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WATER RESOURCES AND THE REGIME OF WATER BODIES

Statistical Modeling of the Global River Runoff Using GCMs: Comparison with the Observational Data and Reanalysis Results

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Abstract—Specific methods are proposed to assimilate the results of the "historical" experiments on 28 climate models. The results of the analysis confirm the hypothesis regarding a stationary character of changes in the global river runoff during "instrumental" period (approximately 150 years). Part of the models (about one third) reproduces the non-stationary changes in the global runoff with respect to the mean. At the same time, the number of such models indicating increased runoff is exactly equal to the number of models that indicate a decrease in runoff. The models generally reproduce well the coefficient of variation of global river runoff in comparison with the observational data, as well as the small value of the coefficient of asymmetry. The model of the Gaussian white noise is optimal for the description of the majority of the annual time series of global river runoff generated by the GCMs.

Keywords: river runoff, global change, climate models

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INTRODUCTION

The aim of the work is to study how the existing GCMs reproduce the global mean river runoff and its long-term variations, in comparison with the appropriate observational and reanalysis results. To date, there are many works devoted to the detecting of the so-called "CO_2 signal" within the runoff of specific rivers—see vast references in the set of papers [11], for instance. At the same time, insufficient attention, in our opinion, is given to studying the changes in the runoff during the "instrumental" period (approximately 150 years) on a global scale. It appears that there are no joint investigations of the globally aggregated (or averaged) river runoff involving all three possible methods: the analysis of observational data, reanalysis and "large" models of the climate system, GCMs. It seems that the solution to this kind of task is of paramount importance for the following reasons.

The evaluation of the global runoff and its changes is of theoretical and ideological interest, as linked to the study of the foundations of the water cycle in the nature and the fundamental principles of the evolution of the Earth System.

The greenhouse signal changes in river flow, if it exists, would primarily occur within globally summarized runoff, the regional changes in the runoff being masked by local factors of different nature.

Estimations of globally averaged runoff using each of two other approaches—observations and calculations of "climatological" runoff using reanalysis—can have considerable errors. Data on the global runoff obtained using GCMs could give additional information to discuss the formulated problems.

In the previous studies of the authors, a hypothesis was proposed that the errors of estimating runoff using indirect methods (reanalysis, climate models) should decrease when you increase the characteristic area of watersheds under consideration. Estimations of the global runoff using GCMs can give additional information on this subject.

In general, the state of the issue is described in a recent monograph of one of the authors [5]. In many ways, the vision of the author of the problem coincides also with the findings of D. Kutsojannis [7].

EXPERIMENTS ON GCMS AND METHODS OF TIME SERIES ANALYSIS

"Historical" experiments on the following GCMs were used in the present study: CanESM2, CCSM4, CESM1-BGC, CESM1-CAM5, CESM1-FAST-CHEM, CESM1-WACCM, CMCC-CESM, CMCC-CM, CMCC-CMS, CNRM-CMS, CNRM-CM5-2, CSIRO-Mk3.6.0, CSIRO-Mk3L.1.2, FGOALS-g2, FIO-ESM, GFDL-CM2.1, GFDL-CM3, GFDL-ESM2G, GFDL-ESM2M, GISS-E2-H, GISS-E2-H-CC, GISS-E2-R, GISS-E2-R-CC, INM-CM4, IPSL-CM5B-LR, MIROC4h, MIROC5, MIROC-ESM-CHEM, MRI-CGCM3, MRI-ESM1, NorESM1-ME. Further analysis revealed that two models, CMCC-CESM and IPSL-CM5B-LR do not reproduce any real magnitude of the runoff. Also, the MIROC4h model was excluded, since the duration of the "historical" experiment on this model was only 56 years, and the results were not comparable with the results obtained on other models. Finally, we operate only with 28 models.

Annual values of the model runoff were calculated using mean monthly runoff values taken from PCMDI website [9]. Since each model has its own spatial resolution and the models use different computational grids ("gaussian," "lonlat" and "curvilinear"), the following procedure was implemented. The map of the land surface was converted into a grid nodes mask with 0.25° × 0.25° resolution, and the results of numerical simulations were interpolated on the same grid. The data about model grids are stored in NetCDF format files, and the interpolation and sampling of data, as well as summarizing the runoff, were conducted using CDO package [1].

The runoff time series were analyzed using a new system of statistical and stochastic estimations proposed by Dobrovolski in [3–5]. The system is based on the theory of stationary random functions (see, for instance, [13, 14]). A new method of recalculating time series into series of sample values of Gaussian random numbers was proposed. In addition, a new economical method of obtaining the Gaussian pseudo-random values was introduced. For this purpose, we used a concept of a "mirror-symmetry" doubling of the generating algorithm. The resulting pseudo-random values possess much better statistical properties in comparison with the random values generated by previous methods: the errors in the mean values and in the standards are less than 0.000001, the coefficient of asymmetry (skewness) is equal to 0.000391, and the excess about the normal is only –0.098242.

On this basis, new formulas for estimating standard deviations and autocorrelation coefficients were introduced. In addition, a new method for calculating the orders of the autoregression models (related to the Maximum Entropy Method—see [12]) was developed, as well as new two-sided criteria of the applicability of a zero-hypothesis on the process stationarity with respect to, separately, mathematical expectation, autocorrelations, and standard deviations. Using these criteria, indexes of stationarity/non-stationarity of the segments of time series were introduced: I_{SM}, I_{SS}, and I_{SR}, respectively. In the stationary cases, these indexes are normally distributed, with zero mean and unit standard deviation.

MAIN RESULTS OF THE GLOBAL RIVER RUNOFF SIMULATION

The basic results of modeling the series of the average annual values of the global runoff, obtained on 28 GCMs, are shown in Table 1. Analysis of these results—the "statistics" statistics," is shown in Table 2.

First, one should pay attention to the relative homogeneity of the time ranges for which the calculations were held. Overall, the study describes the events during slightly more than one and a half centuries: since the mid-19th century until the early 21st century. The main interest of our work is the assessment of global mean long-term runoff: the 4th column in Table 1 and the 4th row in Table 2. The estimates of the mean runoff vary from 0.448 to 0.882 mm/day with a mean value of 0.669 mm/day. Appropriate coefficient of variation is thus 0.179. This relatively large value, however, is almost 2 times smaller than the GCM values of the mean annual river runoff C_V for the major rivers of the Russian Federation, 0.34 (see [5], p. 305).

It is important to compare the global mean river runoff obtained on climate models with estimates of this parameter, formed on the basis of observations and on the basis of atmospheric reanalysis data (so-called "climatic runoff")—see Fig. 1.

Figure 2 shows time series of the global annual average runoff obtained on 28 models, including a shorter series for model MIROC4h. On the same graph estimations of the average global runoff obtained in other ways are shown: using instrumental observations of the runoff (line 1, corresponding to the value of 0.863 mm/day) and using the results of reanalysis projects "20Century" (0.786, line 2) and "NCEP/NCAR" (0.456, line 3). The above three values are from [5], p. 20.

It is obvious that the set of modeled series overlap all three alternative estimations of the global mean runoff, with a considerable range of modeled values (though, as shown above, this diapason is less than the range of the GCM runoff estimations for specific river basins). It should be borne in mind that the estimations obtained by each of the four methods may have significant errors. The source of the errors in "observational" global value is related to the fact that for most part of rivers emptying into the oceans (including the Amazon), long observations of the runoff near the mouth are not available. In addition, the errors arise from the instrumental errors, natural variability of the runoff, and differences in the periods of observations, etc.

In turn, the reanalysis errors arise from the rare, in many regions, observational network, especially over the ocean. In addition, an important source of errors in estimating the components of the global water cycle is related to the unbalanced vertical heat and moisture fluxes through the surface of the ocean and the so-called model drift.

In fact, the reanalysis results and climate models are seemingly calibrated using some a priori considerations or previous results like the classic edition [8]. There is a suspicion that a group of "20Century"

Table 1. Basic parameters of the annual global river runoff time series obtained on GCMs. Here and in Table 2, N is the series' length in years; Year is the first year of the series; Mean is the estimation of the mathematical expectation of the global mean river runoff in mm/year; C_V is the coefficient of variation; C_S is the coefficient of skewness; R_{1G} is the normalized value of the autocorrelation function for shift one year calculated on a number of sample values converted to Gaussian random variables; M_G is the order of stochastic (AR) model based on the time series recalculated into the sample values of the Gaussian random numbers: I_{SM} is the index of stationarity with respect to mathematical expectation; I_{SS} is the same for mean deviations ("standards"); N_{SEGM} is the number of 40-year long segments with index I_{SM} beyond 95% probability

Models	N	Year	Mean	C_V	C_S	R_{1G}	M_G	I_{SM}	I_{SS}	N_{SEGM}
CANESM2	156	1850	0.593	0.0356	0.0625	0.189	0	2.919	0.035	0
CCSM4	156	1850	0.75	0.0336	–0.129	0.234	0	1.415	–0.295	0
CESM1-BGC	156	1850	0.741	0.034	–0.382	0.277	0	2.134	0.875	0
CESM1-CAM5	156	1850	0.697	0.039	–0.131	0.361	6	–4.819	0.322	1
CESM1-FASTCHEM	156	1850	0.742	0.03	–0.105	0.149	0	2.338	–0.804	0
CESM1-WACCM	156	1850	0.681	0.037	0.088	0.168	0	1.373	1.73	2
CMCC-CM	156	1850	0.501	0.030	–0.137	0.131	0	0.195	0.735	0
CMCC-CM5	156	1850	0.511	0.036	0.12	–0.056	0	–0.534	–0.156	0
CNRM-CMS-2	156	1850	0.693	0.024	–0.06	0.237	0	0.86	0.974	2
CNRM-CMS	156	1850	0.685	0.023	–0.022	0.043	0	–0.916	1.018	0
CSIRO-Mk3-6-0	156	1850	0.706	0.05	0.074	0.303	0	–1.79	0.407	0
CSIRO-Mk3L-1-2	155	1851	0.605	0.034	–0.137	0.054	0	–0.891	0.249	0
FGOALS-g2	157	1850	0.798	0.0208	0.38	0.167	0	1.432	–0.07	0
FIO-ISM	156	1850	0.747	0.035	0.235	0.106	0	2.762	–0.054	0
GFDL=CM2p1	145	1861	0.81	0.062	–0.074	0.274	0	2.337	0.023	0
GFDL-CM3	146	1860	0.59	0.029	–0.312	0.429	1	–5.802	–0.236	1
GFDL-ESM2G	145	1861	0.763	0.034	–0.348	0.323	2	–1.455	–0.87	0
GFDL-ESM2M	145	1861	0.718	0.055	0.025	0.273	0	1.502	0.59	0
GISS-E2-H	156	1850	0.505	0.026	–0.209	0.14	0	–1.308	1.308	0
GISS-E2-H-CC	161	1850	0.505	0.027	0.074	–0.04	0	–0.764	–0.353	0
GISS-E2-R	156	1850	0.449	0.026	–0.408	0.135	0	–3.315	–0.994	5
GISS-E2-R-CC	161	1850	0.448	0.025	0.198	0.275	0	–3.383	–0.228	2
inmcm4	156	1850	0.652	0.031	–0.011	0.216	0	3.198	–0.159	0
MIROC5	163	1850	0.8819	0.0345	–0.0431	0.348	3	–0.75	0.0003	0
MIROC-ESM-CHEM	156	1850	0.604	0.029	0.29	0.391	1	2.81	1.701	0
MRI-CGCM3	156	1850	0.796	0.024	0.255	0.09	0	0.876	–1.899	0
MRI-ESM1	155	1851	0.8	0.031	–0.235	0.111	0	0.558	–0.538	0
NorESMI-ME	156	1850	0.768	0.032	0.174	0.074	0	–0.531	0.202	0

Table 2. "Statistics' statistics" of runoff time series generated on GCMs

	Average	Minimum	Maximum	Standard	C_S
Year	1851.607	1850.000	1861.000	3.813614	2.14698
N	155.036	145.000	163.000	4.467845	–1.25972
Mean, mm	0.669	0.448	0.882	0.119770	–0.41964
C_V	0.033	0.021	0.062	0.009347	1.63724
C_S	–0.027	–0.408	0.380	0.207137	–0.03819
R_{1G}	0.193	–0.056	0.429	0.124347	–0.07247
M_G	0.464	0.000	6.000	1.290482	3.48117
I_{SM}	0.016	–5.802	3.198	2.353055	–0.77748
I_{SS}	0.125	–1.899	1.730	0.812696	–0.02401
N_{SEGM}	0.464	0.000	5.000	1.104943	3.02416

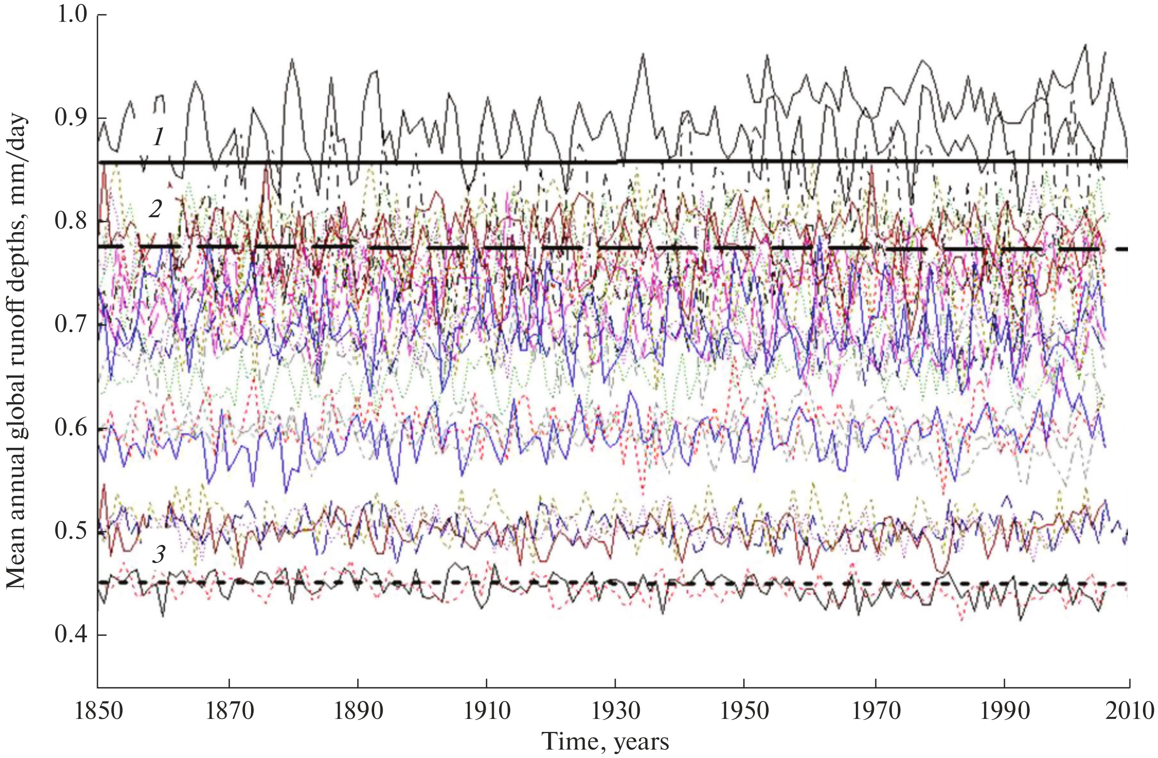

Fig. 1. Realizations of changes in average global annual runoff depths obtained on 28 climate models (plus on MIROC4h model). Horizontal lines—estimations derived from observation data (*1*), according to a reanalysis projects “20Century” (*2*), NCEP/NCAR (*3*): see [5], p. 20.

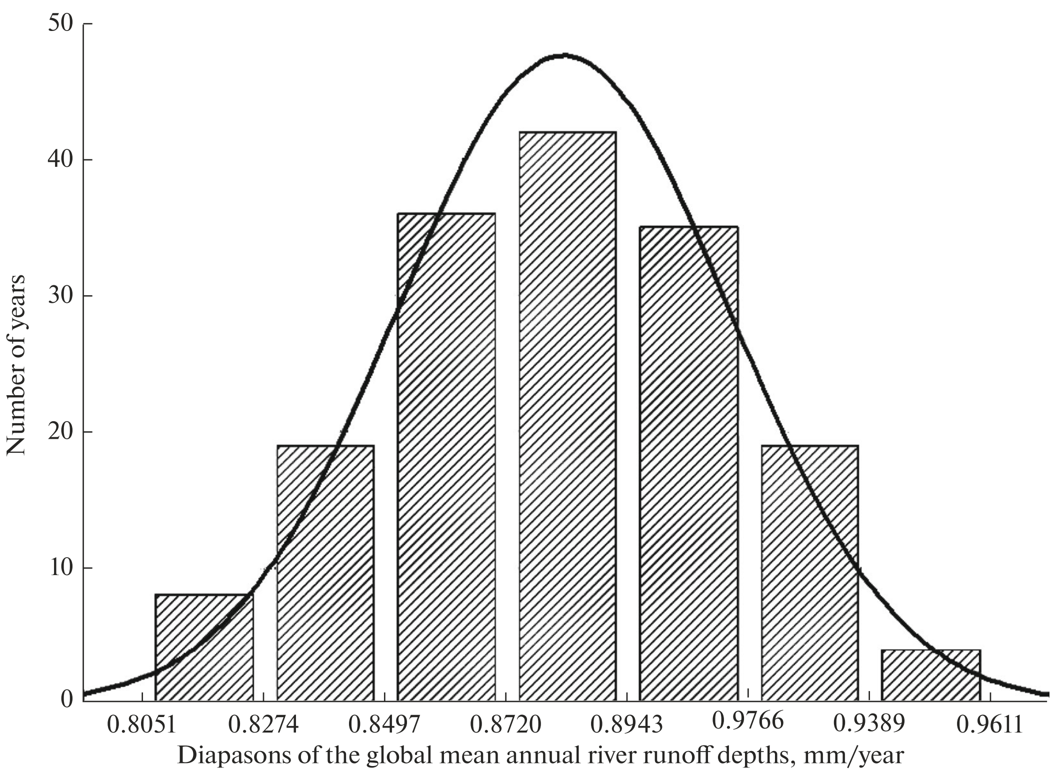

Fig. 2. Histogram of average annual values of global river runoff (in runoff depths, mm/day) obtained on the model MIROC5. Smooth curve corresponds to the theoretical normal distribution.

reanalysis calibrated model parameters so that the average ocean surface evaporation exactly coincides with the 45-year-old assessment of [8]: evidently, the coincidence of the two values with accuracy up to the fourth significant digit (3.836 and 3.837) is impossible. It is obvious that the evaporation from the surface of the ocean is the governing parameter for the whole chain of the global water cycle, and the inevitable big mistakes in assessing global evaporation entail inevitable uncertainty over the river runoff.

However, it is known that both the model and reanalysis results better reproduce the variability of water fluxes, including river flow, than the mean values. The reason for this is that the climate models and atmospheric models participating in the reanalysis originally came from models constructed for the description of the synoptic variability in the atmosphere (which is a primary source of multi-year fluctuations) and did it relatively well. At the same time, the mean values of flows depend on a delicate balance on the ocean–atmosphere and land–atmosphere interfaces, because it is extremely difficult to catch a small difference between the more significant members of the water balance equations (the precipitation and evapotranspiration).

In general, the study of the variability of global runoff series obtained on climate models may confirm the important regularities studied using alternative approaches. So, the coefficient of variation of the average annual runoff for 28 models is 0.033. This value is only 0.001 less than the analogous number obtained on observational data on the global river runoff ([5], p. 132). This gives us hope that the skewness according to 28 models is close to the real, extremely small value of –0.027; a similar observational value is also low: –0.144. As an example, the low asymmetry of the simulated series of the global runoff is illustrated by the probability density histogram in Fig. 2. Here, the annual values of the runoff were derived from the model, giving the closest to observed mean value—the Japanese MIROC5 model. It is obvious that the probability density almost perfectly matches the Gaussian distribution. Thus, we are dealing here with a perfect example of the Central Limit Theorem (Chebyshev theorems) in action.

Thus, the model experiments confirm the pattern of the decrease in the coefficient of variation and the skewness coefficient with the growth of the watershed area. Figure 2 illustrates this pattern in its extreme form, the watershed being almost the entire global land surface.

THE STATIONARITY OF THE GLOBAL RIVER RUNOFF

The stationarity of the global river runoff series generated by climate models (the 9th column in Table 1 and the 9th line in Table 2) is of great interest. The average value of the "stationarity index," I_{SM} (see [4, 5] about this index) is extremely close to zero: 0.016. Moreover, the average values of I_{SM} over the past 75 years (which are characterized by intense emissions of greenhouse gases) have not changed significantly compared to the period from the mid-19th century until the 1920s, when the emissions of greenhouse gases were orders of magnitude less. These results are consistent with the results of the analysis of the reconstructed global runoff series based on observational data [2, 5, 8]. In each of these three variants of series, the I_{SM} index values are fully consistent with the idea of stationarity of the global runoff.

Another, more simple way to assess the possibility of the presence in the modeled series of a monotonous deterministic component is to fit a linear approximation to the series. It was done for each of the 28 series using spatially weighted least-squares method; the results were as follows. Exactly half of the slopes of the approximating line was positive, and another half of the slopes was negative. The average slope corresponds to the average annual increment of 0.0000172 mm/day. Being calculated for the overall period of 155 years, this gives a very small value: 0.0027 mm/day, which is 2.5 orders of magnitude smaller than the average global runoff.

The problem of stationarity of the I_{SM} index for individual models is more complicated. I_{SM} standard deviation is equal to 2.353. Thus, more than one third of global runoff series demonstrates a nonstationary behavior with respect to the mathematical expectation (Fig. 3). This issue requires further study. As we know, climate models do not reproduce the real chronological changes in the runoff of specific rivers [6]. At best, especially in the case of stationary changes, they may describe fluctuations' statistics—however, the above results show that only 2/3 of the simulated time series can be used for this purpose.

Figure 4 shows a histogram of probability density of the index of stationarity with respect to standard deviations, I_{SS} and approximating probability density of normal distribution (1). The dashed curve (2) denotes the probability density function for absolutely stationary, as for standard deviations, process. It is obvious that the curve *2* incomparably better corresponds to the simulated series, than in the case of index on average values (Fig. 3); the small deviations from the stationary distribution of the I_{SS} index can be attributed to the small sample size—only 28 cases.

A study of the possible non-stationarity of the generated global runoff series at smaller time scales was conducted as well. For this purpose, each of the 28 series was divided into 20-year-long segments. Then the I_{SM} and I_{SS} values for each segment were compared with those for adjacent segments. Thus, each series generally contains six such segments, and the total number of segments amounted to 168. The result of calculations was as follows. All in all, 13 pairs of segments with more than 95% probability of non-

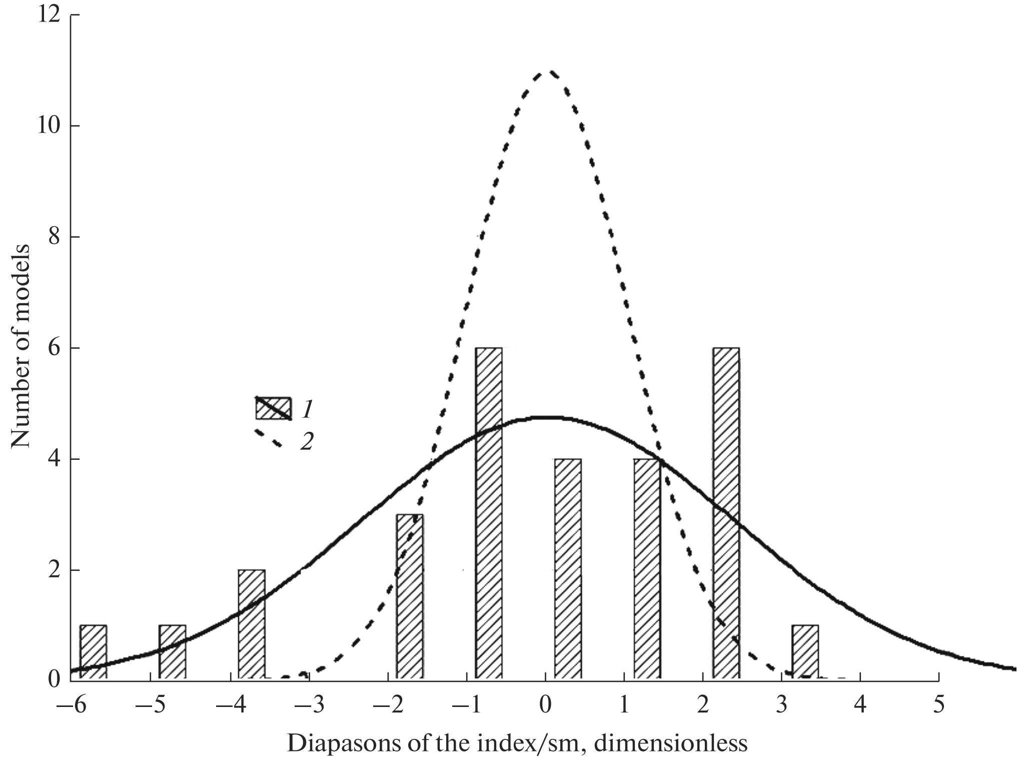

Fig. 3. Probability density histogram of the I_{SM} index. (*1*) Gaussian distribution approximating the histogram; (*2*) probability density function for stationary process.

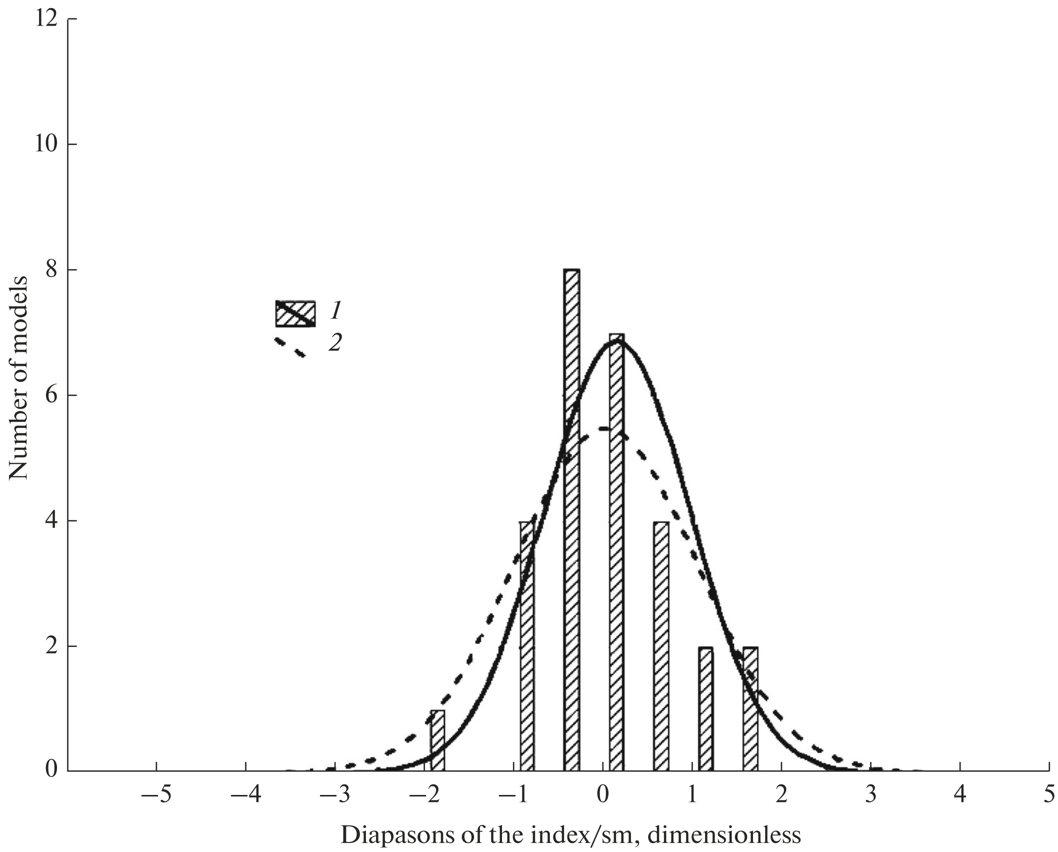

Fig. 4. Probability density histogram of the index I_{SS} (columns) and approximating Gaussian distribution (*1*); probability density function for stationary, as for standard deviations, process (*2*).

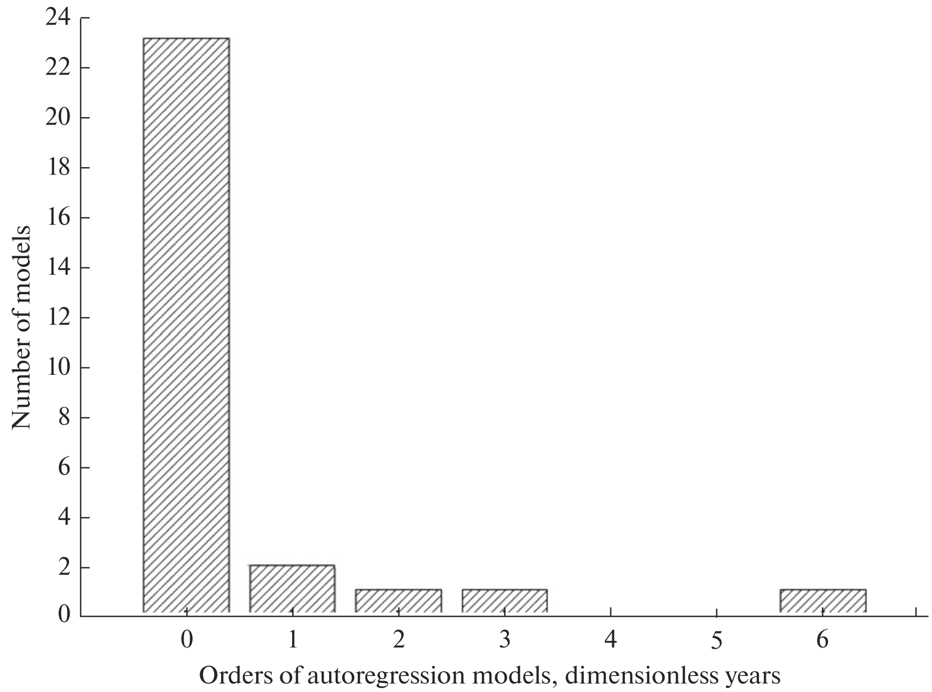

Fig. 5. Histogram of orders *M* of autoregressive models, fitted to the global river runoff series obtained on GCMs.

stationarity were detected (the last column in Table 1). Thus, the percentage of non-stationary pairs is 7.7%, which is close to the theoretical 5% for stationary series. The difference, 2.7% can be explained by the sample variability of estimations. So, a phenomenon of the short-term, "intermittent" non-stationarity (see [10]) is not detected within the modeled series.

STOCHASTIC MODELS OF CHANGES IN THE GENERATED GLOBAL RIVER RUNOFF

Figure 5 shows a histogram of the orders M of autoregressive models, fitted to the global river runoff series obtained on 28 GCMs (the techniques of such fitting are described in [3, 4]). The absolute predominance of the zero-order models is evident; sporadic models of other orders can probably be explained by the sample variability of estimates. If we adopt a normal distribution of the annual generated runoff values, (see above remarks about the extremely small asymmetry in Table 1), it can be said that the basic model for the description of long-term changes in global river runoff, according to climate models, is Gaussian white noise.

CONCLUSIONS

The results of the work can be summarized as follows.

(1) The time series of the global mean annual river runoff, obtained on existing GCMs do not demonstrate a monotonous signal, like CO_2, during about 150 recent years.

(2) About 1/3 of the models generate nonstationary, with respect to the mathematical expectation, global runoff series. However, the number of positive monotonous trends in these series is equal to the number of series with negative trends.

(3) The phenomenon of the "intermittent non-stationarity" in I_{SM} index was not found within the series.

(4) The non-stationarity of both types, with respect to the standard deviation and the autocorrelations, was not found either.

(5) Long-term mean values of the global runoff considerably differ from one model to another, and between GCMs, reanalysis and observations. However, the standard deviation of this parameter is less than that in the case of GCM's modeling of runoff within specific river basins.

(6) The coefficient of variation and the coefficient of skewness of the annual global river runoff are well described by GCMs.

(7) The global river runoff series obtained on GCMs, as well as those obtained using reanalysis and direct observations, are well described by the Gaussian white noise model. Thus, we deal here with an impressing example of the Central Limit Theorem (Chebyshev theorems) in action.

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