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Large-basin hydrological response to climate model outputs: uncertainty caused by the internal atmospheric variability

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Abstract

An approach is proposed to assess hydrological simulation uncertainty originating from internal atmospheric variability. The latter is one of three major factors contributing to the uncertainty of simulated climate change projections (along with so-called "forcing" and "climate model" uncertainties). Importantly, the role of the internal atmospheric variability is the most visible over the spatial–temporal scales of water management in large river basins. The internal atmospheric variability is represented by large ensemble simulations (45 members) with the ECHAM5 atmospheric general circulation model. The ensemble simulations are performed using identical prescribed lower boundary conditions (observed sea surface temperature, SST, and sea ice concentration, SIC, for 1979–2012) and constant external forcing parameters but different initial conditions of the atmosphere. The ensemble of the bias-corrected ECHAM5-outputs as well as ensemble averaged ECHAM5-output are used as the distributed input for ECOMAG and SWAP hydrological models. The corresponding ensembles of runoff hydrographs are calculated for two large rivers of the Arctic basin: the Lena and the Northern Dvina rivers. A number of runoff statistics including the mean and the SD of the annual, monthly and daily runoff, as well as the annual runoff trend are assessed. The uncertainties of runoff statistics caused by the internal atmospheric variability are estimated. It is found that the uncertainty of the mean and SD of the runoff has a distinguished seasonal dependence with maximum during the periods of spring-summer snowmelt and summer-autumn rainfall floods. A noticeable non-linearity of the hydrological models' response to the ensemble ECHAM5 output is found most strongly expressed for the Northern Dvine River basin. It is shown that the averaging over ensemble members effectively filters stochastic term related to internal atmospheric variability. The simulated trends are close to normally distributed around ensemble mean value that indicates that a considerable portion of the observed trend can be externally driven.

Discussion Paper | Discussion Paper | Discussion Paper | Discussion Paper |

1 Introduction

In river basin hydrology, two groups of approaches are usually applied to assess the impact of changing climate on river runoff. The first group of empirical (data-based) approaches is based on treatment of available hydrometeorological records and includes, for instance, time series analysis of runoff characteristics (see reviews presented by Lins, 2005; Shiklomanov, 2008; Bates et al., 2008), an analysis of sensitivity of these characteristics to climate variations, particularly by using "elasticity" indices (Sankarasubramanian et al., 2001; Vano and Lettenmaier, 2014), an analysis of relationships between spatial and temporal runoff variations ("trading space for time") (Peel and Blöschl, 2011; Singh et al., 2011), etc. The second group includes the approaches that are based on hydrological models forced by assigned artificial scenarios of hydrometeorological impact on the river basin. These scenarios are constructed either by a transformation of available series of meteorological observations (for example, "delta-change transformation", Chiew et al., 2009; Motovilov and Gelfan, 2013; "power transformation", Driessen et al., 2010), or using the output of global (GCM) and regional (RCM) climate models simulations (see reviews in Praskievicz and Chang, 2009; Chiew et al., 2009; Peel and Blöschl, 2011; Teutschbein and Seibert, 2010). The latter approach synthesizes up-to-date hydrological models with climate models and provides a better basis for taking into account various physical mechanisms of a hydrological system response to the climate change impacts. However, a development of this approach is hampered by a number of limitations. First of all, this is an inconsistency between spatial/temporal resolution of climate models and characteristic scales of hydrological processes in a river basin, which differ within several orders of magnitude, both in time and space (Blöschl and Sivapalan, 1995). Another serious limitation is related to climate models' capability to accurately reproduce variability and mean state for many meteorological characteristics, especially for precipitation (see, for example, Kundzewicz et al., 2008; Kundzewicz and Stakhiv, 2010; Anagnostopoulos et al., 2010). Explosive increase in computing resources occurred during the last years,

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development of measuring technologies and methods of data treatment, as well as numerical methods, favors improvement of climate models, significant increase in their productivity and spatial resolution, better simulation of regional climate (Flato et al., 2013). This promotes a wider usage of the model-based approach for assessment of the climate change impact on river runoff. However, a considerable uncertainty in these assessments still remains and their interpretation should be considered with caution, especially for practical applications in the field of long-term water management (Wilby, 2010; Kundzewicz and Stakhiv, 2010).

A part of the total uncertainty inherent to assessments of hydrological consequences of climate change is caused by limitations of our knowledge about the dynamics of climatic and hydrological systems, nature of their interrelationships, insufficiency of measurement data, etc., and, potentially, can be reduced with increasing understanding of these systems (epistemic uncertainty). Another part of this uncertainty is a structural one, which does not depend on the acquiring new knowledge and data and is an inherent property of these systems. Evaluation of the impact of this structural, inherent uncertainty is a key issue to realize the potential to obtain reliable assessments of climate-driven changes of river runoff (see, e.g. discussion in Koutsoyiannis et al., 2009).

Uncertainty in assessments of hydrological response to climate change is, primarily, caused by uncertainty in the future climate projections. The latter is related to three independent factors (Hawkins and Sutton, 2009; Deser et al., 2012). The first, so-called "response uncertainty" or "model uncertainty", is caused by the differences in climate response to identical external (e.g. anthropogenic) forcing in different climate models. The model uncertainty arises from structural differences (in particular spatial resolution) between climate models, different parameterizations of physical processes, numerical methods, etc., related to scientific advances in understanding and description of climate system and therefore can be potentially reduced. The second factor is so-called "scenario uncertainty" and represents uncertainties related to prescribed scenarios of future anthropogenic greenhouse and aerosols emissions. The third fac-

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tor is internal, natural variability of climate system (or so-called "climatic noise"), which exists also in the absence of external forcing and results from stochastic nature of atmospheric dynamics, its instability to small perturbations, and also internal (often non-linear) modes of variability in atmosphere and ocean at different time and spatial scales. Climatic noise is a major source of physically based structural uncertainty in climate change projections and it determines a lower limit of uncertainty that can be reached in climate system modeling (Braun et al., 2012).

The major components of climatic noise are stochastic fluctuations in atmosphere and ocean. Large heat capacity, relatively low ocean circulation velocities (relative to atmosphere) and existence of internal oscillatory modes with (quasi) periodicity ranging from years to centuries (Semenov et al., 2010; Latif and Keenlyside, 2011; Latif et al., 2013) provide a certain predictability of the oceanic processes. This so-called "second kind of predictability", particularly predictability on time scale of about ten years that has been recently found to be potentially approached by modern climate models, is currently an object of intense research (e.g. Latif and Keenlyside, 2011). Another source of uncertainty is caused by internal atmospheric variability and related to stochastic dynamics of atmosphere, instability of atmospheric circulation to small perturbation of the parameters. Commonly known as the "butterfly effect", this kind of instability was illustrated in the classical work by Edward Lorenz (1963). Such an uncertainty determines a limit for a weather forecast that does not exceed two weeks and leads to essentially different realizations of atmospheric state beyond this limit given the same boundary and external forcing but small (within the measurement error) changes in initial conditions. Hereinafter, we use the term "climatic noise" to refer only this kind of uncertainty caused by the internal atmospheric variability. Our study focuses on transformation of the climatic noise by hydrological models and its impact on uncertainty of simulated runoff. Note that a role of the climatic noise is most important on time scales from years to first decades and on regional spatial scales (Räisänen, 2001; Hawkins and Sutton, 2009), i.e. on the spatial–temporal scales of water resource management in large river basins.

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Analysis of uncertainty related to internal atmospheric variability is based on ensemble climate model simulations with identical external forcing and different initial conditions ("multireplicate ensemble"). This approach results in ensemble of realizations or trajectories of climate system states that differ from each other solely due to internal variability (Yip et al., 2011; Braun et al., 2012; Deser et al., 2012; Sansom et al., 2013; Semenov, 2014). To obtain reliable statistical assessments of variability within an ensemble, it is necessary to calculate a several dozens of the simulation trajectories as a minimum. Such calculations using GCM require large computational resources. Simulations with climate models participating in the World Climate Research Programme (WCRP) Coupled Model Intercomparison Project Phase 3 and 5 (CMIP3 and CMIP5) (Meehl et al., 2007; Taylor et al., 2012) used for the 4th and 5th IPCC assessment reports respectively include just a few (usually not exceeding ten) trajectories for any particular model (Peel et al., 2014). This fact is partially responsible for the absence, till recently, of studies of climate noise effect on uncertainty in assessments of climate-driven changes in river runoff. The first publications in this area appeared, to our knowledge, in 2014 (Seiller and Anctil, 2014; Lafaysse et al., 2014; Peel et al., 2014).

Seiller and Anctil (2014) constructed climate scenarios using Canadian GCM (CGCM) with spatial resolution of $3^\circ \times 3.75^\circ$ followed by dynamic downscaling of the calculated data to a local scale with resolution of 45 km. Ensemble of realizations calculated under different initial conditions for simulating internal variability of the climate system consisted of 5 members. The realizations were assigned as an input for 20 conceptual runoff models with lumped parameters to calculate river runoff in a small, around 30 km^2, basin in the south-west of Canada. The authors demonstrated that the uncertainty in river runoff assessments caused by climate noise exceeds the uncertainty in hydrological models.

To increase a size of ensemble of climate scenarios, which simulates internal variability, Lafaysse et al. (2014) used stochastic generators and assigned the constructed stochastic scenarios as an input into the ISBA/Durance land surface model. Similar approach was presented by Peel et al. (2014) to increase number of climatic trajectories simulated by five GCMs. The authors developed a stochastic procedure to generate time series of monthly meteorological variables with statistics close to those obtained from GCM simulations. The generated hundred of 250 year meteorological time series were used to force the conceptual PERM hydrological model.

On the one hand, the use of stochastic generators for calculating a large ensemble of climate system trajectories is much more efficient (from the computational point of view) approach to assess climate-driven changes in river runoff when compared to simulation of GCM-realizations ensemble (Hawkins and Sutton, 2009; Yip et al., 2011; Deser et al., 2012; Sansom et al., 2013). On the other hand, the applied stochastic procedures create an additional and ambiguously interpreted source of uncertainty.

In this paper we have tried to assess, using physically based hydrological models, the uncertainty in simulated river runoff characteristics of large river basins taking into consideration internal variability of the atmosphere. The latter was simulated in a large (45 members) ensemble of GCM-realizations of the current climate period (1979–2012) initialized with different initial conditions but using identical boundary forcing (sea surface temperatures and sea ice concentrations). Case studies were carried out for two large watersheds of the Arctic basin: the Lena River (catchment area $F = 2\,488\,000\,\text{km}^2$) and the Northen Dvina River ($F = 357\,000\,\text{km}^2$).

The paper is organized as follows. Section 2 presents the main physical-geographical and climatic characteristics of the basins under consideration. Further one can find a short description of the used hydrological models ECOMAG and SWAP, as well as the results of their validation against hydrological observations in the study basins. Section 4 contains a brief description of the atmospheric general circulation model (AGCM) ECHAM5, the design and results of numerical experiments on simulating internal atmospheric variability. In the "Results and Discussion" Section, runoff characteristics uncertainty caused by the internal atmospheric variability is analyzed on the basis of the simulated runoff ensemble. The main attention is given to the uncertainties of mean and variance of the river discharge averaged over different time intervals (calendar day, calendar month, year), as well as to the uncertainty in long-term trend of the simulated

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annual discharge. The last section summarizes the results and presents the main conclusions.

2 Study basins and datasets

The case studies were carried out for two Arctic river basins: the Lena River and Northern Dvina basins. The Lena River is one of the largest rivers in the Arctic that flows northward from mid latitudes to the Arctic Ocean (Fig. 1), and it contributes about 15 % of total freshwater flow into the ocean. The basin occupies an area of 2 488 000 km^2 extending from 103 to 142° E and from 52 to 74° N. The length of the basin from south to the north is more than 2400 km; its average width is about 2000 km. There are four main types of landscapes within the Lena River basin: arctic wilderness, tundra, forest tundra and forests (taiga), which occupy almost 70 % of the basin area. Main part of the basin has mountain relief with heights in general ranging from 600 to 2000 m (reaching 3500 m in the southern part of the basin). The climate of the territory is extremely continental, with near-surface air temperatures being extremely low in winter (as cold as −50–−65 °C) and high in summer (up to +20–+35 °C). The whole territory of the basin is located in the permafrost zone. Runoff of the Lena River is characterized by spring-summer snowmelt flood, summer and autumn rain floods and extremely low water levels in winter. Maximum discharge of 189 000 $m^3 s^{-1}$ was observed at the lower gauge station Stolb on 1 June 1984. The average annual discharge of the Lena River is about 15 370 $m^3 s^{-1}$. There are more than 80 meteorological and more than 20 runoff hydrological stations within the basin.

The Northern Dvina River basin with an area of 357 000 km^2 occupies vast flat forested territory in the northern part of East European plain from 39 to 56° E and from 58 to 66° N and flows northward to the White Sea basin. The taiga forest covers more than 80 % of the river basin with the northern part changing to tundra landscapes. The climate of the territory is influenced by cyclonic activity. Precipitation exceeds evaporation that leads to excessive wetness. More than 60 % of the annual runoff belongs

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to spring flood period. Maximum discharge of 36 200 $m^3 s^{-1}$ was observed at the lower gauge station Ust-Pinega on 28 April 1953. The average annual discharge of the Northern Dvina River is about 3400 $m^3 s^{-1}$. There are 35 meteorological and more than 10 runoff hydrological stations within the basin.

Due to low anthropogenic burden, absence of reservoirs for regulating the main river flow, the Northern Dvina and Lena River basins, are good objects for case studies aimed at estimation of runoff response to climate variations.

3 Hydrological models

Two hydrological models, ECOMAG (Motovilov et al., 1999) and SWAP (Gusev and Nasonova, 1998), developed at the Water Problems Institute of RAS (Moscow) are used in this study. These models have been successively tested against observation data all over the world.

Physically-based semi-distributed model ECOMAG (ECOlogical Model for Applied Geophysics) developed by Yu. Motovilov, as reported by Motovilov et al. (1999a), has been earlier applied for hydrological simulations in many river basins of very different size and located in different natural conditions: from small-to-middle size Scandinavian basins (e.g. Motovilov et al., 1999b) to the great Volga and Lena Rivers with watershed areas exceeding a million km^2 (Gelfan and Motovilov, 2009; Motovilov and Gelfan, 2013). Since, 2004, the ECOMAG model has been utilized in an operational mode for simulation of hydrological characteristics and water inflow into the Volga-Kama and Angara-Yenisey reservoir cascades in Russia which are among the largest worldwide reservoir cascades.

Physically based land surface model Soil Water-Atmosphere-Plants (SWAP) developed by Ye. Gusev and O. Nasonova, as reported by Gusev and Nasonova (1998), has been intensively validated, in particular, within several model intercomparison projects (PILPS, Rhone-AGG, MOPEX, SnowMIP, GSWP-2) for different river basins and experimental sites located in various natural zones (from areas in tropical zone to regions

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with permafrost) and characterized by different spatial scales (from small experimental sites and catchments to the whole land surface of the Earth). The results of the model testing are presented, particularly, in Gusev and Nasonova (1998, 2003) and Gusev et al. (2011).

Both models describe interception of rainfall/snowfall by the canopy, processes of snow accumulation and melt, soil freezing and thawing, water infiltration into unfrozen and frozen soil, evapotranspiration, thermal and water regime of soil, overland, subsurface and channel flow. Most of the parameters are physically meaningful and can be assigned from literature or derived through available measured characteristics of topography, soil, and land-cover. Some key-parameters of the models are calibrated against streamflow measurements and, if available, measurements of the internal basin variables (snow characteristics, soil moisture, groundwater level, etc.).

The ECOMAG model is forced by daily time series of air temperature, air humidity and precipitation. The SWAP inputs include 3 h data of incoming radiation, precipitation, air temperature and humidity, atmospheric pressure, and wind speed. The forcing data can be taken from meteorological observations or GCM-outputs.

Both models have been applied earlier for simulating runoff hydrographs on the basis of multi-year hydrometeorological observations in the Lena and Northern Dvina River basins and demonstrated good performance of simulations (Motovilov and Gelfan, 2013; Gusev et al., 2011, 2015; Krylenko et al., 2014).

4 Atmospheric general circulation model description and inernal variability simulations

The ensemble simulations were performed with the atmospheric general circulation model (AGCM) ECHAM5 developed at the Max Planck Institute for Meteorology (Roeckner et al., 2003). This model is a climatic version of the AGCM based on spectral weather forecast model of European Centre for Medium-Range Weather Forecasts (ECMWF) that employs state-of-the-art physics. The model version used here has a horizontal resolution of T63 (1.8° × 1.8° latitude × longitude) and 31 vertical levels. All 45 ensemble simulations use identical prescribed lower boundary conditions at atmosphere–ocean interface. These conditions are taken from HadISST1.1 (Hadley Centre, UK) dataset that consists of global empirical analysis of sea surface temperature (SST) and sea ice concentrations (SIC, a portion of model grid cell covered by sea ice) (Rayner et al., 2003). The simulation period is from 1979 to 2012. The start of simulations in 1979 is motivated by beginning of the era of continuous satellite monitoring of the sea ice cover that provides most reliable SIC data. This is important for correct simulations of the climate in high-latitudes (Semenov and Latif, 2012). Greenhouse gas concentrations in the model are kept constant and represent modern climate conditions (348 ppm for CO_2, and 1.64 ppm for methane). All other external forcing parameters (such as orbital parameters, solar radiation, other radiative-active gases and aerosols) also correspond to modern climate conditions and do not vary. The only differences between the simulations are initial conditions of the atmosphere (model atmospheric state at the 1 January of 1979) that are prescribed as instant atmospheric states at different 12 h intervals in December 1978. Thus, the ensemble consists of 45 simulations with identical boundary and external forcing but different initial conditions. Note that characteristics at atmospheric lower boundary over land (soil temperature and moisture, snow cover) are computed by AGCM using a land surface model and simulated heat and water fluxes (Roeckner et al., 2003).

Such ensemble simulations with time-varying SST and SIC according to observational data allow one to estimate a contribution of the varying SST and SIC fields to the observed changes in atmospheric characteristics (mean, trends, variability) during the simulation period (assuming that AGCM correctly reproduces a response to varying boundary conditions). When considering changes of atmospheric variables consisting of changes caused by external (to atmosphere) factors (SST and SIC) that are supposed to be the same in all simulations and internal variability (due to stochastic atmosphere dynamics and thus independently distributed), the averaging over large ensemble members effectively filters stochastic terms (climatic noise) and results in an

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estimate of the external signal (related to SST and SIC changes). A similar approach will be applied in Sect. 5.3 to estimate externally forced part of long-term changes of hydrological characteristics that provides a basis for estimating potential predictability limits for hydrological systems.

To illustrate differences between individual ensemble members arising from the internal atmospheric dynamics, several meteorological characteristics were averaged over the Lena River catchment area. Figure 2 (top panels) show ensemble (45 realizations) of mean annual temperature and precipitation for the period of simulations (1979–2012); Fig. 2 (bottom) demonstrate ensemble of mean daily values of these variables averaged over the simulation period.

A positive trend for both temperature and precipitation (Fig. 2, top panels) agrees with global warming and a tendency of precipitation increase in high northern latitudes accompanying the temperature increase. Intra-ensemble SDs of the annual temperature and precipitation values caused by internal stochastic atmospheric dynamics account for 0.5 °C and 0.08 mm day^{-1}, respectively. The SDs of daily mean temperature vary within 0.4–0.8 °C during a year, while the deviations of precipitation are about 0.02–0.04 mm day^{-1} in winter and reach as much as 0.30 mm day^{-1} for some summer days. The following section will address a question how such an uncertainty is transformed to uncertainty in the river discharge.

An important factor that should be taken into account while analyzing ECHAM5-simulations is a model bias. Even when forced with observed fields of SST and SIC, ECHAM5 simulates mean climate over land areas that differs from observations for the corresponding period. The sources for model bias include deficiencies of parameterizations and incomplete description of some physical processes, numerical schemes, low model resolution. In particular, ECHAM5 similar to majority of climate models (Flato et al., 2013; IPCC AR5) simulates colder climate in winter in high latitudes of the Northern Hemisphere that is related to higher sea level pressure over the Arctic and weakened zonal flow in mid and high latitudes.

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A post-processing procedure, analogous to that proposed by Velázquez et al. (2013), was applied to correct biases in ECHAM5-outputs before using them as inputs into hydrological models. The correction factors were computed based on the difference between the ensemble-mean climate variables modelled for the reference period (1979–2009) and the corresponding observed variables averaged over the basin areas under consideration. The correction factors were then added to the ECHAM5-simulated 6 h meteorological fields. Comparison of the spatial fields of mean annual values of precipitation, air temperature and humidity obtained from data registered in the meteorological stations located within the Lena River basin and processed from the simulated data is illustrated, as an example, by Fig. 3. One can see from this Figure that the applied post-processing allowed us to obtain rather similar fields of the above listed variables taking into account sparseness of the meteorological monitoring network in the basin.

5 Experiment design, results and discussion

Due to stochastic nature of climate, hydrological models can not provide predictions of specific streamflow hydrograph series (even in the past, not to mention the future) on the basis of the climate model outputs. In other words, hydrological models operating on outputs from climate model are confined, similar to the climate models, to making projections rather than predictions (Refsgaard et al., 2014) and able to provide only information on statistical characteristics of runoff series. Below we present approaches to and results of estimating these statistical characteristics from simulated ensembles of multi-year streamflow hydrographs, as well as analysing uncertainty of the estimations.

An ensemble of $\mathrm{NI} = 45$ time series of meteorological variables simulated by ECHAM5 with 6-h time step for the period of $\mathrm{NY} = 34$ years (from 1 January 1979 to 31 December 2012) was assigned as distributed input into ECOMAG and SWAP hydrological models. With the help of these two models, 45-member ensembles of daily streamflow series each of 34 year length were calculated for the Lena River and the Northern Dvina River. From these hydrograph ensembles, the mean values and the

SDs of annual, monthly and daily runoff were estimated. Then, 95 % confidence intervals for the estimates were calculated as an indication of uncertainty in these estimates caused by the internal variability of the atmosphere. Whilst calculating the confidence intervals, it was assumed that these estimates followed the Gaussian probability distribution.

More precisely, the estimates were calculated as follows. Let a calculated water discharge be X_{ij}, where $i = 1, 2, \ldots, 45$ is the realization number referred to the assigned initial conditions in the climate model; $j = 1, 2, \ldots 34$ is the number of year within the simulation period. In this study, X_{ij} can be either annual discharge for a specific year, or monthly discharge for a specific calendar month, or daily discharge for a specific calendar day, derived from ith realization. To obtain the above mentioned statistical characteristics and their confidence intervals, the following formulae were used:

M-estimate of the mean value:

$$M = \frac{1}{(\mathrm{NY} \times \mathrm{NI})} \sum_{i=1}^{\mathrm{NI}} \sum_{j=1}^{\mathrm{NY}} X_{ij} \tag{1}$$

SD-estimate of the SD:

$$\mathrm{SD} = \sqrt{\frac{\sum_{i=1}^{\mathrm{NI}} \sum_{j=1}^{\mathrm{NY}} \left(X_{ij} - M\right)^2}{(\mathrm{NY} \times \mathrm{NI}) - 1}} \tag{2}$$

confidence interval γ_M for M:

$$\gamma_M = \left(M + \Phi^{-1}\left(\frac{1+\alpha}{2}\right)\sigma_M; M - \Phi^{-1}\left(\frac{1+\alpha}{2}\right)\sigma_M\right) \tag{3}$$

confidence interval γ_{SD} for SD:

$$\gamma_{\mathrm{SD}} = \left(\mathrm{SD} + \Phi^{-1}\left(\frac{1+\alpha}{2}\right)\sigma_{\mathrm{SD}}; \mathrm{SD} - \Phi^{-1}\left(\frac{1+\alpha}{2}\right)\sigma_{\mathrm{SD}}\right) \tag{4}$$

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where α is the confidence probability, $\Phi^{-1}(x)$ is the inverse of the cumulative normal distribution function; σ_M is the SD of M, equal to

$$\sigma_M = \sqrt{\frac{\sum_{i=1}^{\mathrm{NI}} (M_i - M)^2}{\mathrm{NI} - 1}}, \tag{5}$$

$$M_i = \frac{1}{\mathrm{NY}} \sum_{j=1}^{\mathrm{NY}} X_{ij};$$

σ_{SD} is the SD of SD, equal to

$$\sigma_{\mathrm{SD}} = \sqrt{\frac{\sum_{i=1}^{\mathrm{NI}} (\mathrm{SD}_i - M_{\mathrm{SD}})^2}{\mathrm{NI} - 1}}, \tag{6}$$

$$\mathrm{SD}_i = \sqrt{\frac{1}{(\mathrm{NY} - 1)} \sum_{j=1}^{\mathrm{NY}} \left(X_{ij} - M_i\right)^2}, \quad M_{\mathrm{SD}} = \frac{1}{\mathrm{NI}} \sum_{i=1}^{\mathrm{NI}} \mathrm{SD}_i$$

Hereafter, the confidence intervals of estimates are evaluated for α = 95 % confidence probability, i.e. $\Phi^{-1}\left(\frac{1+0.95}{2}\right) = 1.96$.

To compare the uncertainty in statistical estimates of runoff characteristics, which differ in their absolute value, we used normalized widths of the confidence intervals. We introduce uncertainty indices UN(M) and UN(SD) of M and SD estimates, respectively, which are considered to be half of the width of 95 % confidence interval of the corresponding estimate divided by its mean value, i.e.:

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$$\mathrm{UN}(M) = \frac{\gamma_M^+ - \gamma_M^-}{2M} = \frac{1.96\sigma_M}{M} \quad (7)$$

$$\mathrm{UN(SD)} = \frac{\gamma_{\mathrm{SD}}^+ - \gamma_{\mathrm{SD}}^-}{2\mathrm{SD}} = \frac{1.96\sigma_{\mathrm{SD}}}{\mathrm{SD}} \quad (8)$$

where $\gamma_\bullet^+$ and $\gamma_\bullet^-$ are the right and the left limits of the confidence interval, respectively.

In the next Subsections, we present the results of ensemble simulation of river runoff for each study basin. First, an analysis of the uncertainty indices of annual, monthly and daily mean estimates for both river basins is presented. The calculated estimates are compared to the corresponding observation data estimates. Then, analogous results are shown for SDs of runoff values averaged over the same time intervals (year, month, day). Finally, uncertainty in trends in annual runoff is calculated and discussed.

5.1 Estimates of mean runoff and their uncertainty

Table 1 demonstrates the uncertainty indices UN(M) for M-estimates of annual, monthly and daily runoff calculated by Eq. (5). Intra-annual variation of uncertainty indices UN(M) for M-estimates of daily runoff is shown in Fig. 4.

The following conclusions can be derived based on the presented results:

1. Uncertainty in the mean runoff values calculated by both of the models for both rivers decreases with the increasing interval of runoff averaging.

   One can see from Table 1 that the uncertainty index UN(M) for the M-estimates of daily runoff varies from 8 to 24 %; UN(M) for monthly runoff – from 7 to 19 %; UN(M) for annual runoff – from 6 to 10 % depending on the model used and the study river basin. However, uncertainty indices for monthly and daily runoff estimates have distinguished seasonal variations, and maximum values of the uncertainty considerably exceed their average values within a year. For example, as can be seen from Fig. 4, uncertainty index UN(M) for daily runoff can be more than 50 %, and UN(M) for mean monthly runoff estimates reaches 41 % (Table 1).

2. Internal atmospheric variability has maximal influence on uncertainty in the estimates of mean runoff during snowmelt/rainfall flood periods for both rivers. Uncertainty in estimates of mean runoff during winter months is small.

   Uncertainty indices UN(M) for M-estimates of monthly runoff during the period of snowmelt floods and rainfall floods amount to 21–24 % for the Lena River and 35–41 % for the Northern Dvina River depending on the applied hydrological model (see Table 1). Uncertainty UN(M) for daily runoff is even greater (Fig. 4): for snowmelt flood this value is 42–55 % for both rivers. Uncertainty UN(M) for monthly runoff during winter periods is much less (2–13 % for the Lena River and 2–19 % for the Northern Dvina River); the same applies to daily runoff during winter (see Fig. 4). Possible explanation of these findings is that physical mechanisms of flood events are more sensitive to intra-ensemble changes of the climate model outputs than more inertial mechanisms of low flow generation.

3. Uncertainty in mean runoff estimates for the Lena River basin turned out to be significantly less than ones for the Northern Dvina River when using both models. Moreover, intra-annual irregularity of UN(M) is more visible for the Northern Dvina simulations both on monthly (Table 1) and daily (Fig. 4) time scales. In other words, the Northern Dvina simulated hydrographs turned out to be more sensitive to the atmospheric variability.

   This difference in uncertainty in mean runoff estimates is related to peculiarities of river runoff generation in the study basins. These peculiarities can manifest themselves, for example, in degree of non-linearity of river basin response to climate impact: increase in non-linearity, generally saying, should lead to increase in uncertainty in the calculated runoff characteristics. Therefore, one can assume that the mechanisms of runoff generation and transformation of climate impact into variations of river runoff are more linear in the Lena River basin than in the Northern Dvina River basin. To validate this assumption, we compared two mean hydrographs for each basin. One was calculated by averaging over the ensem-

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ble of 45 simulated mean hydrographs (an averaged response to ensemble input) and the other one simulated by the hydrological models using one meteorological input obtained by averaging over 45 ECHAM5-outputs (a response to ensemble averaged input).

If the response of the hydrological system to climate impact is linear, these hydrographs should be similar, whereas non-linearity should lead to increased difference between these hydrographs. The results of the comparison are shown in Fig. 5.

As one can see from Fig. 5, both models show that the response of the hydrological system of the Lena River basin is close to linear, while the response of the Northern Dvina River is essentially non-linear. This supports the above mentioned assumption about an increased effect of internal atmospheric variability on uncertainty in mean river runoff estimates in the Northern Dvina River basin due to greater non-linearity of the mechanisms of runoff generation compared with the Lena River basin. Note, that due to the effect of averaging, peak discharge of the ensemble mean hydrographs is always lower than the hydrograph peak simulated from mean outputs (see Fig. 5).

4. Uncertainty in mean runoff estimates determined using different models vary insignificantly, despite the fact that these models require different input data. Thus, average uncertainty indices UN(M) for SWAP-simulated monthly runoff are 11 % for the Lena River and 19 % for the Northern Dvina River; when using ECOMAG, the values are 7 and 19 %, respectively.

As the next step, we compare the obtained M-estimates of the simulated runoff with the corresponding estimates derived from streamflow observations in the basins under consideration.

Figures 6 and 7 present a comparison between M-estimates for annual, monthly and daily discharges calculated at the basin outlets with the corresponding estimates obtained from the time series of the discharges observed for 31 years (1979–2009).

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These Figures also show 95 % confidence intervals γ_M for the calculated estimates of the mean values computed by Eqs. (3) and (5).

A comparison of the calculated estimates with the mean runoff characteristics evaluated by the available observational series has demonstrated that calculation errors, when using both models, increase with decreasing time interval of discharge averaging. Estimates of the mean annual runoff are characterized by the smallest error: 5 and 18 % for the Lena River, and 10 and 33 % for the Northern Dvina River depending on the hydrological model used. Errors of the mean monthly and mean daily runoff estimates are usually much larger. It is especially noticeable for the periods of spring-summer snowmelt flood and summer-autumn rainfall floods for both rivers: error of the mean monthly runoff can reach several dozens of percent, and for the mean daily runoff – hundreds of percent. Winter months are an exception with errors for both mean monthly and mean daily runoff usually not exceeding 30–40 %. It turned out that all calculated estimates of mean runoff were closer to the corresponding estimates based on empirical data for the Lena River than for the Northern Dvina River. This can be explained by a weaker natural variability of the runoff characteristics at the larger basin of the Lena River.

5.2 Estimates of SD of runoff and their uncertainty

While analyzing SD-estimates of runoff, we focused on the same issues, which were discussed in the previous sections when analyzing the corresponding *M*-estimates. Specifically, we considered dependence of uncertainty indices UN(SD) on the interval of runoff averaging, intra-annual changes in UN(SD), difference in UN(SD) for different basins, and comparison of the SD-estimates with the corresponding estimates calculated from the available observed streamflow time series.

Table 2 presents uncertainty indices UN(SD) for SD-estimates of the annual, monthly and daily runoff at the outlet of the studied rivers, which were calculated by Eq. (6). Intra-annual variation of uncertainty indices UN(SD) for SD-estimates for the daily runoff is shown in Fig. 8.

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A comparison of the estimates of uncertainty indices for the SD (Table 2, Fig. 8) and the mean (Table 1, Fig. 4) reveals that uncertainty indices UN(SD) for SD-estimates of runoff characteristics are, unsurprisingly, much higher than uncertainty UN(M) for M-estimates for the same runoff averaging interval. Similar to UN(M), one can see a tendency of an increasing uncertainty of SD when the time averaging interval of water discharge decreases: UN(SD) increases from 24–31 % for annual runoff to 30–52 %, as an average, for monthly runoff, and 36–98 % for daily runoff.

At the same time uncertainty in SD-estimates of monthly and daily water discharges significantly varies within a year, and the maximum values of uncertainty index UN(SD) for these estimates considerably exceed their mean values. For example, UN(SD) for some calendar months is close to 100 % (Table 2), and UN(SD) for daily runoff estimates reaches hundreds of percent (Fig. 8).

Similar to results for uncertainty of mean runoff estimates, the impact of atmospheric variability on SD uncertainty has a distinguished intra-annual variation. Uncertainty UN(SD) for monthly and daily runoff reaches its maximum in the periods of spring–summer snowmelt floods and summer-autumn rainfall floods at both rivers (see Table 2 and Fig. 8). Uncertainty UN(SD) for winter runoff is somewhat smaller but still large in contrast to the uncertainty in mean values during winter months, which, as it was shown above, significantly decreases. This result can be explained by a small variation of winter runoff.

Uncertainty indices UN(SD) for SD-estimates of Lena River runoff for both hydrological models are smaller than for the Northern Dvina River (what is similar to results for UN(M)). Uncertainty in annual runoff varies very slightly (24–36 % for the Lena River and 30–31 % for the Northern Dvina River). However, a decrease of the averaging interval to a month and a day leads to a significant increase of UN(SD) variations for both basins. As it was shown above, the difference of the UN(SD) values can be accounted for stronger non-linearity of the runoff generation mechanisms for the Northern Dvina River than for the Lena River.

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Figures 9 and 10 show a comparison of SD-estimates for the annual, monthly and daily discharges calculated at the basin outlets with the corresponding estimates obtained from the observed time series of the discharge for the period 1979–2009. These Figures also present 95 % confidence intervals γ_{SD} of the calculated estimates of SD (according to Eq. 4).

The calculations demonstrated that the relative errors of the SD-estimates derived by simulated runoff time series were fairly large in comparison with the corresponding estimates based on empirical data. These estimates were most similar for the annual runoff: 3 and 21 % for the Lena River and 41 and 57 % for the Northern Dvina River depending on the hydrological model. When the time averaging interval for water discharge decreases, errors of the estimates increase for both models and both rivers, which is particularly noticeable for the winter season, when the SD-estimates are sometimes lower by hundreds percent in comparison with their observed variability. Similar to the *M*-estimates, the SD-estimates are closer to the corresponding estimates based on empirical data for the Lena River than for the Northern Dvina River.

5.3 Estimate of annual runoff trend and its uncertainty

As it has been already discussed in Sect. 4, an averaging over the ensemble of simulated realizations of runoff hydrographs allowed us to filter off a random component caused by atmospheric variability and to assess the impact of the “signal” caused by factors external relative to atmosphere (related to the prescribed observed SST and SIC changes in our experiments). Such an assessment is presented in this Subsection with an analysis of long-term annual runoff trend.

Figure 11 shows long-term variations of the annual discharge values observed at the outlets of both rivers compared with the corresponding values averaged over the ensemble of 45 realizations of runoff hydrographs calculated using ECOMAG model.

One can see that individual realizations of the calculated annual discharges differ from each other and are, in general, only slightly correlated with the corresponding observed time series. For the Lena River simulations, correlation coefficients vary from

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−0.31 to of 0.56 with mean value of 0.17. Note that the correlation between the observed annual discharges and ensemble mean annual discharges is rather high (0.51). However, the SD of the observed discharge time series (17 616 $m^3 s^{-1}$) is almost 1.3 orders larger than that of the mean ensemble discharge time series (901 $m^3 s^{-1}$). It is necessary to mention, that the corresponding correlations derived from the SWAP simulation experiments are very close to ones listed above: correlation coefficients vary from minimum of −0.29 to maximum of 0.53 with mean value of 0.14.

For the Northern Dvina River, correlation coefficients between individual realizations and the observed annual discharge series are, mostly, statistically insignificant under a reasonable significance level. The coefficients vary from minimum of −0.56 to maximum of 0.30 with mean value of −0.04. The correlation coefficient between the observed annual discharges and mean ensemble annual discharges is also insignificant (−0.19). Again, the corresponding correlations derived from the SWAP simulation experiments are very close to those obtained by ECOMAG simulations: correlation coefficients vary from minimum of −0.40 to maximum of 0.33 with mean value of −0.03, as well as the correlation between the observed annual discharges and mean ensemble annual discharges calculated by SWAP model is insignificant and equals to −0.13.

Figure 12 shows histograms of the linear trends of annual runoff obtained for each realization from the calculated ensembles. Also shown are the trend calculated from the observational data (Slope(fact)) and mean trend calculated by averaging over 45 trends for the individual realizations (Slope(mean calc)). Both models in most cases reproduce well the observed trend of annual runoff changes. Calculated increase of annual discharge at the outlet of the Lena River is around 748 and 581 $m^3 s^{-1}$ per decade for ECOMAG and SWAP models, respectively (235.9 and 183.2 km^3 $decade^{-1}$, respectively). The observational data for 1979–2009 result in the increase of approximately 1000 $m^3 s^{-1}$ per decade (315.4 km^3 $decade^{-1}$). For the Northern Dvina River, the simulated trends are insignificant, as well as the observed trend.

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6 Conclusions

We have presented the analysis of large-basin hydrological response uncertainty originating from the internal atmospheric variability that was to the first time performed with such a large (45 members) ensemble of climate model simulations. The internal variability is considered as one of three main factors of uncertainty of hydrological response to climate change (together with so-called "forcing" and "climate model" uncertainties). Importantly, the role of the internal atmospheric variability is most visible for the time scales from years to first decades and for the regional spatial scales (e.g. Hawkins and Sutton, 2009), i.e. over the spatial–temporal scales of water management in large river basins.

Our study focused on transformation of the internal atmospheric variability by physically based hydrological models ECOMAG and SWAP and on impact of the variability on simulated runoff for large Lena and Northen Dvina River basins located within the Arctic basin. It is important to emphasize, that due to stochastic nature of atmospheric variability, hydrological models driven by output of a climate model are confined, as well as a climate model, to making projections rather than predictions (even in the past, not to mention the future), i.e. the hydrological models are able to provide only information on statistical characteristics of runoff time series.

The internal atmospheric variability was simulated in ensemble simulations with the ECHAM5 atmospheric general circulation model. The ensemble consists of 45 simulations performed using identical prescribed lower boundary conditions (observed sea surface temperature and sea ice concentration for 1979–2012) and constant external forcing parameters corresponded to modern climate conditions. The only differences between the simulations were initial conditions of the atmosphere prescribed as instant atmospheric states changed by small perturbations.

The ensemble of the bias-corrected ECHAM5-outputs was assigned as distributed input for ECOMAG and SWAP hydrological models, and the corresponding ensembles of runoff hydrographs were calculated for the Lena River and the Northern Dvina

River. From these hydrographs, hydrological indicators, namely, mean and SDs of the annual, monthly and daily runoff, annual runoff trend were estimated. Uncertainties of the hydrological indicators caused by the internal variability of the atmosphere were determined as normalized confidence intervals of the corresponding estimates.

The main findings of our research are the following:

1. Uncertainty in estimates of both runoff mean and SD values increases with decreasing time interval of runoff averaging: from minimal uncertainty for annual runoff to maximal one for daily runoff. Wherein, for the same runoff averaging interval, uncertainties of the runoff SD are much higher than uncertainties of the runoff mean value. The mean annual runoff uncertainty originated from the internal variability of the atmosphere was found to be 6–10 % depending on the model used and the study basin. Comparison of the calculated estimates with the corresponding estimates evaluated by the available multi-year observational time series also demonstrated increasing errors of the both models simulations with decreasing time interval of runoff averaging.

2. Atmospheric variability impact on uncertainties of the mean and SD of the runoff has a distinguished seasonal dependence. Uncertainties in monthly and daily runoff reach their maximum values during the periods of spring-summer snowmelt and summer–autumn rainfall floods for both rivers. Possible explanation of this finding is that physical mechanisms of flood events are more sensitive to intra-ensemble changes of the climate model outputs than more inertial mechanisms of low flow generation.

3. The simulated hydrographs for the Northern Dvina runoff are found to be more sensitive to the internal atmospheric variability than those for the Lena River runoff. This is also manifested by the findings that runoff estimate uncertainties and their intra-annual irregularity are much higher for the Northern Dvina River simulations, when using both hydrological models. The increased effect of the internal atmospheric variability on uncertainty in the Northern Dvina River runoff

estimates is shown to be explained by the stronger non-linearity of the mechanisms of runoff generation compared with the Lena River basin.

4. Individual realizations of the simulated annual discharge series differ from each other and are, in general, insignificantly correlated with the corresponding observed time series for both Lena and Northern Dvina River. However, for some individual realizations the linear link to observations is found to be quite strong: maximum correlation coefficients are 0.56 and 0.30 for the Lena and Northern Dvina River simulations respectively.

5. It is shown that the averaging over large ensemble members effectively filters stochastic term related to internal atmospheric variability and results in an estimate of the externally forced signal related, in our experiments, to global sea surface temperature and sea ice concentration changes. We found that both models for ensemble mean results reproduce the observed trend of the annual Lena River runoff. The simulated trends are (close to) normally distributed around ensemble mean value that indicates that a considerable portion of the observed trend can be externally driven. The trend for the Northern Dvina River changes turned out to be insignificant both for the simulation results and the observational data. This suggests a dominant role of internal variability in generating the Northern Dvina runoff changes during the simulation period.

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Table 1. Uncertainty indices UN(M) (in %) for M-estimates of annual, monthly and daily runoff.

Runoff characteristic	Lena River		Northern Dvina River	
	ECOMAG	SWAP	ECOMAG	SWAP
Annual runoff	6	7	10	7
Monthly runoff	7	11	19	19
January	3	9	5	9
February	2	8	2	9
March	1	8	5	23
April	1	24	33	41
May	21	9	10	23
June	6	9	14	18
July	8	9	22	9
August	10	9	32	14
September	13	10	35	17
October	10	11	29	21
November	8	12	22	24
December	5	13	17	19
Daily runoff	8	12	24	21

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Table 2. Uncertainty Indices UN(SD) (in %) for SD-estimates of the Annual and Monthly runoff.

Runoff characteristic	Lena River ECOMAG	SWAP	Northern Dvina River ECOMAG	SWAP
Annual runoff	24	26	30	31
Monthly runoff	32	30	52	33
January	29	35	85	29
February	30	33	95	29
March	30	25	104	36
April	31	23	36	42
May	84	55	24	45
June	25	21	27	39
July	29	17	39	23
August	25	26	46	26
September	26	28	47	27
October	22	34	37	30
November	23	32	33	29
December	28	33	51	35
Daily runoff	45	36	98	45

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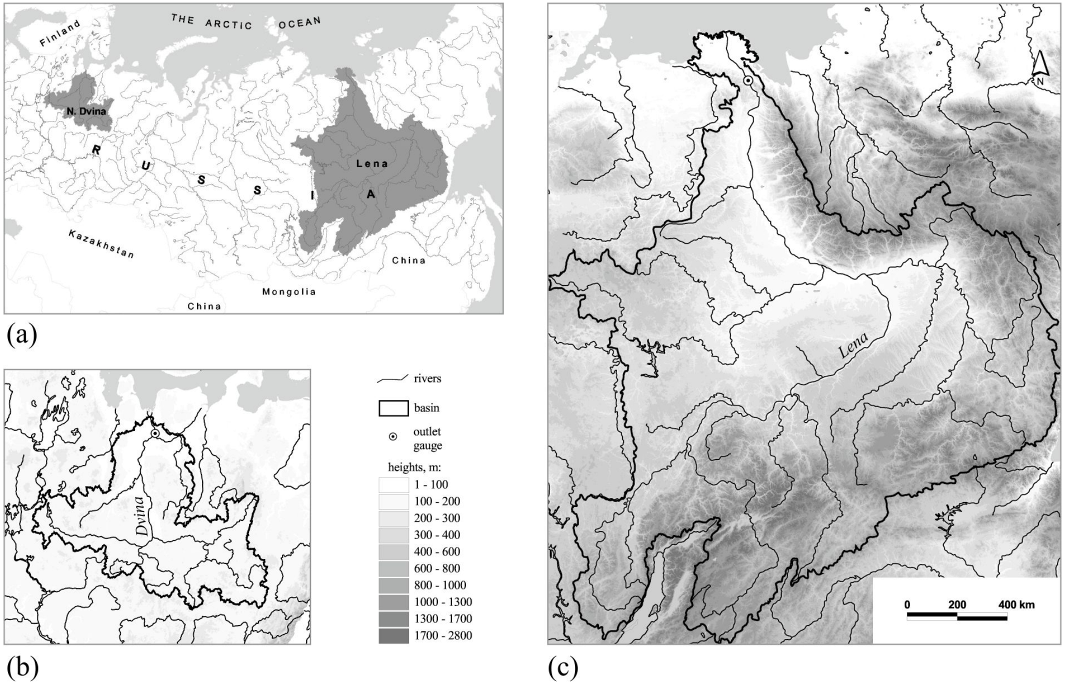

Figure 1. Case study basins: location **(a)**, Northern Dvina River basin **(b)**, Lena River basin **(c)**.

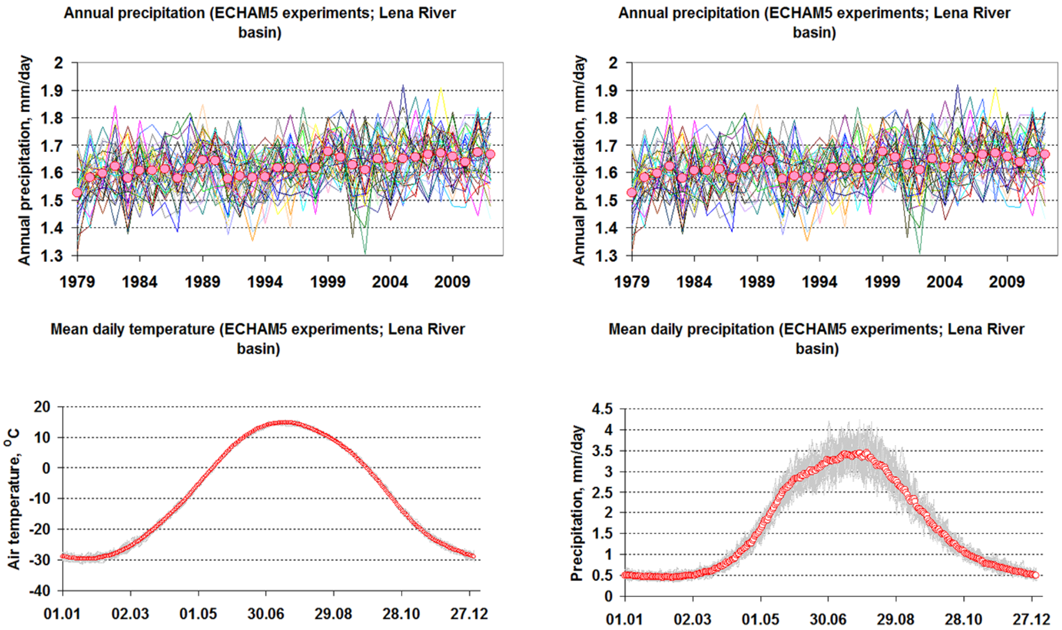

Figure 2. ECHAM5-simulated ensembles of mean annual near-surface air temperature (SAT) (top left panel) and precipitation (top right panel), as well as mean daily SAT (bottom left panel) and precipitation (bottom right panel) averaged over the Lena River basin. Dots in top figures and bold line in bottom figures denote corresponding ensemble mean values.

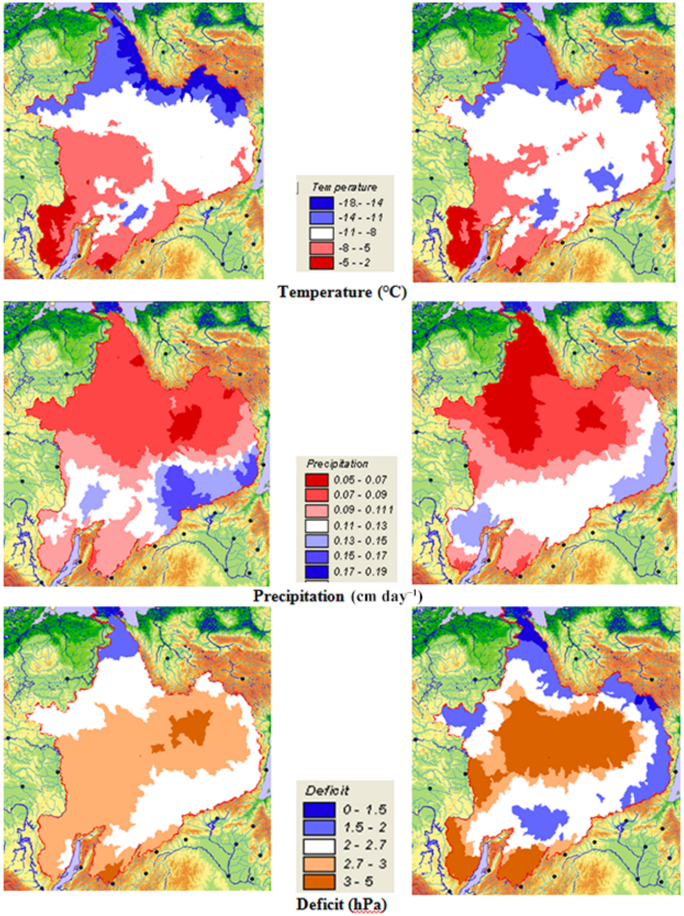

Figure 3. Observed (left panels) and the bias-corrected ECHAM5-simulated (right panels) patterns of mean annual values of air temperature (°C), precipitation (cm day^{-1}) and air humidity deficit (hPa) within the Lena River basin.

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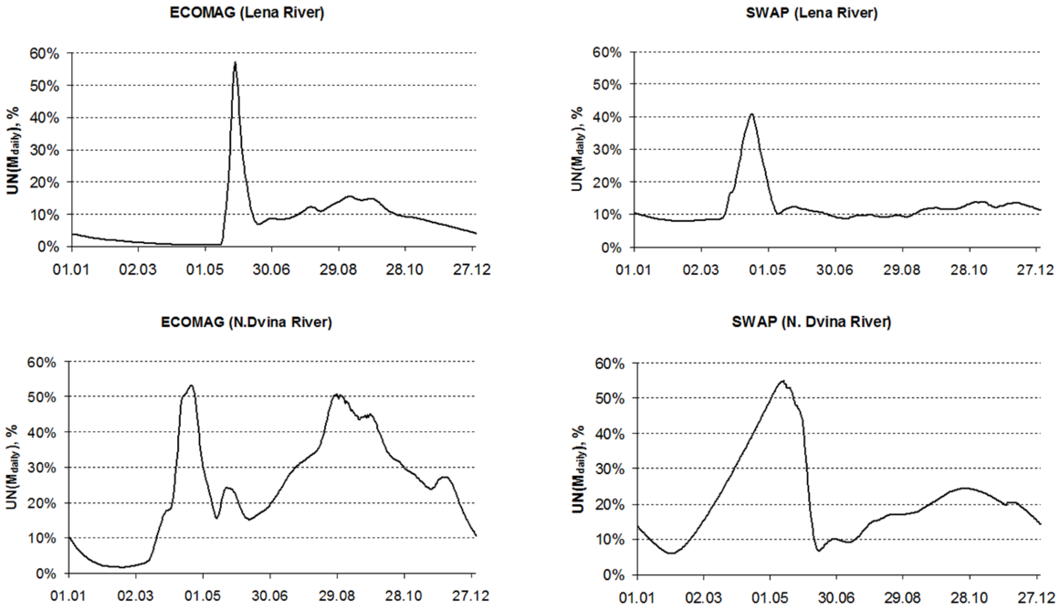

Figure 4. Intra-annual variation of uncertainty indices UN(M) (in %) for the M-estimates of daily runoff.

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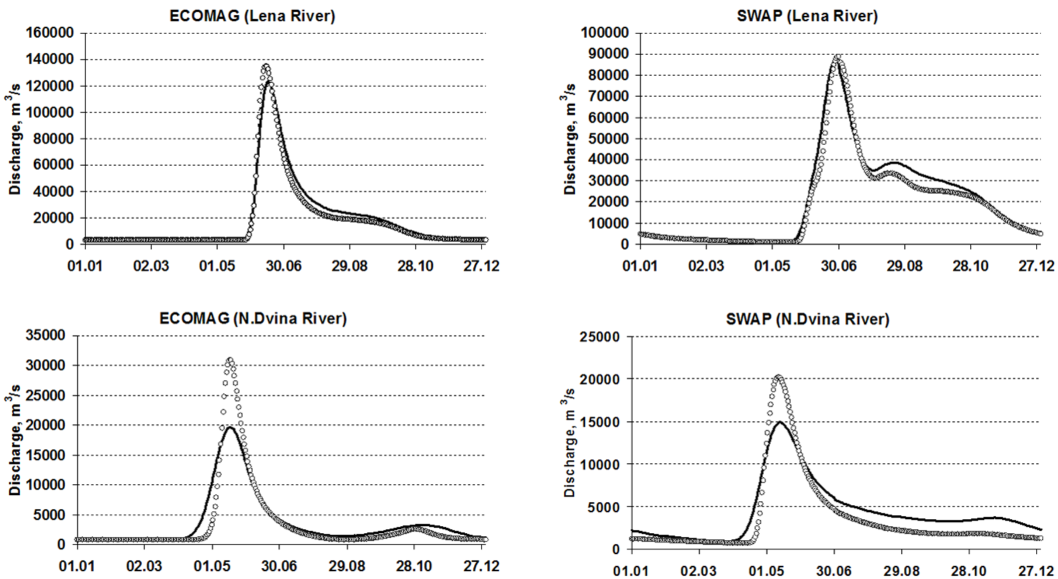

Figure 5. Mean hydrographs calculated as an averaged response to ensemble input (solid line) and as a response to ensemble averaged input (dotted line).

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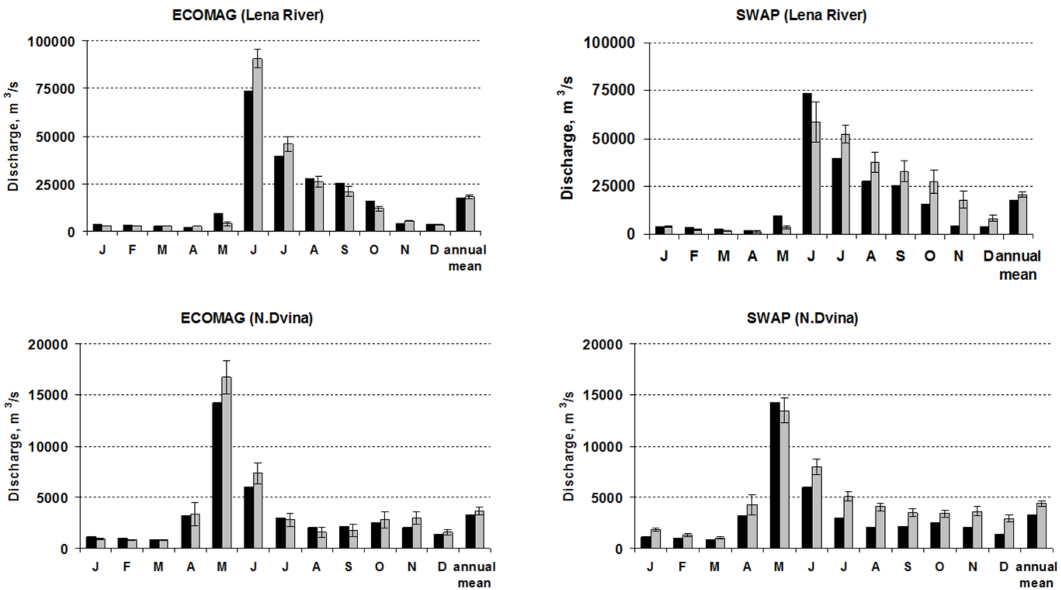

Figure 6. *M*-estimates of annual and monthly discharges at the outlets of the Lena River (top panels) and the Northern Dvina River (bottom panels). Black columns show estimates obtained from the observation data for 1979–2009. Gray columns show estimates obtained from the ensemble simulation (with indicated 95 % confidence intervals γ_M for these estimates).

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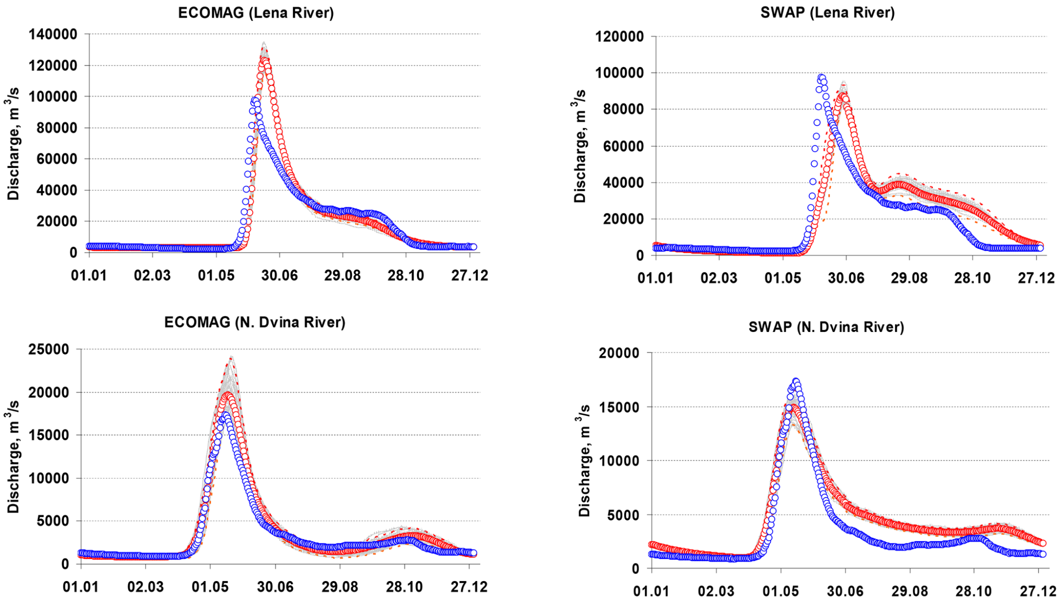

Figure 7. *M*-estimates of the daily discharges at the outlets of the Lena River (top panels) and the Northern Dvina River (bottom panels). Blue points show estimates based on observational data for the period of 1979–2012. Red points show estimates based on ensemble simulations (gray thin lines). Red dotted line shows the boundaries of 95 % confidence interval of mean daily discharges.

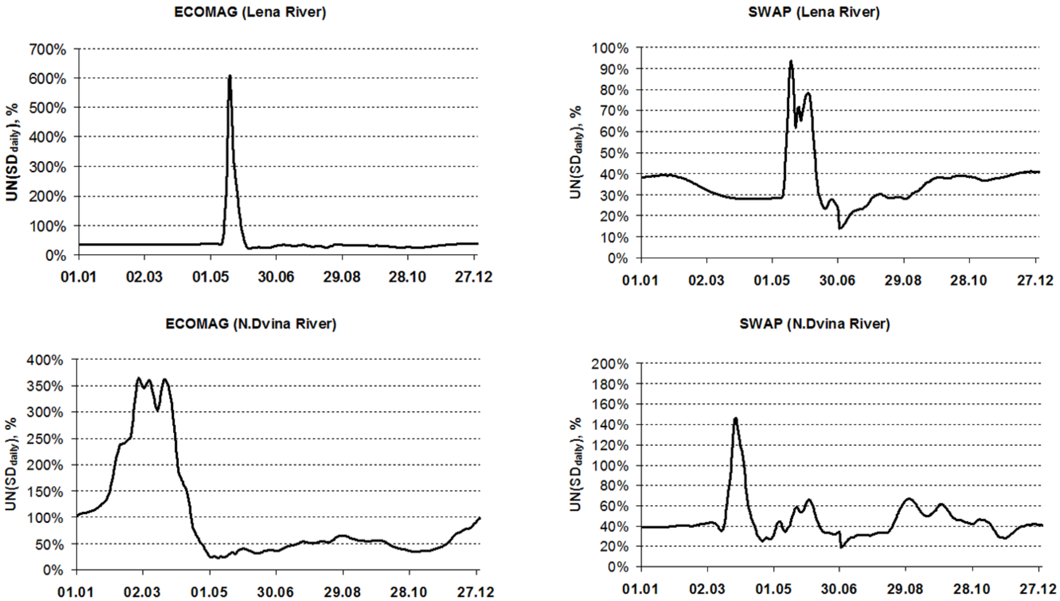

Figure 8. Uncertainty indices UN(SD) (in %) for the SD-estimates of the daily runoff.

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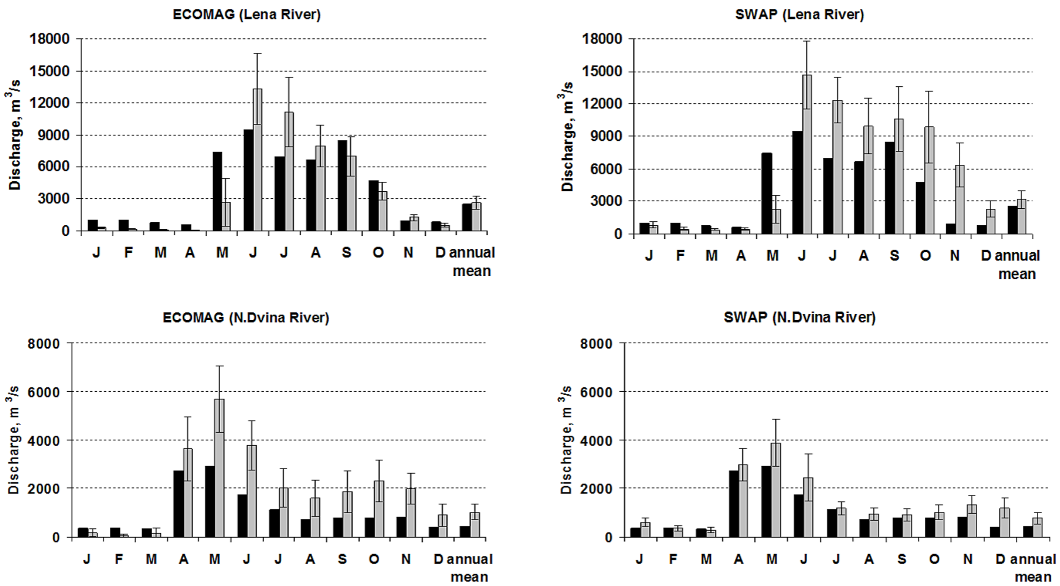

Figure 9. SD-estimates of the annual and monthly discharges at the outlets of the Lena River (top panels) and the Northern Dvina River (bottom panels). Black columns show estimates obtained from the observational data for 1979–2009. Gray columns show estimates obtained from the ensemble simulation (with indicated 95 % confidence intervals γ_{SD} for these estimates).

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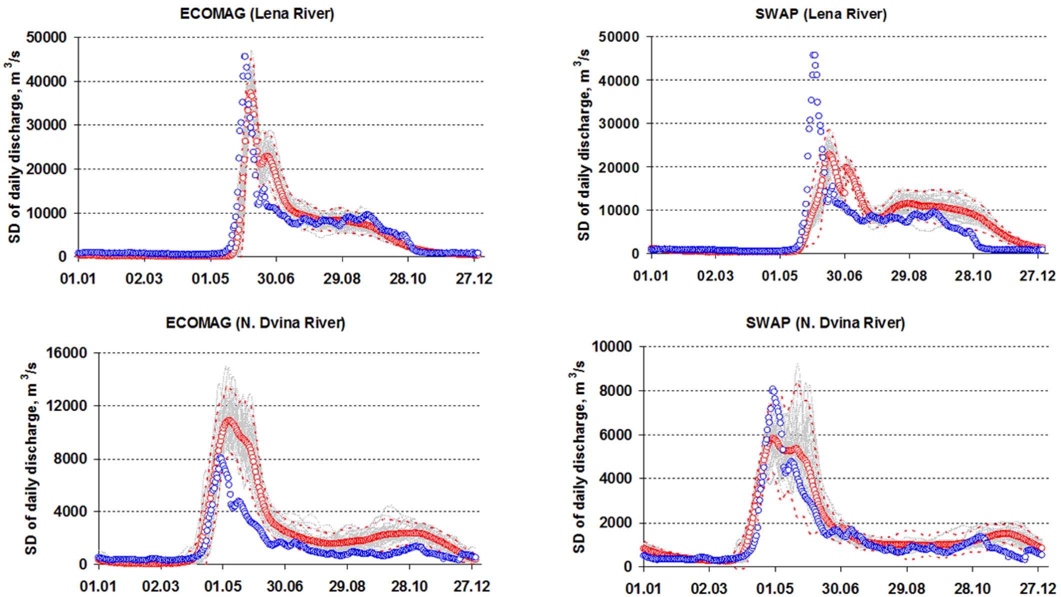

Figure 10. SD-estimates of the daily discharges at the outlets of the Lena River (top panels) and the Northern Dvina River (bottom panels). Blue points show estimates based on observational data for the period of 1979–2012. Red points show estimates based on ensemble simulations (gray thin lines). Red dotted line shows the boundaries of 95 % confidence interval of mean daily discharges.

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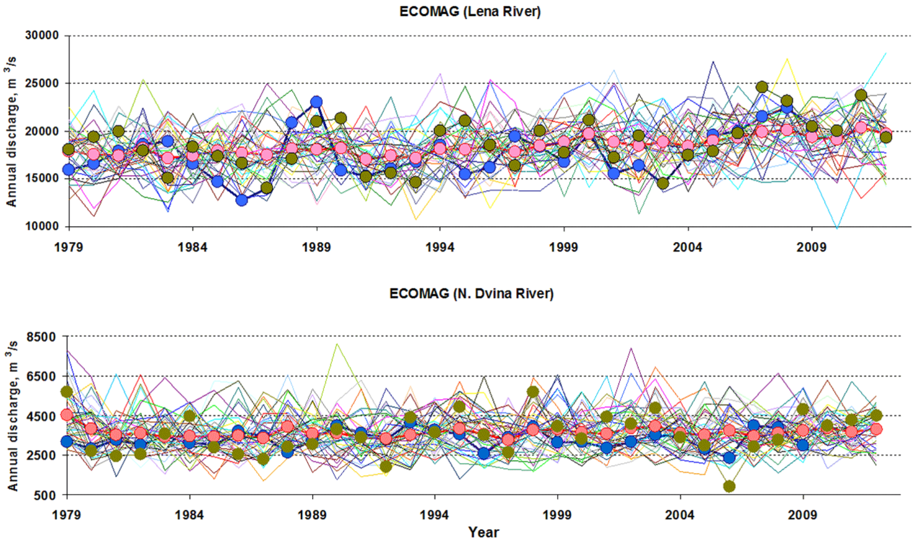

Figure 11. Observed (line with blue markers) and simulated series of annual discharges. Thin lines show ensemble (45 realizations) of the calculated annual discharges, the line with red markers shows the ensemble mean and the line with green markers shows the realization most strongly correlated with the observed time series.

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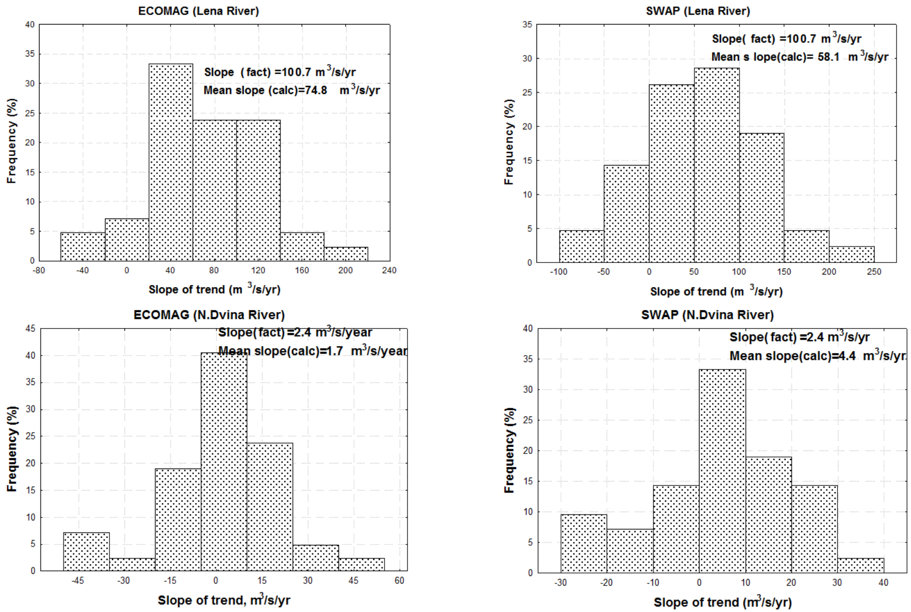

Figure 12. Histograms of the linear trend slope derived from the ensembles of simulated annual discharge time series.

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