Design of the approach for assessment of river flow based on climatic characteristics and its application for prediction for 21st century.

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AOGCMs in theory reproduce all fields of atmosphere, ocean, cryosphere, and the active layer of land surface. However, not all fields are reproduced with the required accuracy. Reliable testing done only for air temperature, atmospheric pressure and geopotential field. This situation makes it necessary to find river flow assessment using limited climatological information.

Our goal is to offer the approach for annual river flow forecast using model-predicted precipitations and surface temperature.

Forecast of annual river flow is expected to do as follows.

The calculations on climate models and the ensemble calculations of semi-Lagrangian model will be used as predictor in the statistical downscaling model. The estimates of small-scale fields of surface temperature and precipitation then will be used for annual river flow estimates.

1. River flow estimates.

$\overline{Y} = \overline{P} - \overline{E},$ (1) The equation of water balance, where

$\overline{Y}, \overline{P}, \overline{E}$ -mean values (mm) of river flow, precipitation and evaporation.

Evaporation $\overline{E}$ is estimated by the formula V. S. Mezentsev

$$\frac{E}{E_o} = (1 + \frac{E_o^n}{P})^{-1/n}, \quad (2),$$

where

E_o - evaporation, n - fitting parameter. Parameter n obtained by least squares.

$n = 3{,}8$

The dependence of the evaporation E_o from the sum of positive monthly average temperatures T described by the regression equation.

$$E_o = 6{,}72 T_o. \quad (3)$$

Statistical detalisation.

We will use linear regression.

$$\hat{f} = R\xi$$

The operator R can be found by minimizing the functional of mean-square error.

$$\Phi(R) = M\|R\xi - f\|^2.$$

The solution is $R = C_{f\xi}C_{\xi}^{-1}$, $C_{f\xi}, C_{\xi}$ - covariance matrixes.

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Statistical detalisation.

Covariance matrixes is estimated by the samples with small size. So, the size of predictor must be decreased.

1)EOF decomposition.

$$\xi = \sum_{i=1}^{n} a_i x_i$$, where x_i – eigenvectors of the matrix C_ξ

$$\tilde{\xi}^k = \sum_{i=1}^{k} a_i x_i$$ - we use instead of ξ.

2) Stepwize regression

$$\Delta\xi_k = \xi_k - \tilde{\xi}$$ - independent part of predictor (after use k components).

$$C_k = M(f\xi_k)$$ - conditional covariance

$$D_k = M(\xi_k \xi_k)$$

$$f^{(k)} = f^{k-1} + C_k \Delta\xi_k / D_k$$ - predictant estimate at k-th step

$$\tilde{\xi}_k = C_{\xi_k z} C_{cc}^{-1} z, \qquad z = [\xi_1, \ldots, \xi_k].$$

At each step we choose the component of predictor with maximal conditional correlation with predictant.

4. Numerical experiments.

a) Verification the ability of proposed approach to reproduce current mean annual flow and compare it with the flow issued by the model.

b) Test downscaling for temperature and precipitations.

c) Verification the ability of statistical downscaling based on (1) - (3) to reproduce annual flow anomalies.

a) Current mean annual flow

Test was performed by comparing the output values of the INM RAS model in the grid 2 × 1,5 ° with objective analysis (daily temperatures and precipitation for the period 1961 – 1989 y. at 2 ° × 2 ° grid, obtained by data assimilation with 667 weather stations using Kresman optimal interpolation), as well as a map layer of mean annual flow, published in a collection of SMIP.

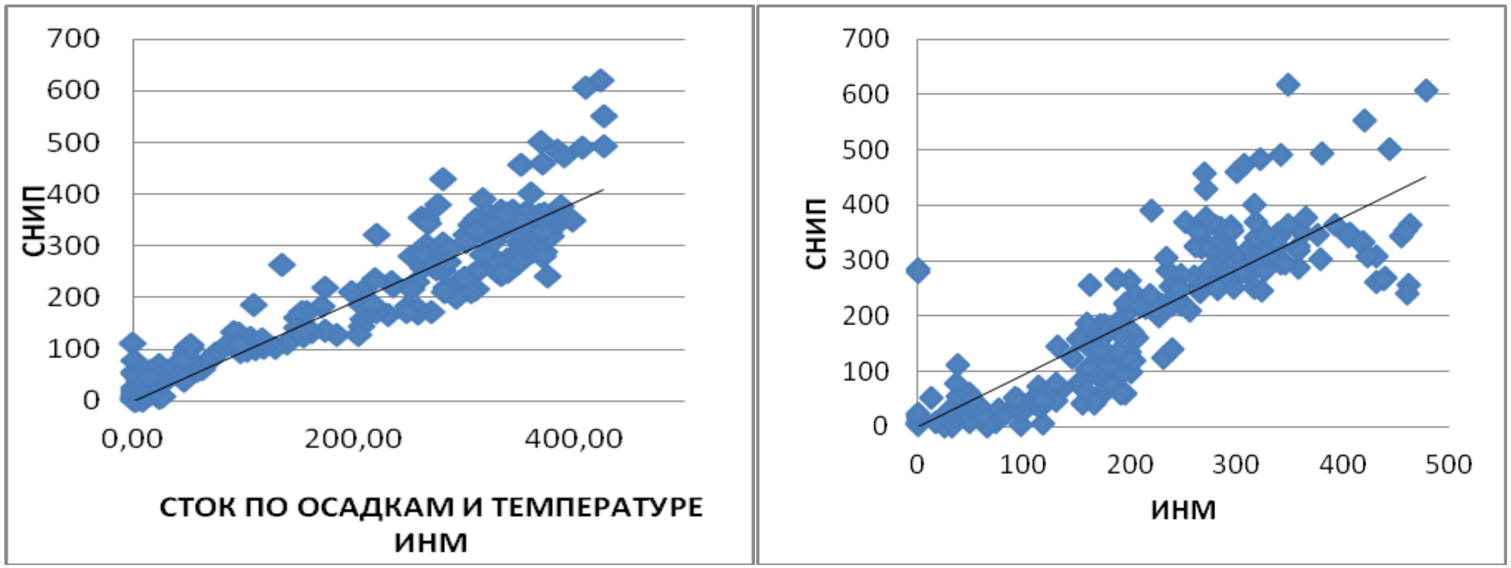


Figure 1 Reproducibility of the average annual flow (mm) AOGCMs (a) and flow calculated using precipitation and temperature from AOGCMs (b).

b) Downscaling of t2m.

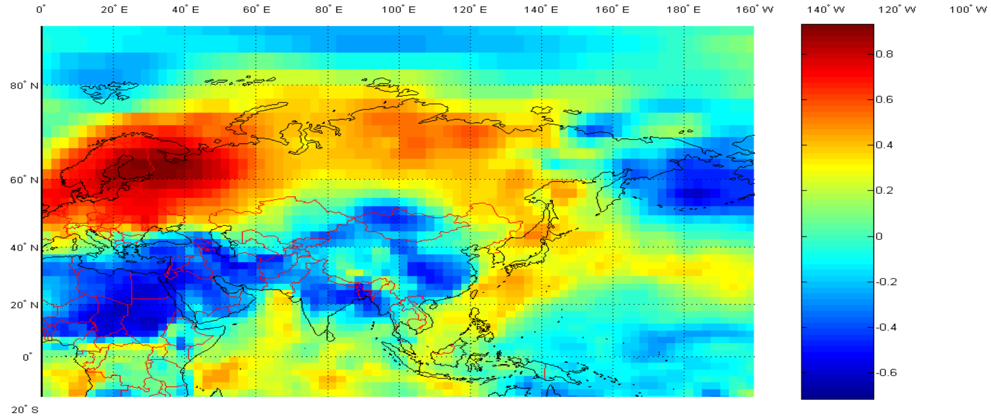
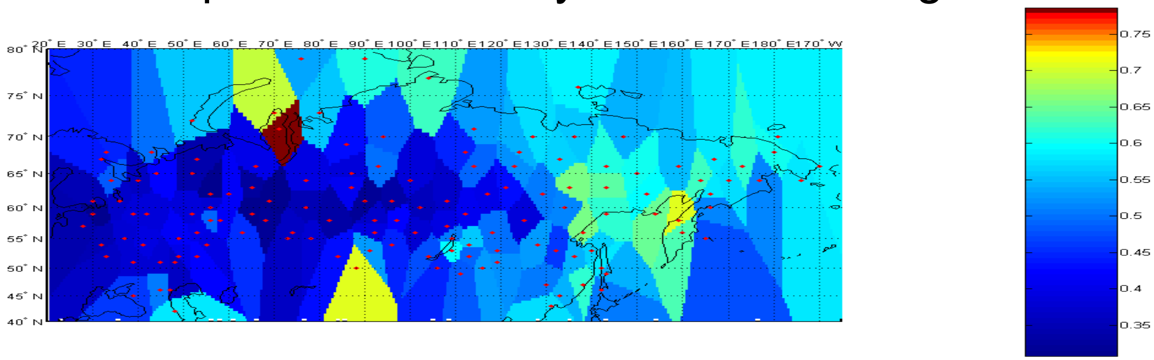


Fig.2 Correlation of temperature measured at the station and temperture of reanalysis at 2.5°×2.5° grid.



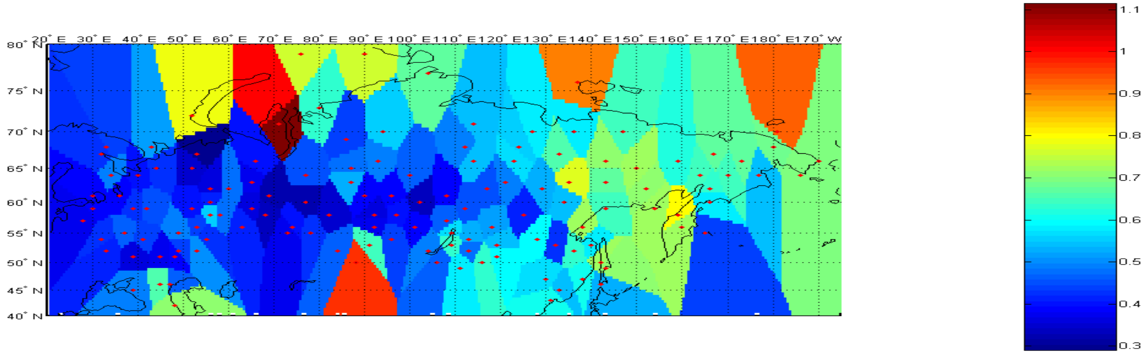


Fig.3 RMSE / variability of statistical downscaling from grid to stations (fig. 3a) and RMES of interpolation (fig. 3b)

b) Downscaling of precipitations

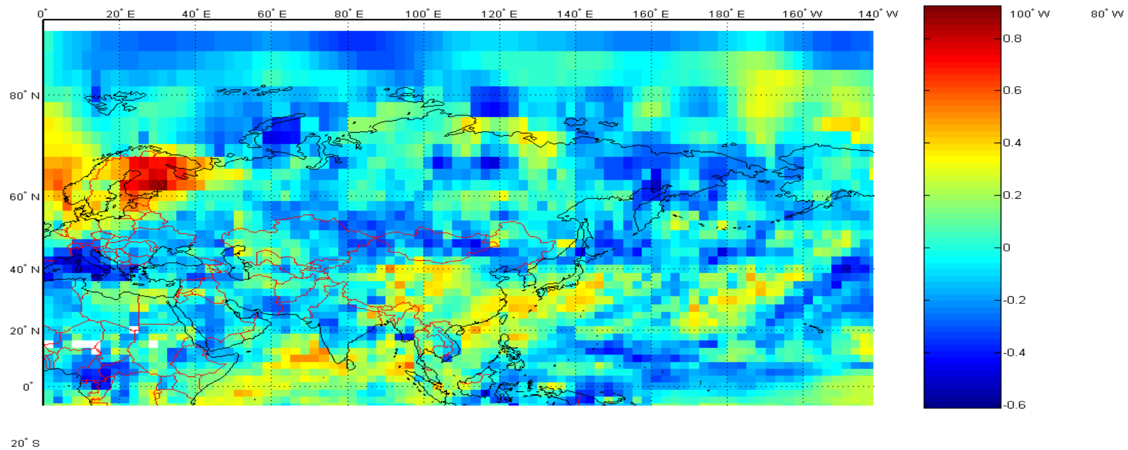
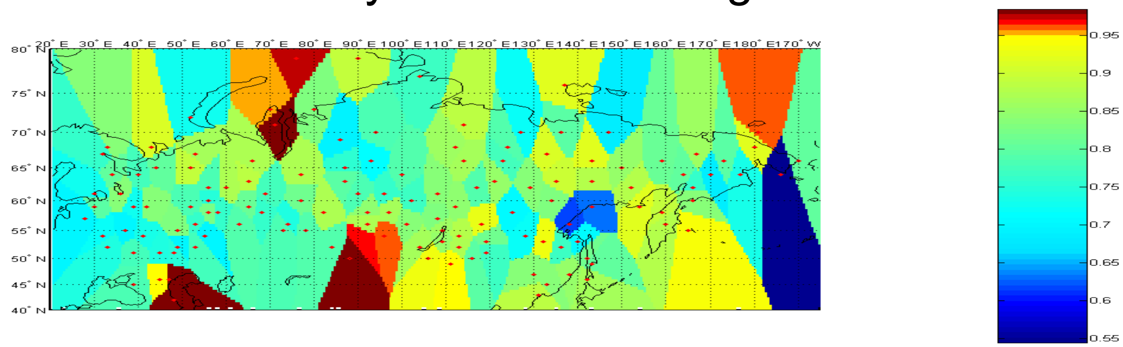


Fig.4 Correlation of precipitations measured at the station and precipitations of reanalysis at 2.5°×2.5° grid.



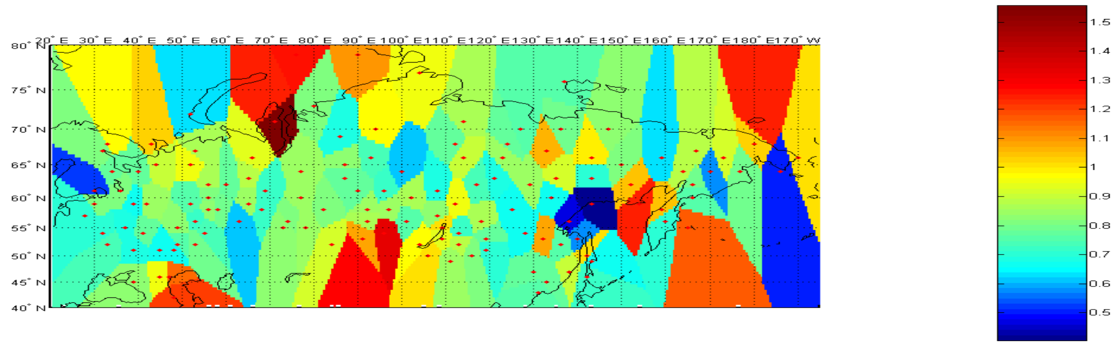


Fig.5
RMSE / variability of statistical downscaling from grid to stations (fig. 5a) and RMES of interpolation (fig. 5b)

c) Flow anomalies estimates.

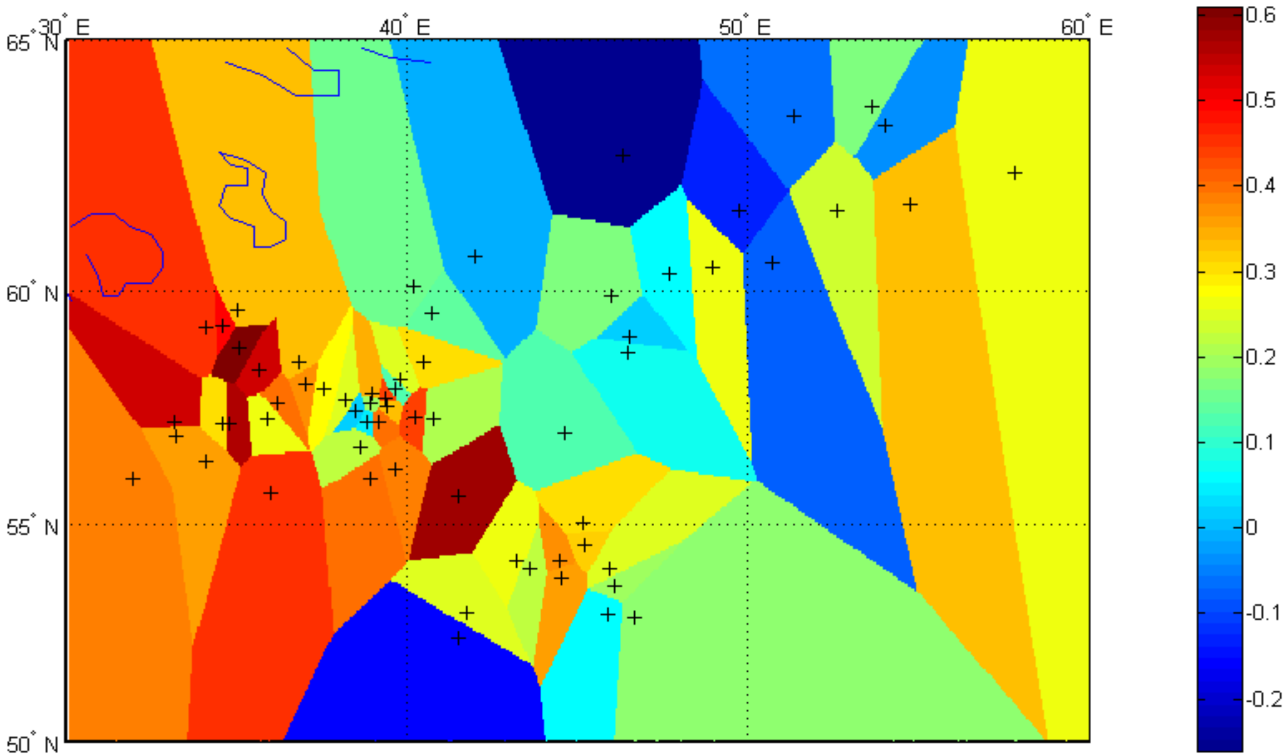


Fig.6 Temporal correlation of the annual flow measured on hydrological posts.

$C_{y_{t,t-1}} = M(Y(t) - MY)(Y(t-1) - MY)$, where *M* is the mathematical expectation

Mean $C_{y_{t,t-1}}$ =0.25

c) Flow anomalies estimates.

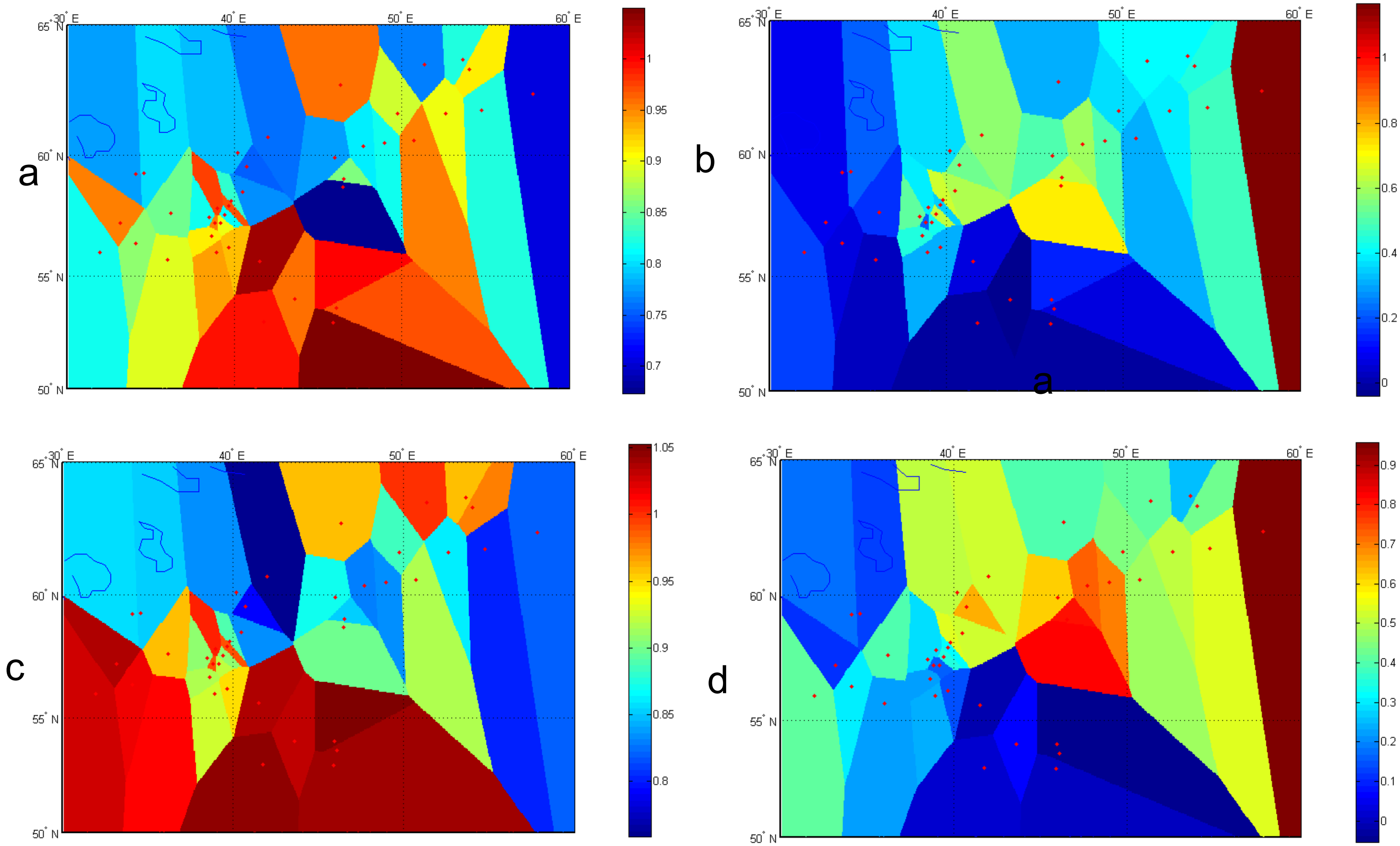


Fig.7 RMSE/variability (a, c) and correlation estimate of calculated and measured flow anomalies (b, d). Upper figures (a, b) were obtained without taking in account temproral correlation. Bottom figures (c, d) were obtained with takong in account temporal correlation.

Conclusion.

1) Proposed approach for assessment of river flow has some advantage compare with AOGCMs flow in reproduction of current mean annual values It can be useful in regions, where we know precipitations and T2m.

2) Statistical downscaling of T2m and precipitations has some advantage compare with interpolation. It can de used to propagate information about precipitations and T2 predicted by AOGCMs from grid to stations.

3) Annual flow anomalies estimates demands farther research.