this region are distributed evenly per year. The runoff

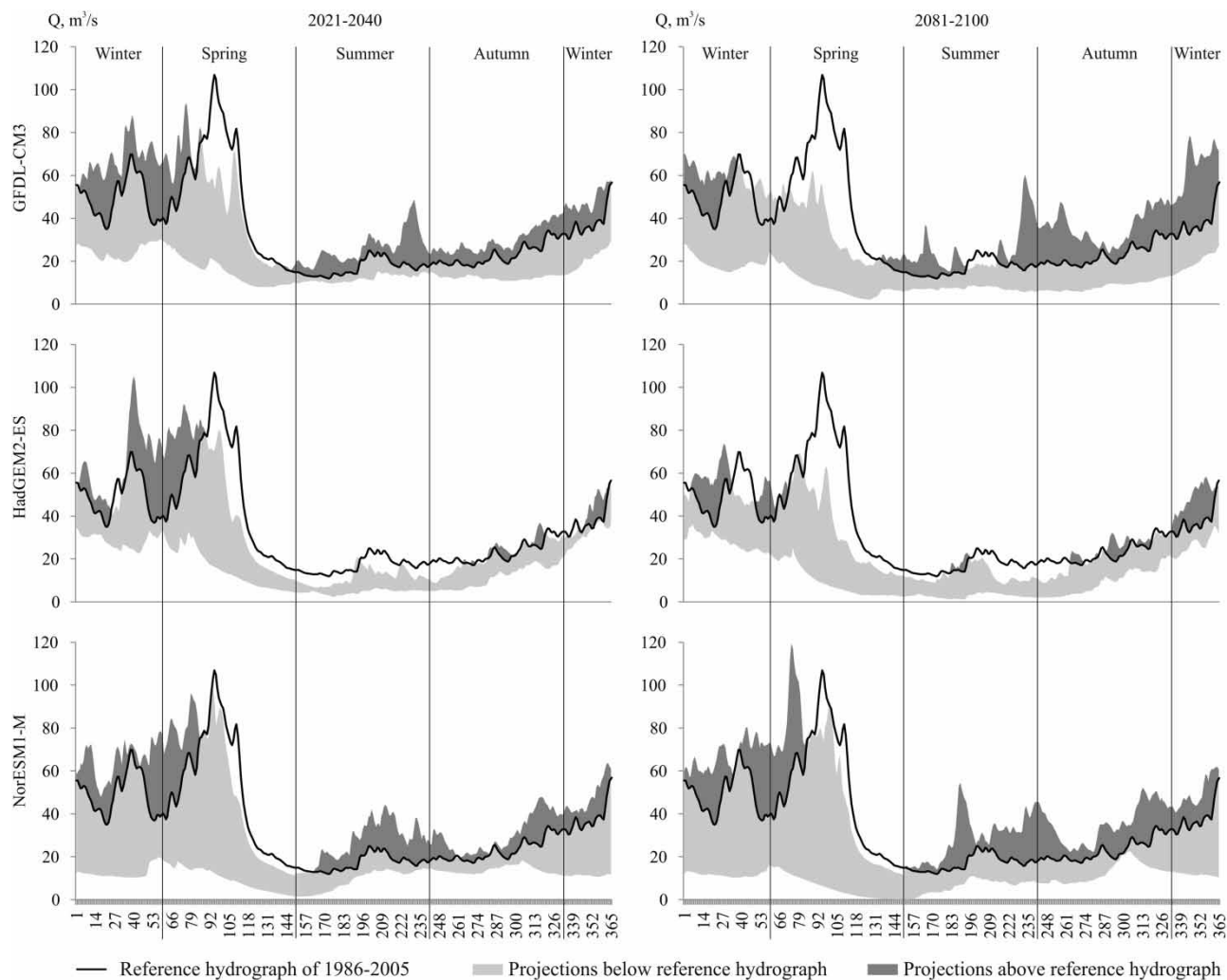


Figure 7 | Uncertainty of runoff projections of Nevėžis River (Dasiūnai WGS) according to GFDL-CM3, HadGEM2-ES, and NorESM1-M GCMs for the periods of 2021–2040 and 2081–2100.

projections of the Šventoji River (Ukmergė WGS) according to different GCMs fluctuated with a wide range (Figure 8). The most noticeable changes in the runoff were observed in the seasons of spring and winter when the decline of spring floods came together with earlier spring peaks. According to different scenarios, the projected increase of winter runoff depended on earlier snow melting. In addition to that, a relatively narrow range of projections for the summer season according to the projections of the GFDL and Nor models was identified, whereby the runoff changed from very low to very high discharges compared to the reference period. Meanwhile, all projections with the Had model provided lower values of discharges.

The variability of projections of the annual runoff was estimated according to the uncertainty sources: climate scenarios (RCPs), GCMs and SD methods. The calculations of the percentage of uncertainty sources revealed which source had the greatest impact on the wide scattering of projected runoff values in the rivers of Minija, Nevėžis and Šventoji (Table 3). In the near and far future, the largest uncertainties of runoff projections of the Minija River (Kartena WGS) were caused by the GCMs. The selected GCMs contributed 44.5 and 41% of the total spread in the ensemble of projections for the near and far future, respectively. A significant influence of SD methods was also estimated, causing the

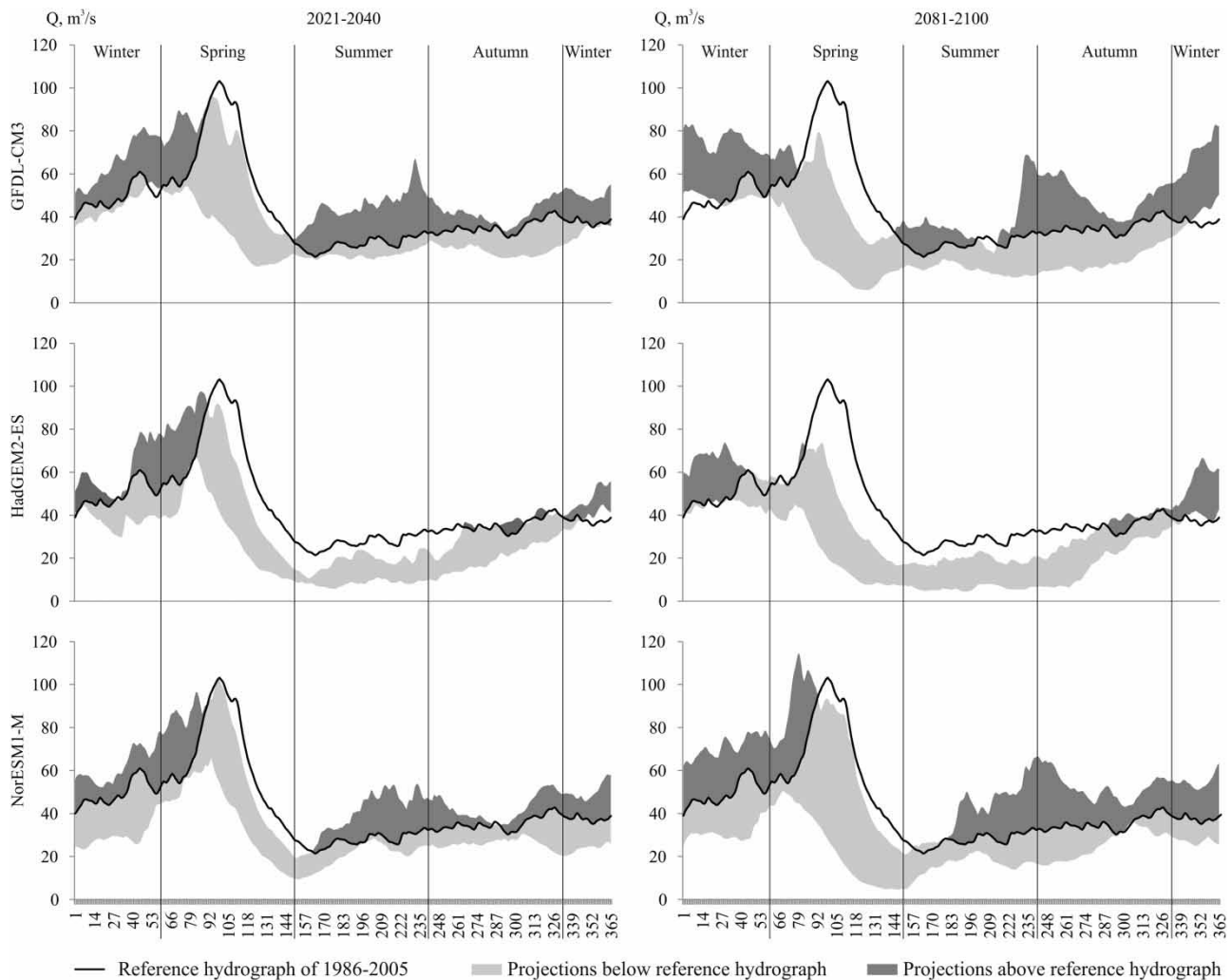


Figure 8 | Uncertainty of runoff projections of Šventoji River (Ukmergė WGS) according to GFDL-CM3, HadGEM-2ES, and NorESM1-M GCMs for the periods of 2021–2040 and 2081–2100.

Table 3 | Uncertainty (%) of annual runoff projections in rivers of Minija, Nevėžis, and Šventoji according to a different source of origin for the periods of 2021–2040 and 2081–2100

	Minija		Nevėžis		Šventoji	
	2021–2040	2081–2100	2021–2040	2081–2100	2021–2040	2081–2100
RCP	16.7	24.3	11.2	24.4	15.7	31.5
GCM	44.5	41.0	27.9	24.3	38.1	29.1
SD	38.8	34.7	60.9	51.3	46.2	39.4

uncertainties of 38.8% and 34.7% in the near and far future, respectively. The smallest dispersion of runoff projections was related to RCP climate scenarios; however,

the influence of RCP increased by 7.5 percentage points in the far future compared to the near future.

In the near future, the variability of projections of annual runoff of the Nevėžis River (Dasiūnai WGS) was as high as 60.9% using SD methods, while the influence of RCP scenarios was only 11.2% (Table 3). The situation is different in the far future because uncertainties caused by SD methods decreased up to 51.3% and uncertainties of RCP increased up to 24.4%. In any case, the variability of annual runoff projections of the Nevėžis River was related to SD methods by more than 50%. Meanwhile, the accuracy of runoff projection caused by GCMs was similar in the near and far future – 27.9% and 24.3%, respectively.

The largest scatter in the annual runoff projections of the Šventoji River was determined for the SD method as well, because uncertainties related to the SD methods amounted to 46.2% in the near future. The rest of the uncertainty sources provided uncertainties of 38.1% (GCMs) and 15.7% (RCPs) (Table 3). In the far future, the influence of RCP scenarios increased; the uncertainties related to RCP scenarios reached 31.5% and were 2.4 percentage points larger than the uncertainties of GCMs. Nevertheless, the greatest scattering of annual runoff projections of the Šventoji River in the far future was caused by the SD methods, because uncertainties of SD were 39.4% compared to the other sources. The analysis of runoff of studied rivers showed the importance of the selection of GCMs and SD methods to create proper projections of river runoff, because the largest uncertainties were related to the mentioned sources of uncertainty.

The uncertainties of projections of annual runoff between the components of uncertainty sources and interrelations between them are displayed in column diagrams (Figure 9). The uncertainty of projections according to the SD methods related to RCP scenarios did not show significant differences between the used climate scenarios. Meanwhile, the SD uncertainties according to different GCMs highlighted the climate models of GFDL and Nor, which provided the largest uncertainties in the rivers of Nevėžis and Šventoji. Summary of the analysis showed that in the far future, larger uncertainties of river runoff projections of all analysed rivers were caused by RCP in comparison to the near future (2021–2040) as well as the differences between projections of RCP scenarios increasing.

The results of the uncertainty of RCP projections showed the largest uncertainties using the output of GFDL depending on the selected GCM. The smallest uncertainties of RCP projections were estimated according to the output of the Had model. In the near future, the analysis of RCP uncertainties (related to SD methods) showed a significant impact of the CF and QM methods. Meanwhile, in the far future, the influence of the CF method increased and a greater part of uncertainties was caused by the mentioned method, which affected larger uncertainties (from 0% to 13.6%) compared to the SD methods of BC and QM.

The uncertainties of GCM projections were strongly impacted by different SD methods. In the Minija River, the largest uncertainties of GCM projections were established according to the BC and QM methods. Meanwhile, in the rivers of Nevėžis and Šventoji, the QM method had the largest impact on uncertainties. The scattering of runoff projections of GCMs did not show a significant influence of different RCPs. Only the obtained uncertainties of RCP2.6 in most of the rivers and periods were higher than other scenarios.

In summary, the GCMs can be regarded as the most dominant uncertainty source (41.0–44.5%) in the Minija River, which is in the western hydrological region of Lithuania. In this region, the topography effect is strongly expressed because of the Žemaičiai Uplands. These uplands collect the greater part of moisture from air masses and have the highest annual precipitation compared to other regions. Therefore, the primary projections of precipitation are significantly related to the GCM and it is necessary to select a particular GCM for runoff projections very carefully. These results coincide with Lawrence & Haddeland (2011), where, in runoff projections of three analysed catchments in Norway the largest uncertainty sources are also related to GCM.

In the Nevėžis River (LT-C), uncertainties were linked to SD methods (51.3% and 60.9%). In this region, the lowland topography has the opposite influence to uplands and the grid cell of GCMs is sufficiently large, so SD methods, in some cases, did not properly adjust the output of GCMs to local climatic conditions of the specific area. Especially, it is important for corrections of precipitation data; therefore, the selection of SD method causes the greatest uncertainties in LT-C. Due to a large part of rivers' feeding source as snowmelt, the floods in rivers of this region are usually caused by the thick cover of snow. Since in the future an increase in air temperature is projected, the period of snow accumulation will get shorter or will be absent in some years. Accordingly, the projections of river runoff had a wide range according to various scenarios during the winter and spring seasons. In another similar study, Lawrence & Haddeland (2011) found that the estimated uncertainties in runoff projections of two river catchments which had generally been dominated by the spring

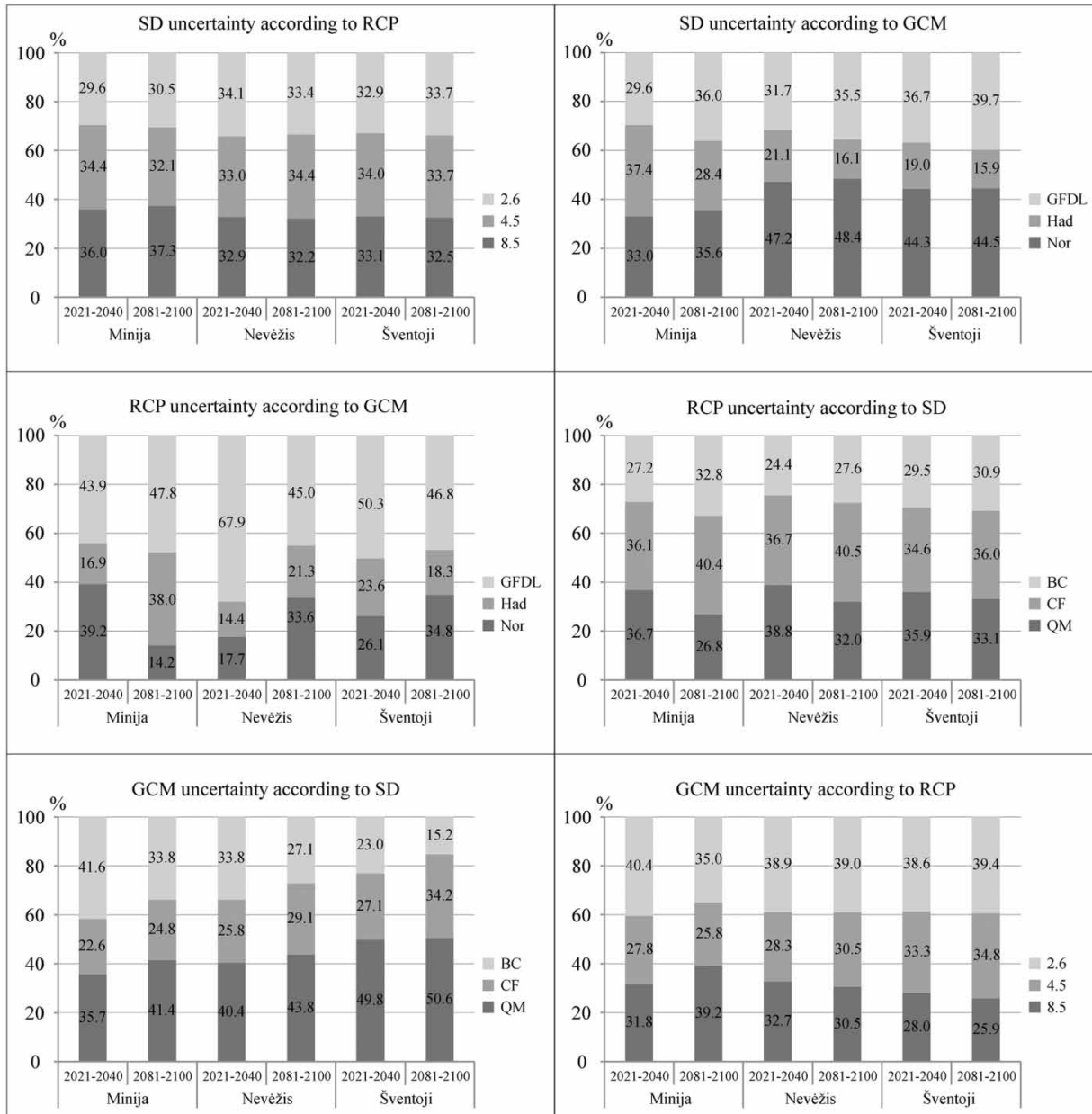


Figure 9 | Uncertainty (%) of annual runoff projections in the rivers of Minija, Nevėžis, and Šventoji between different sources of uncertainty (RCP, GCM, and SD) for the periods of 2021–2040 and 2081–2100.

snowmelt were mostly related to the SD methods (48% and 60%) as well.

In the Šventoji River (SE-LT), the influence of SD (46.2% and 39.4%) was established as well. This region is characterised by the widespread permeable sandy soils, which effectively absorb water from snow melting and later gradually release it, supplying rivers in the low-flow

period. The annual discharge of rivers of southeastern Lithuanian is distributed rather equally. In the Šventoji River catchment, GCMs do not have a significant impact, therefore the importance of the SD methods increases since SDs determine the way meteorological data are adjusted for particular regional conditions. Results of *Kriaučiūnienė et al. (2013)* established that the largest

uncertainties were associated with emission scenarios in the investigated rivers of Lithuania.

CONCLUSIONS

In this study, the projections of climate change impacts on hydrological processes in three Lithuanian catchments from different hydrological regions were based on scenarios from three GCMs generated by three RCP climate scenarios. The output data (T, P) of three GCMs according to RCP (2.6, 4.5 and 8.5) climate scenarios were adjusted to Lithuanian conditions by applying the SD methods of BC with variable, CF with variable and QM. Applying the HBV software, the following corrected data of T and P series were used to simulate projections of daily discharge in the near (2021–2040) and far future (2081–2100).

In the near and far future, the deviations of runoff projections from modelled runoff in the reference period varied over a wide range. In the selected rivers, the largest deviations of annual runoff projections were determined by the RCP8.5 climate scenario as well as the Had climate model. Meanwhile, the lowest deviations of river runoff projections were observed according to the output of the Nor climate model. The largest dispersion of deviations was provided by RCP2.6 and GFDL model. Such different deviations of projected runoff values require additional analysis to assess the uncertainty of each uncertainty source (RCPs, GCMs and SDs).

The GCMs were the most dominant uncertainty source (41.0–44.5%) in the runoff projections of the Miniija River which belongs to the western hydrological region. In this region, the main feeding source of rivers is precipitation, which is the highest compared to other regions. Primary projections of precipitation are significantly related to the GCM, since the selected GCMs provide a wide range of the amount of precipitation in western Lithuania. Meanwhile, uncertainties of the Nevėžis and Šventoji rivers (from central and southeastern regions of Lithuania) were linked to SD methods, respectively (51.3%–60.9%) and (39.4%–46.2%). The grid cell of GCMs is quite large. Consequently, SD does not always properly adjusted GCM output data to an area with specific local conditions. Therefore, the selection of an appropriate SD method is very important,

because the selected SD method must represent the climate conditions of the reference period very precisely. At the same time, accurately selected SD methods will allow the creation of better fit projections under climate change conditions.

Analysis of uncertainty sources showed the widest scattering of results related to different GCMs. The largest uncertainties of RCP projections were caused by the GFDL-CM3 climate model and the largest uncertainties of SD projections were sensitive to the NorESM1-M climate model, especially according to the QM method. Therefore, the accurate selection of GCMs and SD methods is essential for the projections with the lowest uncertainties. Understanding the uncertainty of runoff projections allows better identification of which uncertainty source has the most significant influence on the final results and consequently provides an opportunity to create more accurate runoff projections for different river catchments.

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