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Parameter Optimization for Simulating Runoff from Highlatitude River Basins Using Land Surface Model and Global Data Sets

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1. Introduction

Currently, high latitude regions characterized by a long and severe cold season are receiving more and more attention from the hydrometeorological modelling community (Bowling et al., 2000; Slater et al., 2001; Bowling et al., 2003; Nijssen et al., 2003; Etchevers et al., 2004; Su et al., 2005; Tian et al., 2007; etc.) because these regions are among the most sensitive to natural and anthropogenic effects and it is necessary to predict the consequences of such effects. At the same time, northern regions are poorly covered with measurements, which are necessary to provide the atmospheric forcing data and to estimate the land surface parameters for model simulations. One of the possible ways to provide a model with input data is to apply, along with existing measurements, available global datasets, which contain meteorological data, land-use information, and soil and vegetation characteristics.

Nowadays there are a lot of global data sets, which differ in spatial and temporal resolution, as well as in accuracy and reliability (e.g., Meeson et al., 1995; Hall et al., 2003; Zhao & Dirmeyer, 2003). Differences in global datasets are connected with uneven coverage of the land surface with ground-based observation systems, difficulties in collecting measurements, the problems with instruments, differences in procedures of filling in the missing data and interpolation of point measurements into grid boxes (Zhao & Dirmeyer, 2003). Nevertheless, this source of information is quite attractive for modellers (as it saves them from a quite difficult time- and labour-consuming procedure of model input data preparation) and global datasets are widely used for atmospheric and hydrological applications (e.g., Oki et al., 1999; Nijssen et al., 2001; Su et al., 2005).

However, the accuracy of most streamflow hydrograph simulations in high latitudes is not high, in spite of a good model structure and calibration of a number of model parameters against measured river runoff from the whole basin under study or from its sub-basins or small catchments, located within the basin. This raises a question: where can one find the potentialities to improve the agreement between observed and simulated streamflow hydrographs? We believe that one of such potentialities is to introduce adjustment factors for the most influencing atmospheric forcing data, along with the land surface characteristics, into a set of calibrated parameters.

As a matter of fact, according to the logic of construction and operation of hydrological and land surface models, both the land surface parameters and forcing data represent input

information, which can suffer from errors and uncertainties. If the forcing data are based on reanalysis products, they contain systematic errors (which reflect the biases and errors in the underlying general circulation models), resulting in errors in simulated heat and water balance components (Zhao & Dirmeyer, 2003; Nasonova et al., 2008). If the forcing data are derived from in situ measurements, their accuracy depends on density and representativity of meteorological stations, and interpolation techniques used to obtain gridded data. In this case, the accuracy of forcing data can be rather low due to low accuracy of precipitation (especially snowfall) measurements, insufficient gauge density, and absence of incoming radiation observations. This is a typical situation of the northern regions.

One of the ways to improve measured precipitation is an application of different correction factors (the major of which is wind correction) to measured precipitation. However, this is not a trivial way. Wind corrections can be estimated by means of different regression equations for different types of precipitation (solid, liquid, and mixed) and gauges using observed wind speed and air temperature (Goodison et al., 1998; Yang & Ohata, 2001). These equations allow one to take into account wind-induced undercatch of precipitation and provide estimates of wind correction factor of positive sign. The equations are recommended for wind speeds lower than 6.5 m s^{-1} at the gauge height, and in the absence of blizzards (Goodison et al., 1998). At the same time it is known that in Arctic and sub-Arctic climates, snowfalls typically occur under strong winds and blizzard conditions. A number of investigations of measurement techniques for solid and mixed precipitation in pan-Arctic regions have shown that in windy conditions with snow on the ground, blowing snow from the ground enters the gauges causing "false" precipitation (Bryazgin & Dement'ev, 1996; Bogdanova et al., 2002a,b). Annual "false" precipitation in some pan-Arctic regions can reach 30-40% of the measured annual totals. Evidently, that in this case, "overcatch" of snowfall takes place rather than "undercatch", and the wind correction factor should be negative. Bogdanova et al. (2002 a,b) suggests a bias-correction model for the Tretyakov gauge allowing an estimation of the amount of false snow, which depends not only on air temperature and wind speed, but also on the state of snow cover surface (fresh snow, old snow, snow compressed by wind etc.), weather conditions (blizzard, blowing snow), duration of blizzard, the degree to which the gauges are sheltered from surroundings and so on. The main difficulties associated with application of this model we see in a large amount of input data required, some of which may be inaccessible, particularly, characteristics of the blizzard condition and the state of the snow cover surface.

One more source of uncertainties in forcing data is associated with a 'point' character of measurements of meteorological variables, when their spatial distribution is needed. Generally, point measurements are distributed in space over the catchment by interpolation techniques. In the case of sparse observational network, inadequate gauge density may provide unrepresentative interpolated estimates of meteorological variables (especially precipitation). This also contributes to errors in runoff simulations.

As to incoming fluxes of shortwave and longwave radiation, they are not measured at regular networks and their values are estimated using, in particular, standard meteorological observations. Such estimates are not free from uncertainties. Uncertainties in the estimates of shortwave radiation are mainly caused by the necessity to take into account cloudiness. For this purpose empirical formulae are used. These formulae, firstly, are not universal and, secondly, need information both on the amount and the type of clouds. The data on the clouds' type are often inaccessible; the information on the amount of clouds is not very accurate because of visual character of observations. For calculating incoming

longwave radiation, a lot of empirical formulae have been developed. However, as a rule, they were derived under milder climate conditions (compared to Arctic and sub-Arctic climate) and their application to the regions with a severe climate results in strong biases (Gusev et al., 2006a). At the same time the sensitivity of snowmelt-driven streamflow to incoming longwave radiation is rather high, because this radiation greatly influences the rate of snow processes.

One of the ways to solve the problem of uncertainties in the major forcing data is calibration of these data within the accuracy of their measurement or estimation. It should be noted that the idea of calibration of the main forcings is not novel. Calibration of precipitation and potential evapotranspiration (representing the forcing data for some hydrological models) was performed in Gan et al. (2006) for SAC-SMA model. Xia (2007) has shown that in the cold regions in the Northeast United States, where measured precipitation has large systematic biases, calibration of a land surface model using observed annual streamflow can be successful, if model parameters and precipitation biases are calibrated simultaneously. It is reasonable to expect that this statement will be also valid for other cold regions.

The aim of the present study is to reveal to what extent optimization (within reasonable bounds) of the most important land surface parameters and adjustment factors for atmospheric forcings can improve simulating river runoff in high latitudes by a physically based land surface model (LSM) SWAP (Soil Water – Atmosphere – Plants).

2. Methodology

2.1 Model SWAP

The land surface model SWAP represents a physically based model describing the processes of heat and water exchange within a soil–vegetation/snow cover–atmosphere system (SVAS). Different versions of SWAP were detailed in a number of publications (e.g. Gusev & Nasonova 1998, 2002, 2003, 2004a; Gusev et al. 2006b). The last version of SWAP treats the following processes: interception of liquid and solid precipitation by vegetation; evaporation, melting and freezing of intercepted precipitation, including refreezing of melt water; formation of snow cover at the forest floor and at the open site during the cold season; partitioning of non-intercepted precipitation or water yield of snow cover between surface runoff and infiltration into a soil; formation of the water balance of aeration zone including transpiration, soil evaporation, water exchange with underneath layers and dynamics of soil water storage; water table dynamics; formation of the heat balance and thermal regime of SVAS; soil freezing and thawing.

The model can be applied both for point (or grid box) simulations of vertical fluxes and state variables of SVAS in atmospheric science applications (Gusev & Nasonova, 1998, 2004; Gusev et al., 2004) and for simulating streamflow at different scales — from small catchments to continental-scale river basins located in different natural conditions (Gusev & Nasonova, 2000, 2002, 2003; Boone et al., 2004; Gusev et al., 2006a). In the case of a small river basin (up to the order of 10^3–10^4 km^2), a kinematic wave equation is used to simulate runoff at the basin outlet. In the case of a larger river basin, the basin area is divided into a number of computational grid boxes connected by a river network. Runoff is modelled for each grid box and then transformed by a river routing model to simulate streamflow at the river basin outlet (with accounting for a contributing area of each box). Such a transformation may be performed by different ways. Herein, a simple linear transfer model in river channels to simulate river discharge is used (Oki et al., 1999).

The basic equation for this model is the conservation equation of the water storage in a river channel of each computational grid box, which can be written as

$$\frac{dS_r}{dt} = Y_{in} - Y_{out} \tag{1}$$

where S_r is the water storage in a river channel located within a grid box, Y_{in} is the sum of runoff, generated within a grid box, and inflow from neighbouring grid boxes, Y_{out} is the streamflow at a grid box outlet. The directions of lateral water flow among grid boxes may be determined on the basis of Total Runoff Integrating Pathways (TRIP) (Oki & Sud, 1998). The value of Y_{in} is usually assumed to be constant within the computational time step Δt, used for description of runoff transformation in the channel network. Parameterization of Y_{out} is based on the following equation

$$Y_{out} = \frac{u_e}{d_c} S_r \tag{2}$$

where u_e and d_c are the effective velocity and the distance between grid boxes, respectively. Mean global value u_e is approximately 0.35 - 0.36 m s^{-1} (Oki et al., 1999). Via substitution of (2) into (1) and solving the obtained equation, the following recurrence relation that describes water dynamics in the river channel is derived

$$S_r(t_{i+1}) = C_{\Delta t} S_r(t_i) + (1 - C_{\Delta t}) \frac{d_c Y_{in}}{u_e} \quad , \quad C_{\Delta t} = \exp(-\frac{u_e}{d_c} \Delta t) \quad , \quad \Delta t = t_{i+1} - t_i \tag{3}$$

where $S_r(t_i)$ and $S_r(t_{i+1})$ are the water storages in the channel at time steps t_i and t_{i+1}. On the basis of (1-3) and in accordance with the channel network connecting computational boxes and schematized in the form of graph, the dynamics of the water storages in the channel of each grid box, streamflow at the box outlet and river discharge are calculated.

During the last 10 years, different versions of SWAP were validated against observations including characteristics both related to energy balance or thermal regime of SVAS (sensible and latent heat fluxes, ground heat flux, net radiation, upward longwave and shortwave radiation, surface temperature, soil freezing and thawing depths) and related to hydrological cycle or water regime of SVAS (surface and total runoff from a catchment, river discharge, soil water storage in different layers, evapotranspiration, snow evaporation, intercepted precipitation, water table depth, snow density, snow depth and snow water equivalent, water yield of snow cover). The model validations were performed for "point" experimental sites and for catchments and river basins of different areas (from 10^{-1} to 10^5 km^2) on a long-term basis and under different natural conditions (e.g., Gusev & Nasonova 1998, 2000, 2002, 2003, 2004; Gusev et al., 2006a; Boone et al., 2004). The results have demonstrated that SWAP is able to reproduce (without calibration) heat and water exchange processes occurring in SVAS under different natural conditions adequately, provided that input data of high quality are available. In the case of streamflow simulation, the accuracy of modelling can be increased due to optimization of model parameters, which influence runoff to the greatest extent, using streamflow observations. This approach is very effective if measurements required for parameter estimation are absent (Nasonova et al., 2009). This situation is typical of most northern river basins of Russia.

2.2 Study basins and their schematization

Three river basins, located in the northeast of the European part of Russia (Figure 1), were chosen for investigation: the Mezen River basin (area: 78 000 km²), the Pechora River basin (area: 312 000 km²) and the Northern (Severnaya) Dvina River basin (area: 348 000 km²). All three basins represent flat forested planes. Forests (with the predominance of coniferous species) cover nearly 80% of the area of each basin.

Fig. 1. Location of the three river basins

The climate in the study region is characterized by a short (3-4 months) cool summer and long (5–7 months) cold winter with a stable snow cover and soil freezing. There is a permafrost in some areas. Mean air temperature of January ranges across the basins from -13 to -17°C, mean air temperature of July is 14-17°C. Mean annual precipitation varies from 650 to 800 mm over the Mezen and the Northern Dvina basins and from 400 to 600 mm over the Pechora basin. Nearly 30-40% of precipitation falls as snow. Mean annual streamflow is 310, 360 and 400 mm/year, respectively, for the Northern Dvina, Mezen and Pechora Rivers. Streamflow of each river can be mainly characterized as snowmelt (up to 50-80%) and rain driven. Their annual hydrographs have maximum flood peaks in spring (caused by spring snowmelt), low baseflow during winter and summer periods, and relatively small flood peaks in autumn (caused by rainfall, along with low evapotranspiration).

For modelling purposes, the Mezen River basin (from the head of the river down to the Malonisogorskaya gauging station) was represented by ten 1°×1° computational grid boxes in accordance with a global river channel network TRIP (Figure 2). The Pechora River basin (down to the Oksino gauging station) was schematized by 57 (Figure 3) and the Northern Dvina River basin (down to the Ust-Pinega gauging station) by 62 one-degree grid boxes (Figure 4). Such a spatial resolution seems to be insufficient for hydrological applications. However, it may be acceptable, provided that subgrid effects are taken into account in model parameterizations (e.g., in SWAP, spatial heterogeneity of soil hydraulic conductivity at saturation is taken into account (Gusev & Nasonova, 1998)). This is confirmed by the results of participation of SWAP in the international Rhone-aggregation LSM intercomparison project (Rhone-AGG) (Boone et al., 2004). The main goals of the project were to investigate how participating LSMs simulate the water balance components of the Rhone River basin (covering 86 000 km^2 and characterized by a wide variety of natural conditions) compared to observations, and to examine the impact of changing the spatial resolution of the basin schematization on the simulations. For the SWAP model, it was found that differences in the basin-averaged annual runoff and evapotranspiration simulated with spatial resolution 8x8 km and 1°×1° were not more than 3.5 and 1.0%, respectively. This fact allows us to assume that coarse (1-degree) spatial resolution will not lead to significant errors in the simulated runoff from the chosen river basins.

2.3 Atmospheric forcing data

Atmospheric forcing data for the SWAP model represent near-surface meteorology including air temperature and humidity, precipitation, incoming shortwave and longwave radiation, air pressure and wind speed. Here, three versions of atmospheric forcing data were used: (1) global reanalysis dataset, (2) global reanalysis product hybridized with observations, and (3) measurements from meteorological stations located within the basins.

2.3.1 Global datasets

Global atmospheric forcing data were taken from 3-hourly near-surface meteorological datasets with 1-degree spatial resolution produced for the Second Global Wetness Project (GSWP-2) (Dirmeyer et al., 2002; Zhao & Dirmeyer, 2003) for the period from 1 July 1982 to 31 December 1995. The first version of global data used here (hereafter, referred to as "Version-1") is based on pure reanalysis product produced by the National Centres for Environmental Prediction/Department of Energy (NCEP/DOE) (Kanamitsu et al., 2002). As it was above mentioned, any reanalysis product contains systematic errors. One of the possible ways to solve this problem is to combine (hybridize) the 3-hourly reanalysis estimates with global gridded observations. The latter are usually available at lower spatial resolution and cannot be directly used in LSMs. Hybridization of NCEP/DOE reanalysis product with global gridded datasets from observations, presented in the International Satellite Land-Surface Climatology Project (ISLSCP) Initiative II (Hall et al., 2003), was performed for the GSWP-2 project (Zhao & Dirmeyer, 2003). Fully hybridized meteorological data, provided within the framework of GSWP-2 and recommended for baseline simulations, we used as the second version of atmospheric forcing data (hereafter, referred to as "Version-2") (see Zhao & Dirmeyer (2003) for more details).

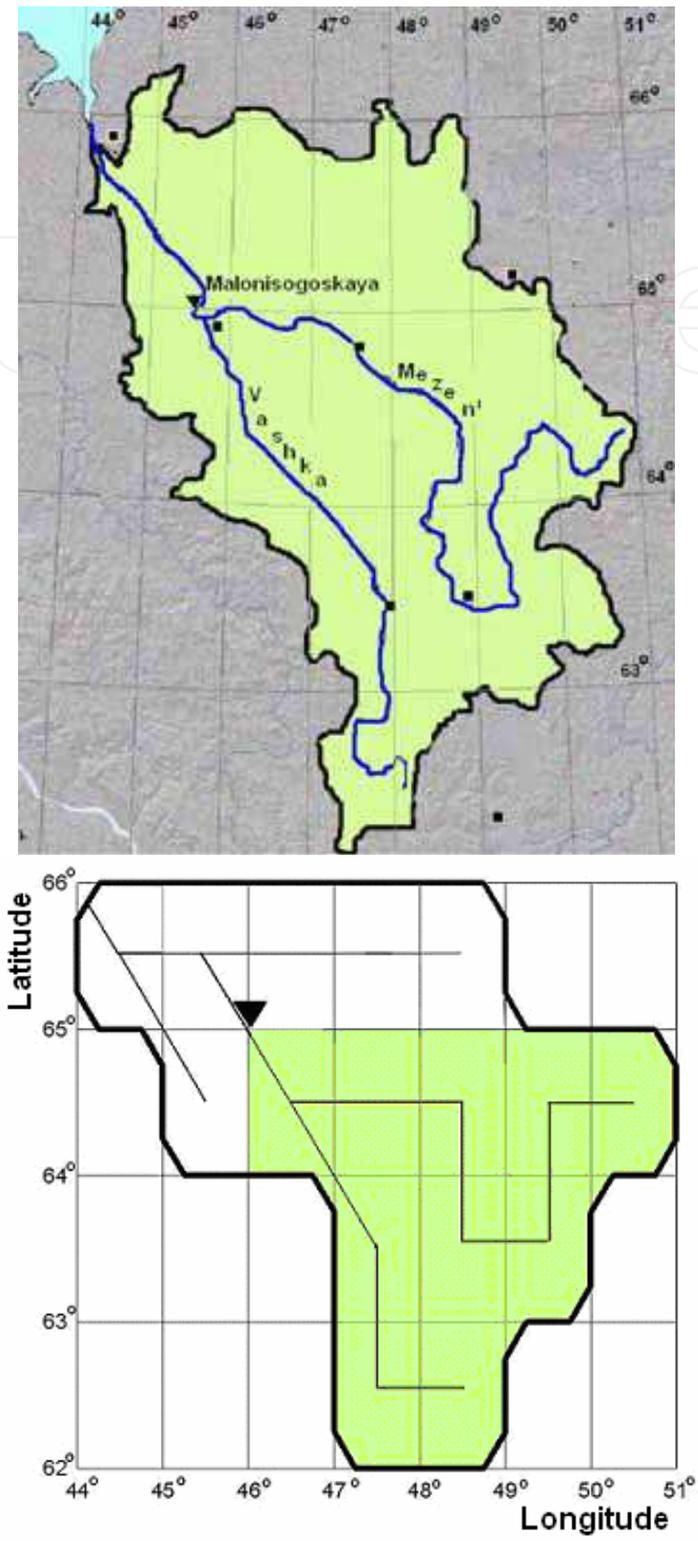

Fig. 2. The Mezen River basin and its schematization for streamflow modelling. Streamflow gauging station location (triangle) and meteorological stations (squares)

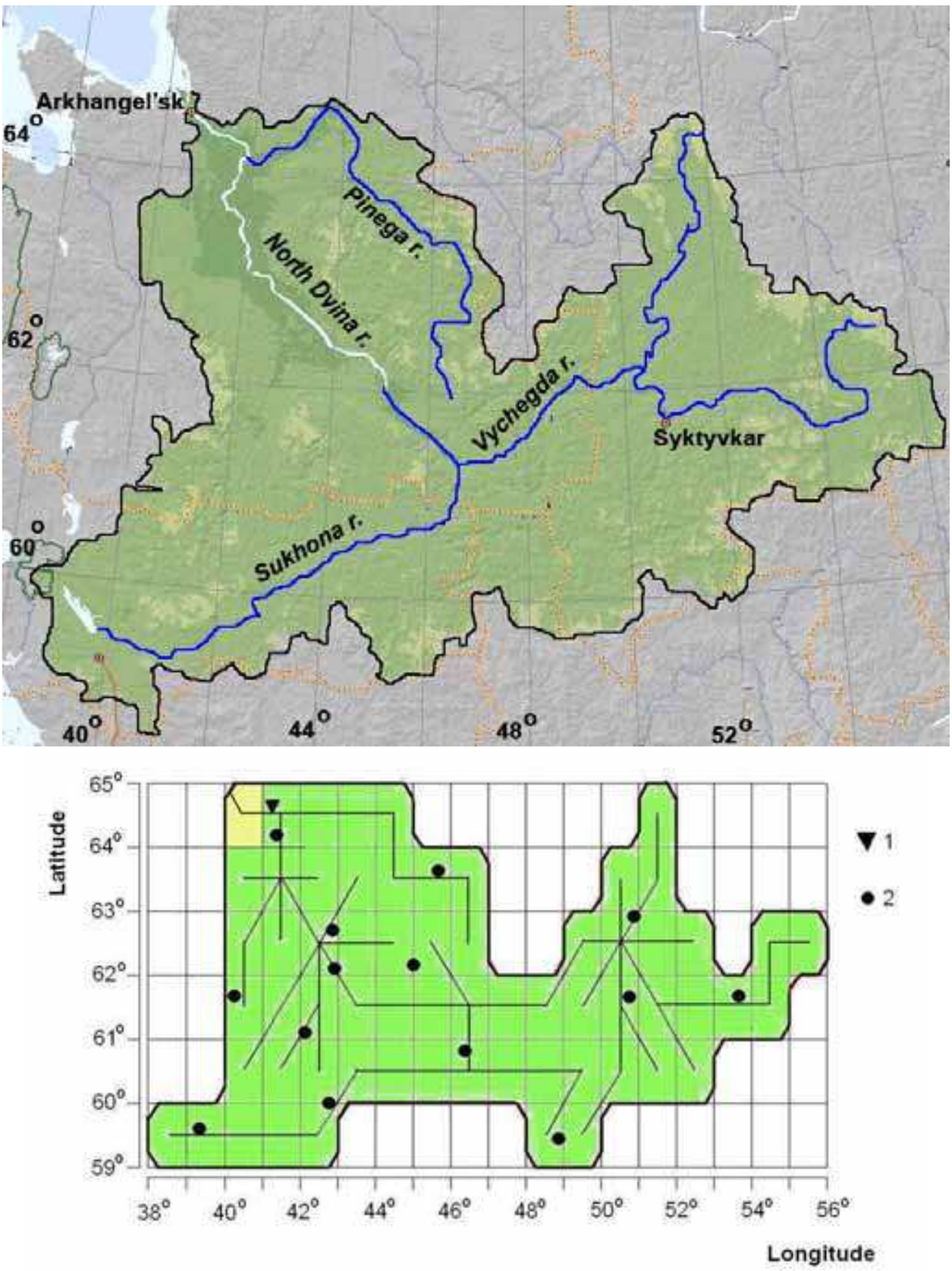

Fig. 3. The Northern Dvina River basin and its schematization for streamflow modelling (1 is streamflow gauging station locations, 2 is meteorological station locations)

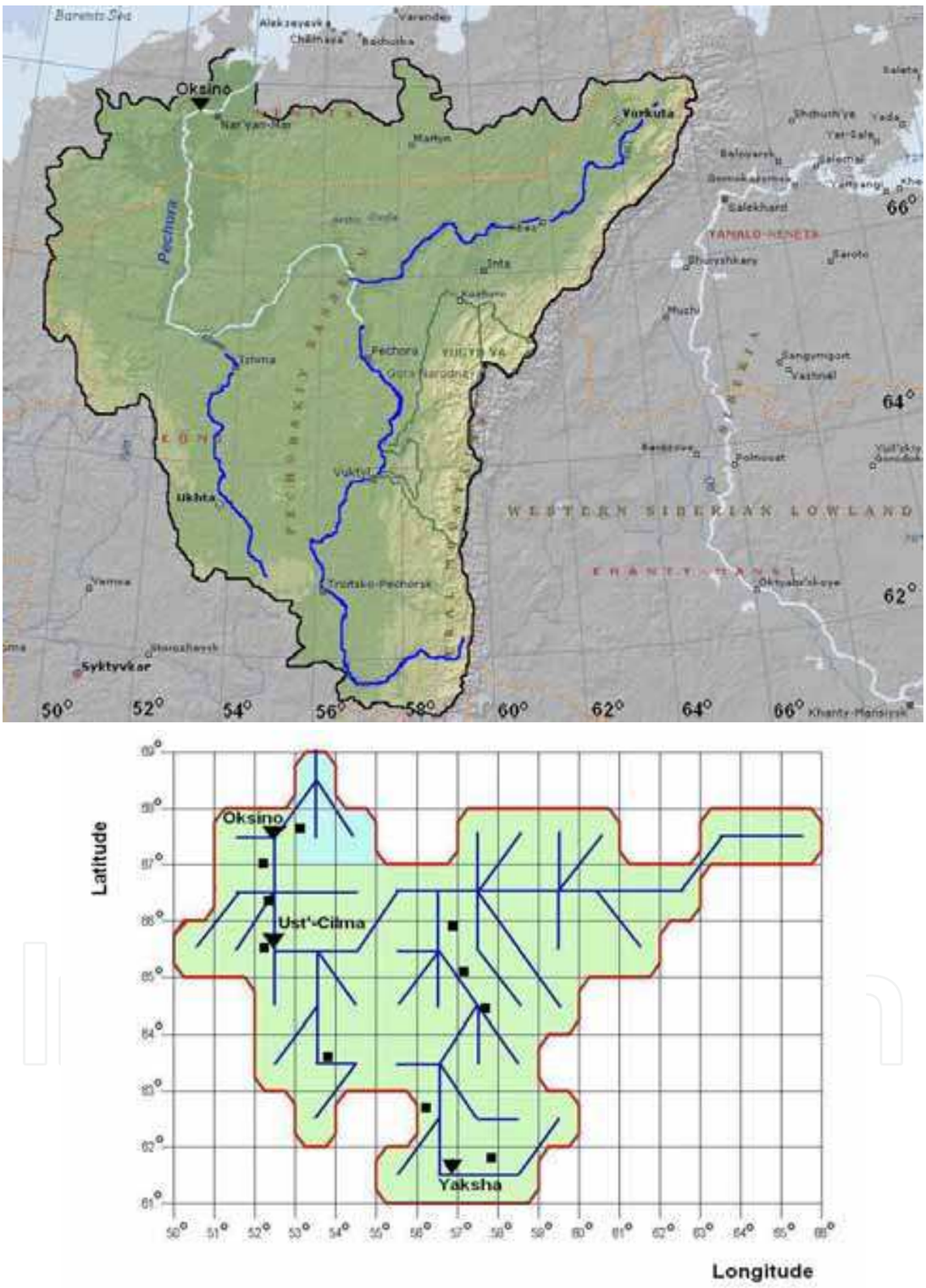

Fig. 4. The Pechora River basin and its schematization for streamflow modelling. Streamflow gauging station locations (triangles) and meteorological stations (squares)

2.3.2 Meteorological observations

Locations of meteorological stations over the basins are shown in Figures 2-4. Meteorological observations are far from perfect, especially snowfall measurements, which can suffer both from positive and negative biases due to overcatch or undercatch of snow by precipitation gauges. At the same time, in high latitudes, where snow is a significant contributor to formation of annual streamflow hydrograph, the accuracy of snowfall measurements is of great importance. Besides that, distribution and density of meteorological stations over the Mezen River and the Pechora River basins cannot be treated as satisfactory. Most of the stations are situated along the rivers and may be not representative for watershed areas. Insufficient density of meteorological observations, their possible non-representativeness, along with the necessity of their spatial interpolation to the computational grid boxes, can lead to uncertainties and biases in forcing data for model simulations. This mostly concerns precipitation due to its complicated stochastic nature resulting in the great problem of estimating area averages from point measurements. Incoming fluxes of shortwave and longwave radiation were not measured at meteorological stations, they were derived from standard meteorological observations using techniques, described in Gusev et al. (2006a).

Interpolation of meteorological observations to the centers of grid boxes was performed using the kriging procedure (Globus, 1987). The classic kriging procedure was slightly modified. Its description can be found in Gusev et al. (2008). The obtained forcing data set will be referred to as "Version-3".

2.4 Land surface parameter datasets

The soil and vegetation parameters were prepared using global one-degree datasets provided within the framework of GSWP-2 (Dirmeyer et al., 2002). Global one-degree vegetation datasets contained information on the land surface types in accordance with the International Global Biosphere Project (IGBP) classification, which includes 17 types of the land surface, and their fractions within each one-degree grid box, as well as time-varying monthly values of biophysical parameters (leaf area index, greenness fraction, roughness length, zero-plane displacement height, snow-free albedo, root depth) for 1982-1995. Global one-degree soil datasets included data on sand, clay, silt and organic matter fractions; texture classes (12 soil texture classes according to the classification of US Department of Agriculture (USDA)); depth of active soil column and soil hydrophysical parameters (porosity, field capacity, wilting point, hydraulic conductivity at saturation, saturated matric potential, B-exponent parameter, soil snow-free albedo) for each grid box. First of all, the values of the soil and vegetation parameters were analyzed and checked for consistency (they must be reasonable and in a good agreement with each other) as it was described in Gusev et al. (2006b). In so doing, some corrections were performed. In addition, several SWAP model specific parameters were derived. As a result, a set of a priori parameters was obtained.

The last group of data represents topographic characteristics including mean elevation of grid boxes, taken from the EROS (Earth Resources Observation Systems) Data Centre (EDC), and the slopes of the surface of each box in the meridianal and latitudinal directions, required for the simulation of runoff transformation within a box. The latter were derived from mean elevations of neighbouring grid boxes.

2.5 Optimization procedure

The goal of a model parameter optimization procedure is to find the values of parameters that minimize an objective function *Ext*, which is a measure of the discrepancy between the model outputs and observations. The objective function is usually expressed as

$$Ext = \frac{1}{\Delta t}\sum_{t=1}^{\Delta t} w_t \left| Cal_t - Obs_t \right|^l \tag{4}$$

where Cal_t and Obs_t are, respectively, the simulated and measured values of output variable (here, daily river runoff *R*), which is used for parameter optimization, at time *t*; Δt is the length of optimization period; *l* is a parameter, equalled to 1 or 2; w_t is the time-varying weight. The values of the two last characteristics depend on the goals of the users. In particular, if correct runoff reproduction is important for each moment of a year, parameters l=2 and w_t=1 are used (these values will be used here). When correct simulation of spring flood hydrograph is of the most importance, the values of w_t must be higher for the spring compared to the rest seasons.

Overview of different methods of finding the minimum of the objective function *Ext* is given in a number of publications (e.g., Törn & Zilinskas, 1989; Pintér, 1996). As it was shown there, when the objective function does not have an analytical expression (as in the present study), application of minimization techniques like a gradient search (Jacobs, 1977) is impossible. In this case, methods of direct search are usually used if *Ext* is a single-extremum function; otherwise, methods of global optimization are applied (Rosenbrock, 1960; Powell, 1964; Nelder & Mead, 1965; Solomatine et al., 1999; Duan, 2003). Many of them are based on the statistical methods of finding the extremum of *Ext* (vector of optimized parameters) (Rastrigin, 1968; Gupta et al., 1998; Solomatine et al., 1999). It should be noted, that the method of blind random search in the parameter space with the pseudo-uniform distribution of points is n-times (where n is the total number of parameters) as effective as the method of search on the deterministic grid (Rastrigin, 1968).

Here, optimization of parameter values was performed using an automatic procedure for two different global optimization algorithms. The first one, based on ideas from Bastidas et.al. (1999) and Solomatine et.al. (1999) and detailed in Gusev et al. (2008), applies a statistical method for direct search of the optimum (or Random Search Technique - RST) of an objective function. The second one is the Shuffled Complex Evolution algorithm (SCE-UA) developed by Duan et al. (1992). The SCE-UA has been found to be robust, effective, and an efficient optimization algorithm (Duan et al., 2003) and it is widely used in hydrological modelling. Two objective functions were calculated during optimization: *Ext*=1-*Eff*, where *Eff* is the Nash–Sutcliffe coefficient of efficiency (Nash & Sutcliffe, 1970), and the relative value of systematic error *Bias* (mean difference between the modelled and observed values of the output variable normalized by the mean observed value):

$$Eff = 1 - \frac{\sum_{\Omega}(x_{sim} - x_{obs})^2}{\sum_{\Omega}(x_{obs} - \bar{x}_{obs})^2} \tag{5}$$

$$Bias = \frac{\sum_{\Omega}(x_{sim} - x_{obs})}{\sum_{\Omega} x_{obs}} \cdot 100\ \% \tag{6}$$

where x_{sim} and x_{obs} are simulated and observed values of a variable x and Ω is a discrete sample set of variable x.

Application of *Bias* along with *Eff* was motivated by the fact that maximum values of *Eff* do not guarantee low *Bias*. This becomes clear if *Eff* is expressed in the terms of root-mean-square error RMSE

$$Eff = 1 - \left(\frac{\mathrm{RMSE}}{\mathrm{STD}_{obs}}\right)^2 \tag{7}$$

where STD is the observed standard deviation. Since RMSE includes the systematic and random errors, the same value of RMSE (and, evidently, *Eff*) may correspond to different values of the systematic error (bias). Consequently, among the sets of "optimal" parameters corresponding to the lowest RMSE (or the highest *Eff*) one should select the parameter set that provides the lowest bias.

2.5.1 RST

Random search technique (RST) has several stages (Gusev et al. 2008). At the first stage, sufficiently wide feasible parameter space is specified by fixing the lower and upper parameter bounds defined from the maximum plausible ranges for the parameters based on physical reasoning. A prescribed number of model runs (realizations) are performed using different values of calibrated parameters, which are determined within their fixed bounds using a generator of uniformly distributed random numbers. For each realization, streamflow simulation and estimation of *Ext* and *Bias* are carried out. Then, the "best" realizations, i.e. with the lowest values of *Ext* and near-zero values of *Bias*, are selected and corresponding values of calibrated parameters are used to reduce ("manually") the feasible parameter space. At the next stage, a new search of the optimum of the objective functions is performed for the reduced parameter space that allows one to reduce the number of realizations. This is especially important for a large set of optimized parameters, because if the feasible parameter space is fixed during optimization, the number of realizations needed to find the optimum with the specified accuracy grows exponentially with an increase in the number of parameters (Solomatine et al., 1999). If it is necessary, further reduction of parameter space may be done and searching the optimum may be continued until there will be no progress in minimization of *Ext*. When the optimization procedure is stopped, N points (N=4-5) with the lowest values of *Ext* and near-zero values of *Bias* are selected. The values of optimized parameters corresponding to these points are averaged (with the weights that may differ from 1.0). The obtained mean values of parameters are considered to be optimal and their standard deviations, divided by $\sqrt{N}$, allows one to assess the accuracy of estimating the optimal values of model parameters. Figure 5 illustrates the described optimization algorithm for the case of two parameters X and Y.

Figure 5b gives an example of relation between *Ext* and *Bias* obtained from a large number of model runs within the boundaries of Region-1 at the first stage of realization of algorithm.

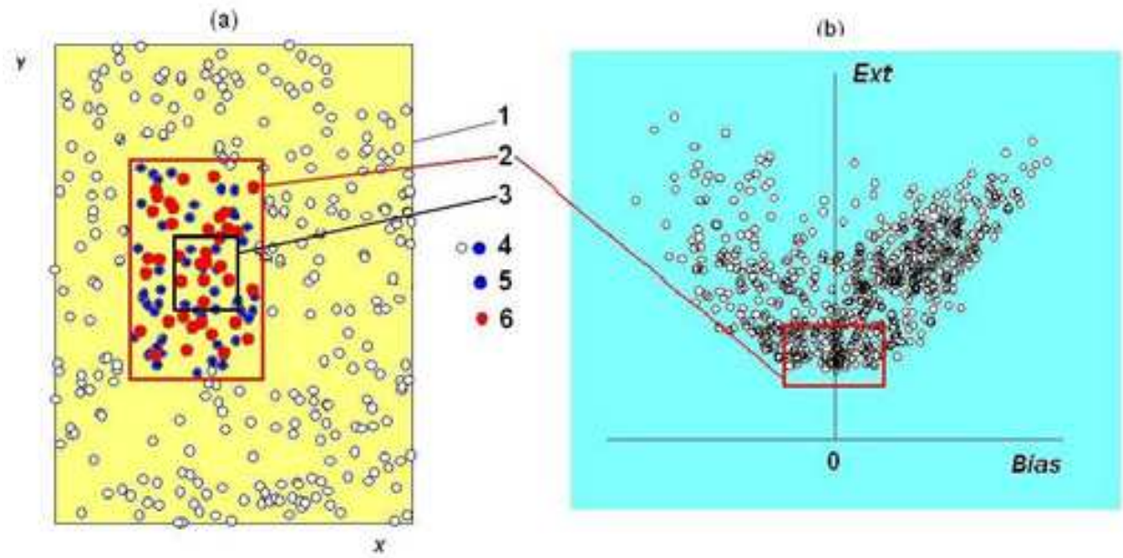

Fig. 5. An example of a direct search of the minimum of the objective function *Ext* (b) for 2-dimentional case (a). Here, 1 is the boundary of Region-1 with initial population of quasi-random points (4) with coordinates (*X, Y*); 2 is the boundary of Region-2 with the best points (5) from the initial population; 6 – points from the repeated optimization within the boundaries of Region-2; 3 is the boundary of Region-3 with the best points (close to optimal) generated during the repeated optimization.

Selecting the group with the "best" realizations, i.e. with the lowest values of *Ext* and near-zero values of *Bias* (marked in Figure 5b by the red rectangle), and the corresponding range of the parameter values (the red rectangle in Figure 5a), we reduce the feasible parameter space (from Region-1 to Region-2) and continue to search optimal values of the parameters within the new boundaries. If it is necessary, further reduction of parameter space (from Region-2 to Region-3 in Figure 5a) may be done and searching the optimum may be continued until there will be no progress in minimization of *Ext*.

2.5.2 SCE-UA

The SCE-UA algorithm has been described in detail in Duan et al. (1992). At the first step, the SCE-UA selects an initial population of optimized parameters by random sampling throughout the feasible parameter space for n parameters, based on given parameter ranges. For each point, the objective function values are calculated. Then, the population is partitioned into several communities (complexes), each consisting of $2n+1$ points, based on the corresponding objective function values. Each community is made to evolve independently for a prescribed number of times based on the downhill simplex method (Nelder and Mead, 1965). The communities are periodically consolidated into a single group and the population is shuffled to share information and partitioned into new communities. As the search progresses, the entire population tends to converge toward the neighbourhood of global optimum, provided the initial population size is sufficiently large. The evolution and shuffling steps are repeated until a prescribed convergence criterion is satisfied.

SCE-UA is a single-objective optimization algorithm. To apply SCE-UA for our two objective functions *Ext* and *Bias*, we decided to minimize *Ext* under condition that the

absolute value of *Bias* did not exceed 5%. If the fulfilment of this condition resulted in relatively low *Eff* ($Eff<0.9 \cdot Eff_0$, where Eff_0 is the efficiency without this condition, i.e. the efficiency corresponding to global optimum), we removed this condition and the point with $Eff=Eff_0$ was treated as an optimum. Evidently, that in this case absolute value of *Bias* is larger than 5%.

The distributive diskette for the SCE-UA code was taken from the site http://www.sahra.arizona.edu/software/.

2.5.3 Selection of parameters to be optimized

Since LSMs usually contain a lot of model parameters, the procedure for selection of parameters to be optimized is very important. The total number of optimized parameters should not be too small to ensure sufficient degrees of freedom for obtaining a good agreement between the simulated and observed daily streamflow. At the same time the number should not be too large to obtain the steady values of the calibrated parameters under a reasonable number of realizations. Evidently, those parameters, whose changes influence daily streamflow to the greatest extent, should be calibrated.

Our significant experience has shown that in high latitudes the following SWAP model parameters can be calibrated: (1) soil hydrophysical parameters: hydraulic conductivity at saturation K_0, parameters describing the dependence of soil water potential φ on soil moisture W (B-exponent parameter and saturated matric potential φ_0 in the parameterization of function $\varphi(W)$ by Clapp and Hornberger (1978)), plant wilting point W_{wp}, field capacity W_{fc}, soil porosity W_{sat}, soil column thickness h_0 (here, the depth from the soil surface to the upper impermeable layer); (2) vegetation parameters: the root layer depth h_r, the leaf area index LAI, the snow-free vegetation albedo α_{sum}, the vegetation albedo in the winter period (with snow on tree crowns) α_{win}; (3) albedo of snow on the ground α_{sn}; (4) parameters controlling the transformation of runoff both within a grid box (the Manning roughness coefficient n) and in a river channel network (effective velocity of water movement in a channel u_e).

Only seven land surface parameters from the above listed were chosen for calibration: K_0, h_0, h_r, α_{sum}, α_{sn}, n, and u_e (the other parameters were taken from the GSWP-2 global datasets) because of the following reasons. The hydraulic conductivity at saturation K_0 is one of the most important parameters of SWAP because it controls partitioning of water reaching the soil surface between infiltration and surface runoff. Besides that, in SWAP, subgrid effects are taken into account through K_0. Thus, when modelling infiltration and surface runoff, subgrid spatial variability of K_0 is considered by using not only mean value of K_0 for each grid box, but also root-mean-square deviation (Gusev and Nasonova, 1998). SWAP is also sensitive to the soil column thickness h_0, which, affecting the total soil water storage, controls to a great extent (along with some other factors) the partitioning of water entering a soil between an increment of soil water storage and drainage from the soil column. The root layer thickness h_r affects the maximum water storage available for transpiration, which occurs from this layer. The parameter α_{sum} determines the amount of non-reflected incoming solar radiation, which influences heat and water exchange at the land-atmosphere interface. The value of alb_{sn} influences energy balance at the snow surface and, consequently, the rate of snow formation processes, in particular, snow evaporation, snow accumulation and snowmelt; this is especially important for formation of flood peaks of streamflow hydrograph in spring. The shape of the streamflow hydrograph is also influenced by the parameters n and u_e.

Since the sensitivity of runoff, simulated by SWAP, to the parameters B and φ_0 is not significant, they were excluded from the list of calibrated parameters. As to W_{wp}, W_{fc}, W_{sat}, and LAI, analysis of their values, taken from the global datasets, has shown that they are quite reasonable for the three river basins and their calibration within narrow physically meaningful bounds will hardly improve the quality of runoff simulation. Besides that, first attempts of model calibration have shown correlation between the impact of these parameters and the parameters h_0 and h_r on the value of $Ext(\vec{par})$ (where $\vec{par}$ is the vector of calibrated parameters) (in particular, decrease in W_{fc} together with increase in h_r does not practically change Ext) that makes the search of the optimum of Ext using the indicated parameters extremely complicated.

The meteorological forcing data, as it was mentioned in Introduction, suffer from uncertainties and errors, therefore some authors began to calibrate the most influencing meteorological characteristics along with parameters of hydrological and land surface models (Gan et al., 2006; Xia, 2007). Since precipitation and incoming radiation influence runoff formation to the greatest extent, we decided to use the following adjustment factors for these forcings: k_{lp}, k_{sp}, k_{sw} and k_{lw} for rainfall, snowfall, shortwave and longwave radiation, respectively.

To reduce the list of calibrated parameters the following steps were undertaken. When adjustment factors for forcing data are involved in the process of parameter optimization, one of the four parameters α_{sum}, α_{sn}, α_{win} and k_{sw} must be excluded from the list because in the model these parameters are presented as a product of the corresponding albedo and the intensity of shortwave radiation. The parameter α_{win} with rather realistic values for the river basins was excluded. The parameters α_{sn}, n, u_e and the adjustment factors k_{sw}, k_{lw}, k_{lp} and k_{sp} were assumed to be the same for all the basin grid boxes, while the values of K_0, h_0, h_r and α_{sum} varied from a box to a box that resulted in a great number of parameters, which require calibration. To reduce the number of calibrated parameters and to increase their stability, instead of K_0, h_r and α_{sum} for each grid box, we decided to calibrate their adjustment factors k_{K0}, k_{hr} and $k_{\alpha sum}$, which were taken to be constant for the entire basin. In addition, we set $h_0=k_{h0}\cdot h_r$ for each box, where k_{h0} is also an adjustment factor taken to be constant for each basin. As a result, the total number of calibrated parameters was reduced to 11: seven for the land surface: k_{K0}, k_{hr}, $k_{\alpha sum}$, k_{h0}, α_{sn}, n, u_e and four for the forcing data: k_{sw}, k_{lw}, k_{lp} and k_{sp}.

2.6 Model calibration and validation

Daily streamflow hydrographs, measured at the Malonisogorskaya gauging station (Figure 2b), the Ust-Pinega station (Figure 3b) and the Oksino station (Figure 4b) during the period of 1986-1995 and taken from the GRDC (Global Runoff Data Centre) database, were used for parameter optimization and validation. The period from 1986 to 1990 was used for parameter optimization, which was performed for each river basin and for each version of the forcing data. To reveal the impact of optimization of adjustment factors for forcing data we performed calibration with and without application of the adjustment factors. In the former case, 11 parameters were calibrated, while in the latter case 8 (11 minus 4 adjustment factors and plus α_{win}) parameters.

Validation of the model with different sets of parameter values was performed for the period of 1991-1995. The results of daily streamflow simulations were compared with observations and with each other. The agreement between simulated and observed

streamflow for each river basin was estimated at daily time scale using several goodness-of-fit statistics: the Nash-Sutcliffe coefficient of efficiency *Eff*, systematic error *Bias* and the coefficient of correlation *r*. Hydrographs were also compared visually to reveal how the model reproduces the shape of hydrograph, including timing of peaks, recession slopes and low flows.

The agreement between simulations and observations is usually considered to be satisfactory if $Eff > 0.5$ (if $Eff = 1$ the simulation is ideal). If $Eff < 0$, temporal variability of variable x is reproduced badly (in this case, a simple averaging of observations is better than model simulation). Generally speaking, the threshold values of *Eff* characterizing the quality of simulations are subjective and depend on the problem to be solved. The scale of accuracy commonly used for evaluation of the quality of streamflow forecasts is as follows (Appolov et al., 1974): the accuracy is regarded as "good" when $Eff \geq 0.75$, as "satisfactory" when $0.36 \leq Eff < 0.75$, and as "unsatisfactory" when $Eff < 0.36$. As to the *Bias*, it should be taken into account, that a systematic error in daily, monthly, and annual values of the measured river runoff is on the average not less than 5% (this value can be much greater for flood periods). Therefore, we can assume that when $|Bias| \leq 5\%$, the quality of modelling can be considered as "good".

3. Results

3.1 Comparison of RST and SCE-UA optimization algorithms

Optimization of 11 model parameters using RST and SCE-UA optimization algorithms allowed us to compare their effectiveness. Four sets of optimal values of calibrated parameters were obtained for each river by application of RST and SCE-UA algorithms for Version 1 and Version 2 of forcing data. Then streamflow simulations were performed using the optimized parameter values. Table 1 summarizes the results of comparison of simulated and measured daily streamflow for the calibration and validation periods and for the entire calculational period.

Analysis of the results shows that application of the two different optimization algorithms for the same set of calibrated parameters gives closely consistent values of daily *Eff* and *Bias*. On average, RST-set of optimal parameters results in daily *Eff* equalled to 0.82, 0.81 and 0.81 for the calibration, the validation and the entire 1986-1995 period, respectively, while absolute *Bias* for the same periods is 1.8%, 5.8% and 2.6% respectively. Application of SCE-UA provides *Eff* equalled to 0.83, 0.82 and 0.83, while absolute *Bias* is 3.6%, 2.6% and 1.8%, respectively, for the calibration, the validation and the entire periods. Visual comparison of hydrographs reveals negligible differences. The differences can be explained by a limited number of realizations in both cases. These results mean that RST calibration technique is as effective as SCE-UA. The advantage of the former is that a user can interfere in the process of calibration and to speed up it by analyzing the preliminary results and reducing the feasible parameter space. For example, calibration of parameters for the Northern Dvina River by SCE-UA technique took us about two weeks against 2-3 days by RST (increase of the number of realizations in the latter case could improve the results, which are somewhat worse than in the former case, especially with respect to the validation period). If the time is not limited, it is more convenient to use the SCE-UA procedure, which does not need user interference and, consequently, depends on a user's experience to a less extent and is a less labour-consuming procedure.

River	Optimization algorithm	Version 1			Version 2		
		Bias,%	*Eff*	*r*	*Bias*, %	*Eff*	*r*
Calibration period (1986-1990)							
Mezen	RST	-4	0.72	0.85	-1	0.80	0.89
	SCE-UA	-6	0.75	0.87	2	0.83	0.91
Pechora	RST	-	-	-	0	0.89	0.94
	SCE- UA	0	0.87	0.94	4	0.85	0.92
Northern Dvina	RST	4	0.84	0.93	0	0.87	0.93
	SCE-UA	6	0.85	0.93	0	0.89	0.94
Validation period (1991-1995)							
Mezen	RST	-7	0.82	0.91	1	0.84	0.91
	SCE-UA	2	0.73	0.86	6	0.82	0.91
Pechora	RST	-	-	-	-6	0.75	0.88
	SCE- UA	-6	0.85	0.92	-1	0.76	0.87
Northern Dvina	RST	-11	0.80	0.90	4	0.85	0.92
	SCE-UA	-3	0.90	0.95	1	0.90	0.95
Entire period (1986-1995)							
Mezen	RST	-5	0.75	0.87	0	0.82	0.90
	SCE-UA	-1	0.74	0.86	4	0.82	0.91
Pechora	RST	-	-	-	-3	0.81	0.91
	SCE- UA	-3	0.86	0.93	2	0.80	0.90
Northern Dvina	RST	-3	0.81	0.91	2	0.86	0.93
	SCE-UA	1	0.88	0.94	1	0.90	0.95

Table 1. Statistical estimation of two optimization algorithms

3.2 Streamflow simulations with different sets of forcing data and optimal parameters

Table 2 summarizes the results of statistical estimation of agreement between measured and modelled daily streamflow for three rivers in different model runs with three versions of forcing data and with different sets of parameter values: a priori estimated parameters (Run-1) and optimized parameters without (Run-2) and with (Run-3) involving adjustment factors for forcing data. Optimization was performed by SCE-UA procedure.

Comparison of Run-1 and Run-2 results shows that calibration of eight model parameters has resulted in substantial improvement of the quality of streamflow simulations for each version of forcing data as compared to a priori estimated parameters. This is clearly seen from Figure 6, which shows the results averaged over three rivers. Thus, in Run-1, *Eff* was mainly negative, while in Run-2 mean *Eff* reached 64%, 72% and 84%, respectively, for Version 1, Version 2 and Version 3 of forcing data for the calibration period. The corresponding values of *r* were 0.87, 0.89 and 0.92, while the mean absolute *Bias* was 28%, 26% and 5%. Therefore, the best progress was archived for Version 3 of forcing data (when real observations form meteorological stations were used). As to the global forcing datasets, hybridized product was better than reanalysis one in terms of efficiency, while differences in the mean values of *r* and *Bias* were rather small. If we consider the validation period, the statistics for Version 3 was again the best. At the same time the quality of model performance using Version 1 of forcing data was even higher than with Version 2. For the entire period, the results for Version 1 and Version 2 were nearly the same. All this mean

Model run	River	Version 1			Version 2			Version 3		
		Bias,%	*Eff*	*r*	*Bias, %*	*Eff*	*r*	*Bias, %*	*Eff*	*r*
Calibration period (1986-1990)										
Run-1	Mezen	32	0.45	0.84	30	-0.34	0.83	-47	0.00	0.35
	Pechora	-28	-0.26	0.19	3	-0.66	0.45	-60	-0.16	0.25
	Northern Dvina	68	-0.68	0.76	56	-0.93	0.83	-46	0.29	0.69
	Mean	**43**	**-0.16**	**0.60**	**30**	**-0.64**	**0.70**	**51**	**0.04**	**0.43**
Run-2	Mezen	26	0.58	0.78	33	0.70	0.87	-3	0.82	0.91
	Pechora	0	0.83	0.91	1	0.78	0.89	-11	0.83	0.92
	Northern Dvina	57	0.52	0.91	45	0.67	0.91	0	0.88	0.94
	Mean	**28**	**0.64**	**0.87**	**26**	**0.72**	**0.89**	**5**	**0.84**	**0.92**
Run-3	Mezen	-6	0.75	0.87	2	0.83	0.91	0	0.90	0.95
	Pechora	0	0.87	0.94	4	0.85	0.92	3	0.92	0.96
	Northern Dvina	6	0.85	0.93	0	0.89	0.94	-4	0.89	0.94
	Mean	**4**	**0.82**	**0.91**	**2**	**0.86**	**0.92**	**2**	**0.90**	**0.95**
Validation period (1991-1995)										
Run-1	Mezen	38	0.37	0.79	42	-0.34	0.86	-43	0.14	0.46
	Pechora	-23	-0.03	0.36	2	-0.56	0.51	-57	0.05	0.50
	Northern Dvina	48	-0.38	0.64	55	-0.62	0.80	-40	0.40	0.75
	Mean	**36**	**-0.01**	**0.60**	**33**	**-0.51**	**0.72**	**47**	**0.20**	**0.57**
Run-2	Mezen	31	0.71	0.87	42	0.69	0.87	-7	0.86	0.93
	Pechora	-5	0.79	0.89	2	0.71	0.86	-11	0.69	0.84
	Northern Dvina	38	0.71	0.90	53	0.68	0.91	0	0.90	0.95
	Mean	**25**	**0.74**	**0.89**	**32**	**0.69**	**0.88**	**6**	**0.82**	**0.91**
Run-3	Mezen	2	0.73	0.86	6	0.82	0.91	-4	0.90	0.95
	Pechora	-6	0.85	0.92	-1	0.76	0.87	3	0.76	0.89
	Northern Dvina	-3	0.90	0.95	1	0.90	0.95	-5	0.89	0.95
	Mean	**4**	**0.83**	**0.91**	**3**	**0.83**	**0.91**	**4**	**0.85**	**0.93**
Entire period (1986-1995)										
Run-1	Mezen	35	0.41	0.81	36	-0.34	0.85	-45	0.08	0.40
	Pechora	-25	-0.13	0.29	3	-0.60	0.49	-59	-0.04	0.40
	Northern Dvina	58	-0.50	0.69	56	-0.74	0.81	-45	0.36	0.72
	Mean	**39**	**-0.07**	**0.60**	**32**	**-0.56**	**0.72**	**50**	**0.13**	**0.51**
Run-2	Mezen	29	0.66	0.83	38	0.69	0.87	-5	0.84	0.92
	Pechora	-3	0.81	0.90	2	0.75	0.87	-11	0.76	0.87
	Northern Dvina	47	0.64	0.90	49	0.67	0.91	0	0.89	0.95
	Mean	**26**	**0.70**	**0.88**	**30**	**0.70**	**0.88**	**5**	**0.83**	**0.91**
Run-3	Mezen	-1	0.74	0.86	4	0.82	0.91	-2	0.90	0.95
	Pechora	-3	0.86	0.93	2	0.80	0.90	3	0.83	0.92
	Northern Dvina	2	0.88	0.94	1	0.90	0.95	-4	0.89	0.95
	Mean	**2**	**0.83**	**0.91**	**2**	**0.84**	**0.92**	**3**	**0.87**	**0.94**

Table 2. Statistical evaluation of different model runs. Mean *Bias* was obtained for absolute values

that, first, forcing data based on real meteorology are of better quality than forcing data taken from the global datasets; second, high correlation between measured and simulated streamflow in all three cases, along with lower values of *Eff* and *Bias* in Version 1 and Version 2 compared to Version 3, confirms that global forcing data contain systematic errors (in spite of hybridization of pure reanalysis product with observations, which was undertaken to decrease the errors); third, these errors are not compensated by optimization of the land surface parameters, therefore to reduce their impact on streamflow simulations the adjustment factors for the key forcing data are required.

Further improvement of the above results was archived by means of involving adjustment factors for forcing data in the process of parameter optimization. This is confirmed by comparison of the results from Run-2 and Run-3 (see Figure 6 and Table 2). For Version 1

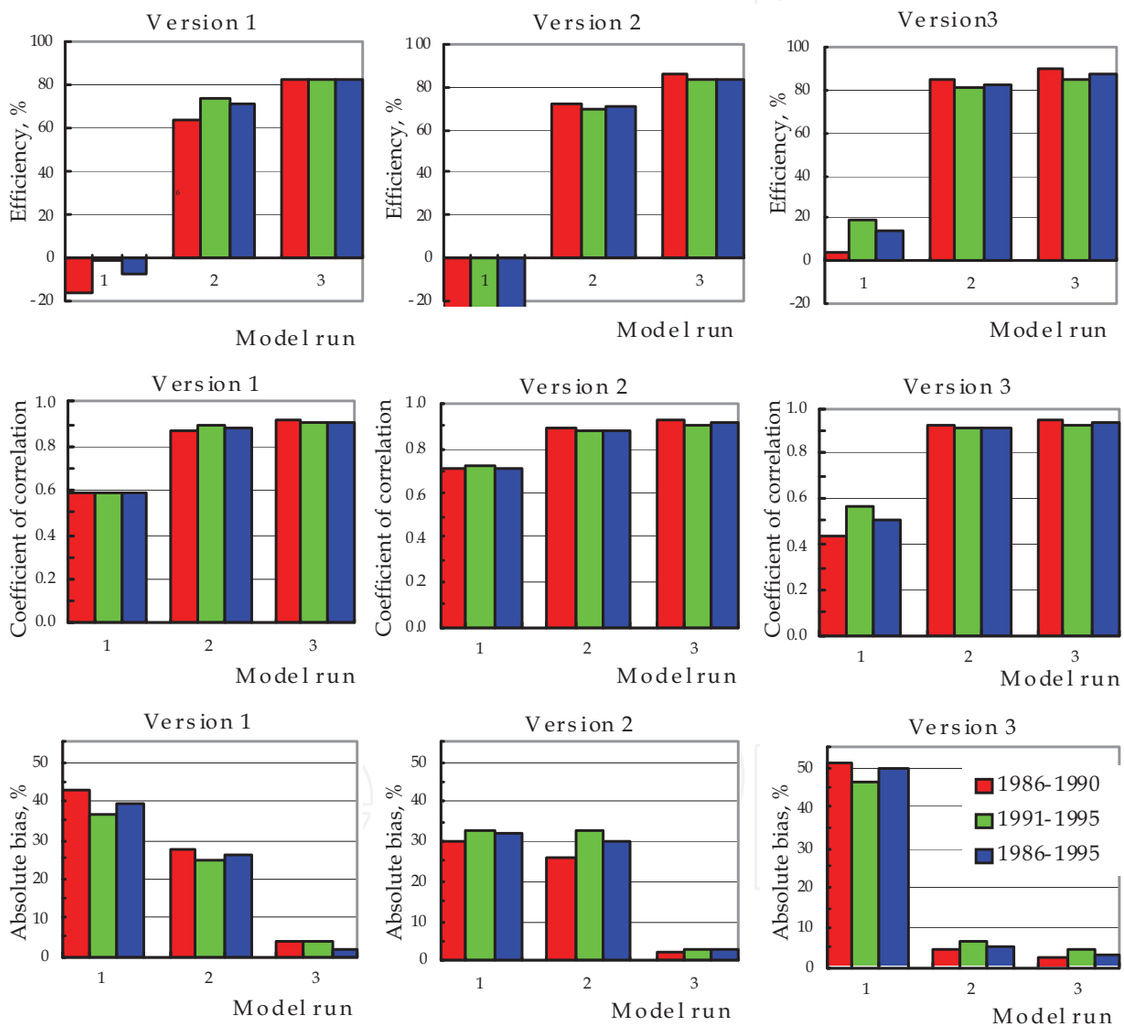

Fig. 6. Averaged over the three considered rivers daily efficiency, coefficient of correlation and absolute value of *Bias* from a priori simulations (model run 1) and calibrated results without (model run 2) and with (model run 3) application of adjustment factors for forcing data for the calibration period (red), the validation period (green) and the entire period (blue). The results are given for three versions of forcing data. All statistics are averaged over the three rivers.

and Version 2, the progress in model performance was significant, especially with respect to *Eff* and *Bias*. For the entire calculational period, mean *Eff* increased by 13-14% and mean absolute Bias decreased by 24-28% as a result of calibration of adjustment factors for forcing data. For Version 3, the improvement in mean *Eff* was only 4% and in mean absolute bias 2%. Therefore the quality of forcing data based on observations from meteorological stations, on average, was rather good. At the same time for the Mezen River and Pechora River, increase in *Eff* and decrease in absolute *Bias* sometimes reached 7-9%, while for the Northern Dvina the differences were much smaller, i.e. in the latter case the quality of forcing data was higher.

The obtained results have shown that optimization of model parameters and adjustment factors for forcing data makes it possible to use global datasets for streamflow simulations and to obtain results of a good quality. The lower the quality of input data the more effectiveness of such optimization. This is clearly illustrated by Figure 7 where hydrographs simulated for the Northern Dvina River in different model runs are compared with the measured hydrograph for the period of 1986-1995. The grey hydrographs were simulated without any optimization. Their agreement with measurements is very poor. Differences between grey hydrographs in the upper and middle panels are due to differences in the global atmospheric forcing data (the values of model parameters are the same here). In these cases both forcing data and model parameters (which were also taken from global datasets) contribute to the low accuracy of streamflow simulation. In the bottom panel, poor simulation (without calibration) is due to inadequate values of a priori estimated model parameters (taken from global datasets), while real meteorology, as it was shown above, is rather good. Optimization of parameter values allowed us greatly improve the modelled hydrographs (compare grey lines with blue lines in all panels). Further improvement was made by means of simultaneous optimization of model parameters and adjustment factors for forcing data (compare blue lines with green lines). Coincidence of green and blue hydrographs in the bottom panel confirms the above made conclusion that there is no necessity to use the adjustment factors for forcing data if the quality of forcing data is rather high.

At last, Figure 8 shows that it is possible to obtain a good accuracy of streamflow simulations using any of three versions of forcing data if optimization of model parameters and (if it is necessary) adjustment factors has been performed in a proper way. As can be seen from Figure 8, three hydrographs modelled by SWAP using different versions of forcing data are in a good agreement with each other and with measured hydrograph.

4. Conclusions

The main conclusions from this investigation can be summarized as follows.

- Direct application of the global data on meteorological characteristics and land surface parameters, developed within the framework of the ISLSCIP-II and GSWP-2 projects, for simulating streamflow for three northern rivers, located in the European part of Russia, by the LSM SWAP leads to poor results (low Nash-Sutcliffe efficiencies and large biases). Optimization helps to compensate to some extent uncertainties and shortcomings in input data and model parameters. Uncertainties and errors in forcing data can be partly compensated by application of adjustment factors for those meteorological characteristics, which influence runoff generation to a greater extent. Calibration of such factors together with model parameters allows one to reduce the influence of systematic errors in forcing data on optimization of model parameters and

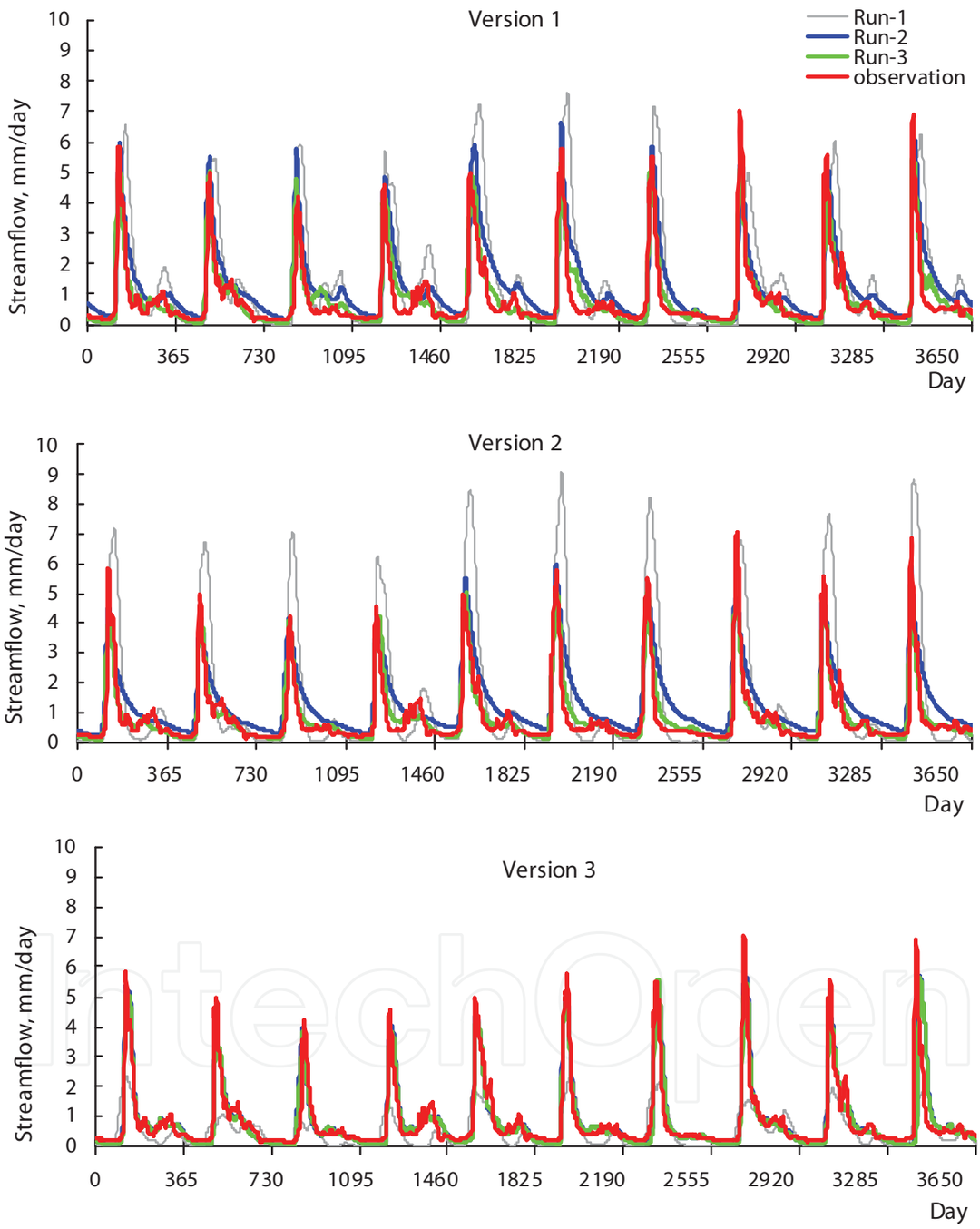

Fig. 7. Measured and simulated streamflow of the Northern Dvina River. Simulations were performed for three versions of forcing data using a priori (Run-1) estimated parameters and optimized parameters without (Run-2) and with (Run-3) application of adjustment factors for forcing data. The days are numbered from the 1 January 1986.

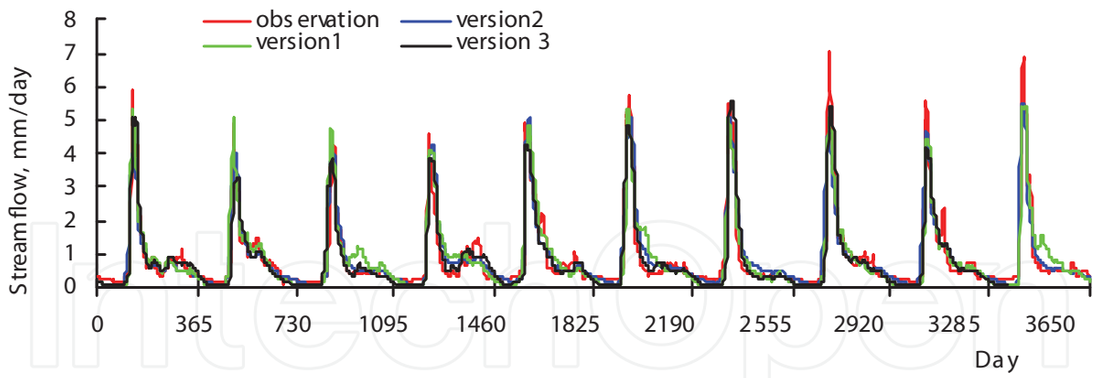

Fig. 8. Measured and simulated (Run-3) streamflow of the Northern Dvina River. The days are numbered from the 1 January 1986.

on model performance. All calibrated parameters should be kept within a reasonable range so as not to violate physical constraints while providing a close match between simulated and measured daily streamflow.

- Forcing data based on real meteorology from the meteorological stations located within a basin require adjustment factors only in the case of low quality of data (if the density of measurements is poor, or location of the stations cannot provide the study basin with representative information, or measurements contain errors etc.).
- Application of two different global optimization algorithms (RST and SCE-UA) has shown that both algorithms lead to practically the same results. The advantage of the former is that a user can interfere in the process of calibration and to speed up it by analyzing the preliminary results and reducing the feasible parameter space. SCE-UA does not need user interference and, consequently, depends on a user's experience to a less extent and is a less labour-consuming procedure. At the same time SCE-UA is a more time-consuming procedure, but if the time is not limited, it is more convenient to use SCE-UA optimization technique.
- Application of the LSM SWAP with global parameter datasets and with different versions of atmospheric forcing data (based on (1) global reanalysis product, (2) global reanalysis product hybridized with gridded observations and (3) real meteorology from meteorological stations) allows one to reproduce hydrographs of the northern rivers of the European part of Russia after optimization of a set of model parameters and adjustment factors for forcing data with a good accuracy, which is confirmed by statistical estimation of agreement between simulated and measured hydrographs and their visual comparison.

Future research should be concentrated on the solution of the following problems. First, development of methodology for predicting changes in river runoff due to climate change and anthropogenic effects. Second, development of methods for modelling river runoff in ungauged basins, i.e. when streamflow measurements are absent and it is not possible to perform optimization of model parameters and to validate the results. These problems are difficult; however, the possible ways for their solutions may be as follows. The former problem can be solved on the base of application of LSMs, along with climate forecast generators and land use scenarios of a high spatial and temporal resolution. The second problem can be solved on the base of LSMs and construction of relations between calibrated model parameters and natural characteristics of river basins.

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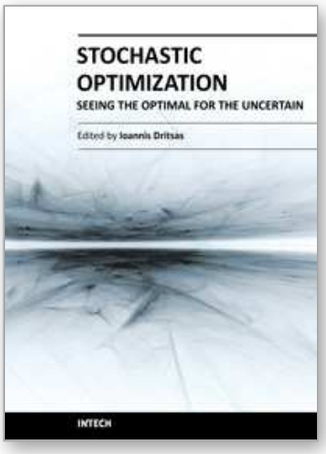

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Stochastic Optimization Algorithms have become essential tools in solving a wide range of difficult and critical optimization problems. Such methods are able to find the optimum solution of a problem with uncertain elements or to algorithmically incorporate uncertainty to solve a deterministic problem. They even succeed in â€œfighting uncertainty with uncertaintyâ€. This book discusses theoretical aspects of many such algorithms and covers their application in various scientific fields.

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