Model-based approach to seasonal ensemble forecast of snowmelt water inflow into a reservoir

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1. The present-day Russian practice of the long-term forecasting of snowmelt runoff

2. How process-based modelling can increase the information content of the forecast and increase its accuracy

3. Transition from deterministic to ensemble forecast: improving forecast uncertainty assessment

4. Case study of spring inflow into Cheboksarskoe reservoir: developing deterministic and ensemble forecasts with ECOMAG model

5. Results and discussion

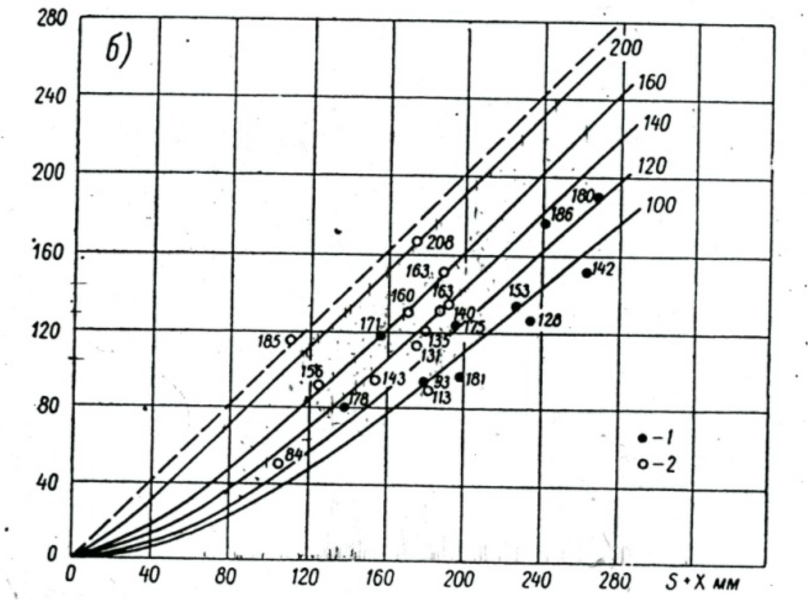
6. Conclusions

"…Snowmelt runoff is one of the few natural phenomena for which relatively accurate long-term forecast can be made"

Lettenmaier & Waddle (1978)

Long-term forecasting of snow-melt runoff volume: Physical-statistical methods (Russian practice)

$$Y^*_{sum} = \left(SWE + P^*_{sum}\right) - LMAX\left[1 - \exp\left(\frac{-\left(SWE + P^*_{sum}\right)}{LMAX}\right)\right]$$



Dependence of snowmelt flood volume on snow water equivalent and soil water content before spring melt

Current long-term spring flood forecasts for Russian rivers are based on regression relationships between flood volume and the main runoff factors (snow water equivalent, soil moisture content, depth of frozen soil before spring melt). Typically, it is assumed that precipitation *P during the lead-time period equals to the mean (climatological) values.**

Refinement of the regression-based forecasts can be expected through the use of ever longer homogeneous time series of observations and thus longer calibration periods

But this is not the case…Why?

- **the available observation series are non-homogeneous as a consequence of changes in land use, modernisation of data collection techniques, and so on**
- **some data obtained using modern technologies (e.g. satellite observations) cannot be incorporated into the existing regression relationships, which are based on traditional ground-truth observations**
- **the accuracy of the forecasts turns out to be insufficient to satisfy the growing demands of its users**

Process-oriented hydrological modeling offers scope for improvement of a forecast accuracy

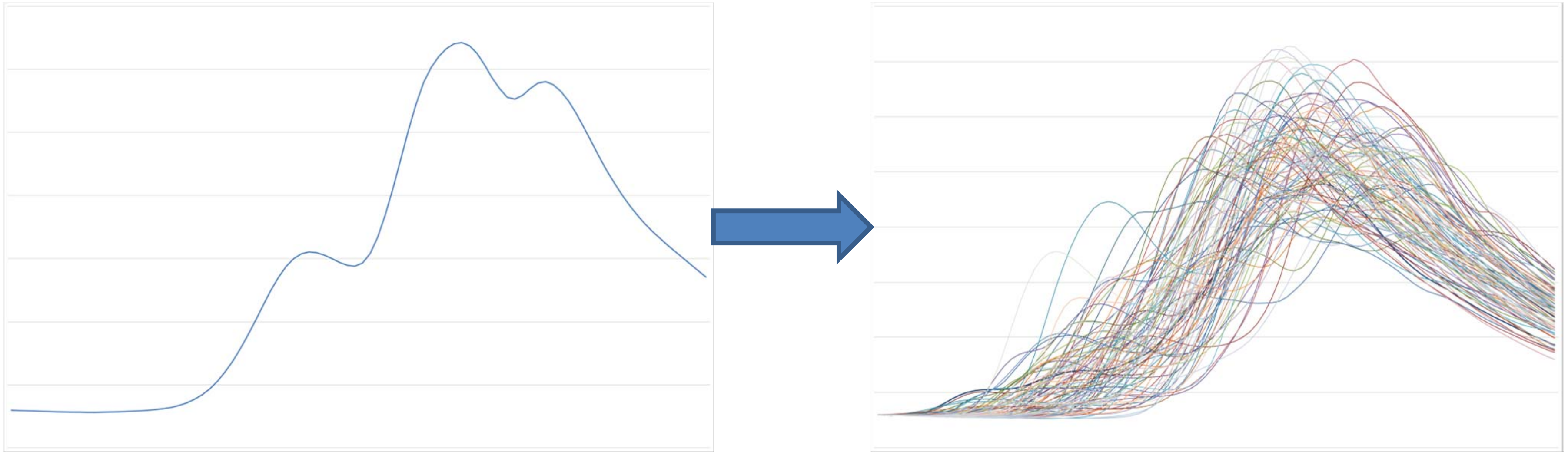
For what reasons?

- **models are based on physical principles. This means that they generally reproduce the main processes of runoff generation that allows extending physical content of the forecast and overcoming the restrictions inherent in regression-based methods**
- **It may be possible to widen informational basis of the forecast by using modern measurement technologies (including satellite data)**
- **using the model, it may be possible to obtain the predicted hydrographs, rather than just the runoff volume, thus resulting in increased potential benefits for decision makers**

5 Background

“A deterministic format forces the forecaster to suppress information and judgment about uncertainty” and “…may create the illusion of certainty in a user’s mind”

Krzysztofowicz, 2001



For many years, the prevailing techniques used in operational hydrological forecasts, including long-term ones, were deterministic. These methods used a single set of input values to produce a single set of predicted outcomes (runoff volume, river discharges, etc.), which were then assumed to represent the most likely conditions of runoff. By taking into account the forecast uncertainty, ensemble forecasting offers an approach that could improve the accuracy of hydrological forecasts in comparison with the deterministic approach.

Two approaches to process-based models application for long-term ensemble forecasting of snow-melt runoff were suggested (Kuchment L.S., Gelfan A.N. (2007a,b; 2009):

1. **Use of the historical, observed weather patterns (assumed to be equally likely) to drive the model, starting at the forecast date**

2. **Use of artificial weather patterns, generated by a stochastic model ("weather generator"), persisting the probabilistic properties of observed weather variables**

In the current study the approach was improved:

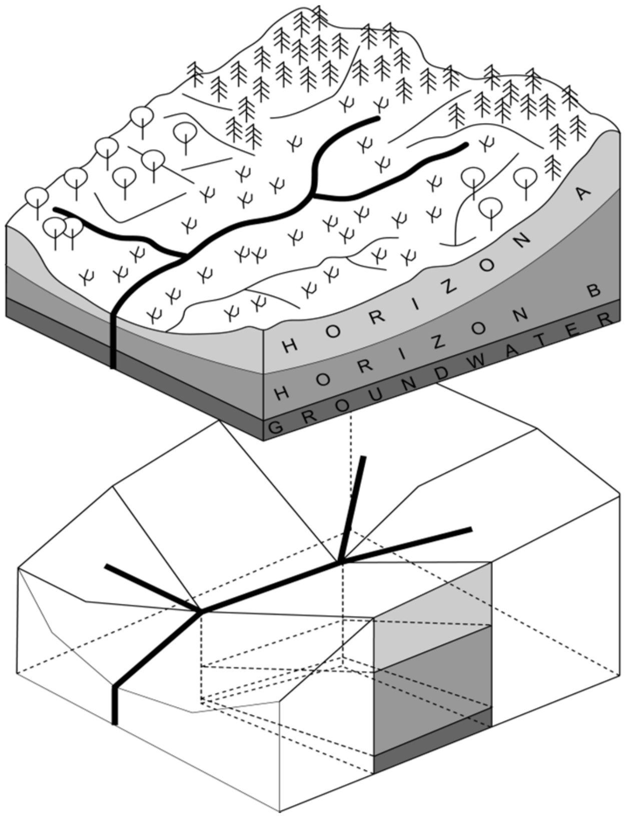
- **Large-scale hydrological model was used**
- **Weather time-series for the lead time constructed by multi-site weather generator**
- **Long-term forecast into large reservoir**

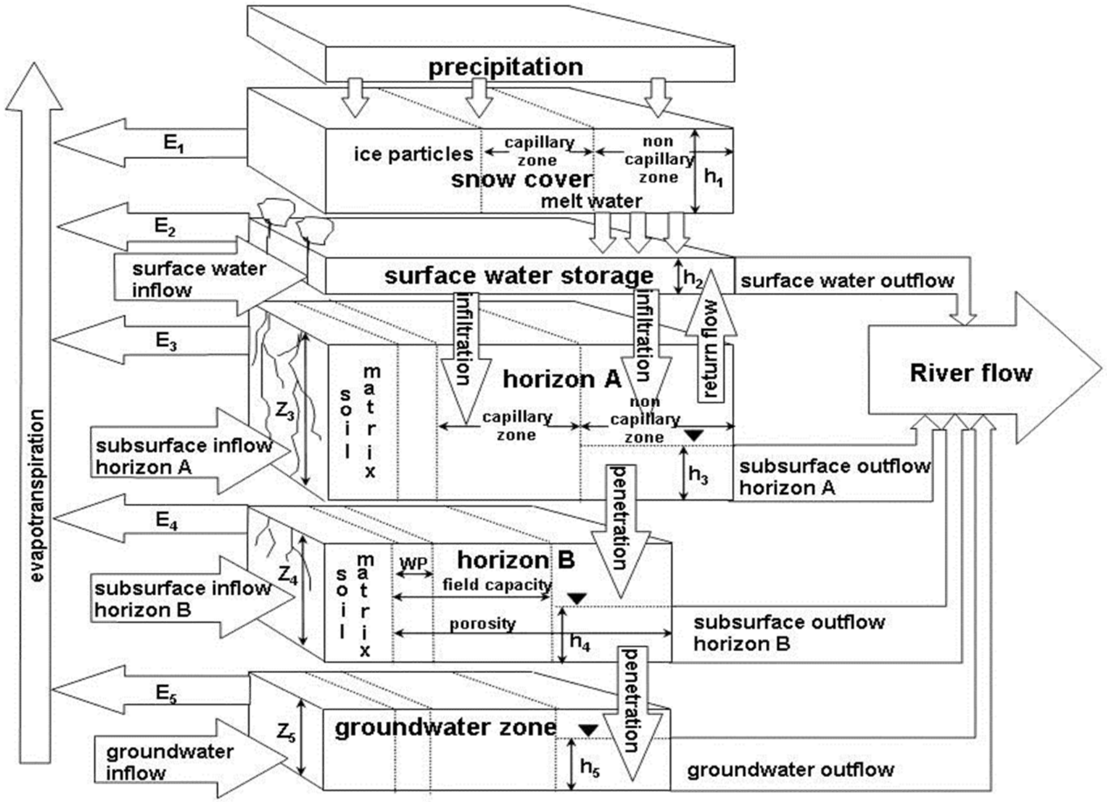
Kuchment L.S., Gelfan A.N. (2007a). Long-term probabilistic forecasting of snowmelt flood characteristics and the forecast uncertainty. IAHS Publ. 313, 2007 213-221

Kuchment L.S., Gelfan A.N. (2007b). Long-Term Ensemble Forecast of Snowmelt Runoff with the Help of the Physics-Based Models of Runoff Generation. Russian Meteorology and Hydrology, 2007, Vol. 32, No. 2, pp. 126–134.

Kuchment L.S., Gelfan A.N. (2009) A Study of Effectiveness of the Ensemble Long-term Forecasts of Spring Floods Issued with Physically Based Models of the River Runoff Formation. Russian Meteorology and Hydrology, 2009, Vol. 34, No. 2

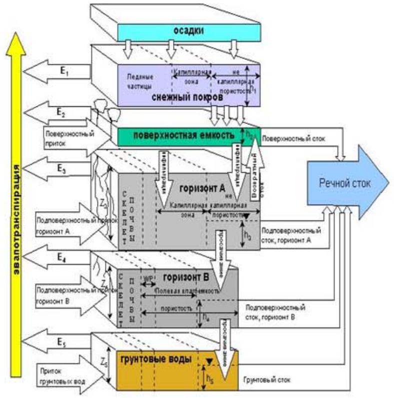
Physically-based semi-distributed model ECOMAG (ECOlogical Model for Applied Geophysics)

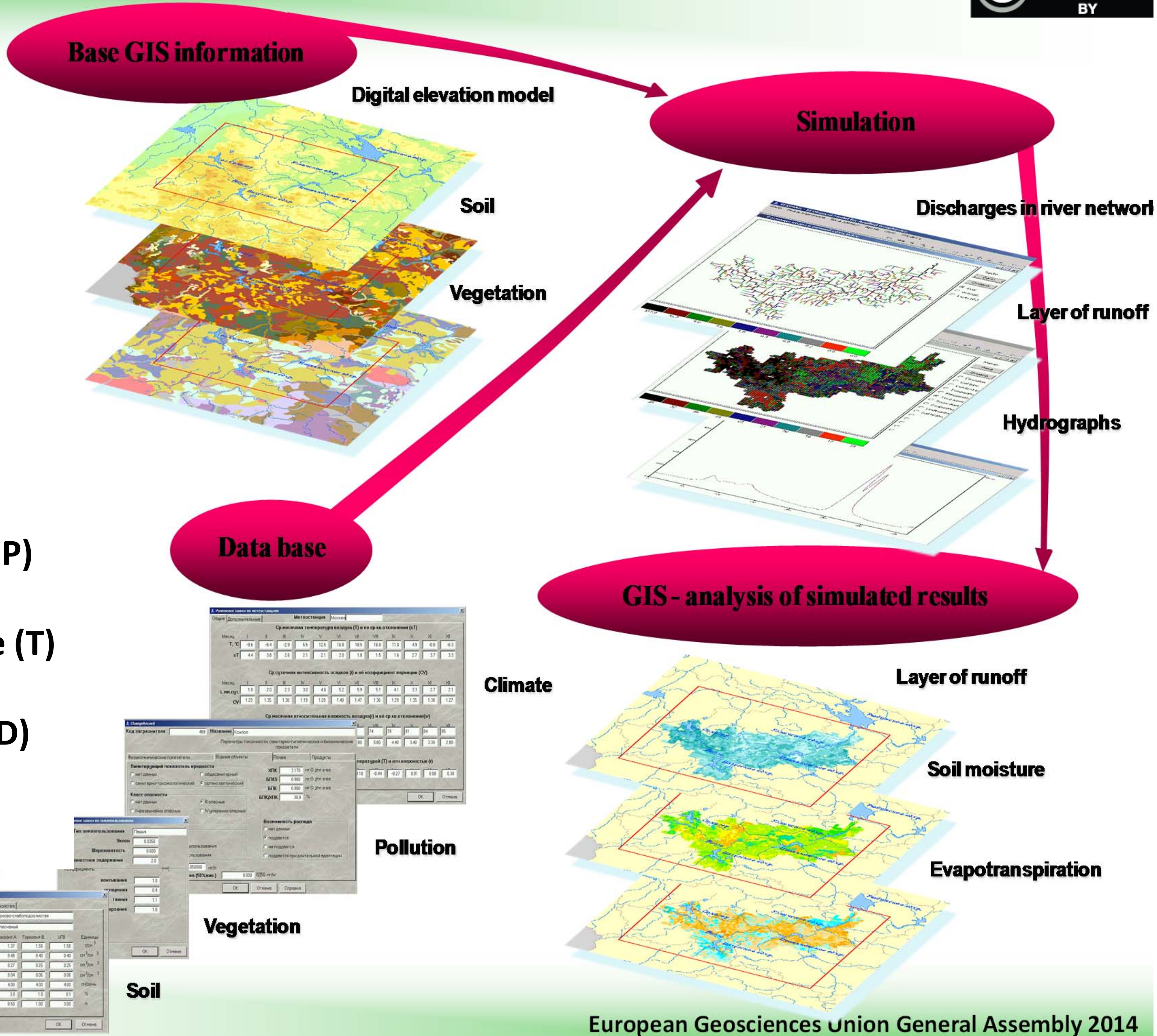




Motovilov, Yu., Gottschalk, L., Engeland K. & Rodhe A. (1999) Validation of a distributed hydrological model against spatial observation. Agric. For. Meteorol. 98–99, 257–277.
Motovilov, Yu., Gottschalk, L., Engeland, K., & Belokurov, A. (1999) ECOMAG – regional model of hydrological cycle. Application to the NOPEX region. Department of Geophysics, University of Oslo, Institute Report Series no. 105.
Gottschalk, L., Beldring, S., Engeland, K., Tallaksen, L., Salthun, N. R., Kolberg, S. & Motovilov, Yu. (2001) Regional/macroscale hydrological modelling: a Scandinavian experience. Hydrol. Sci. J. 46(6), 963–982.

Vertical structure of ECOMAG





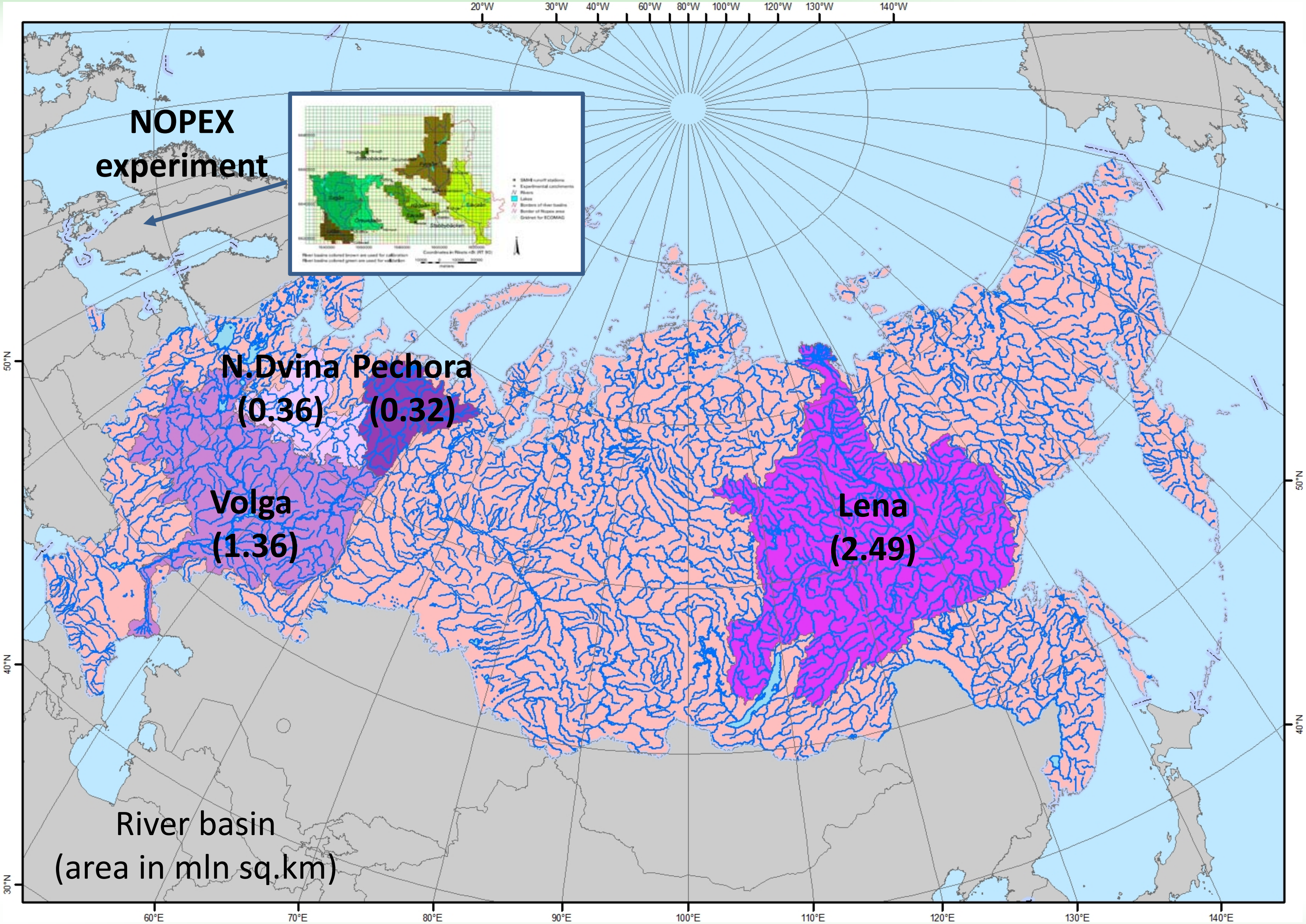
Input variables:

Daily precipitation (P)

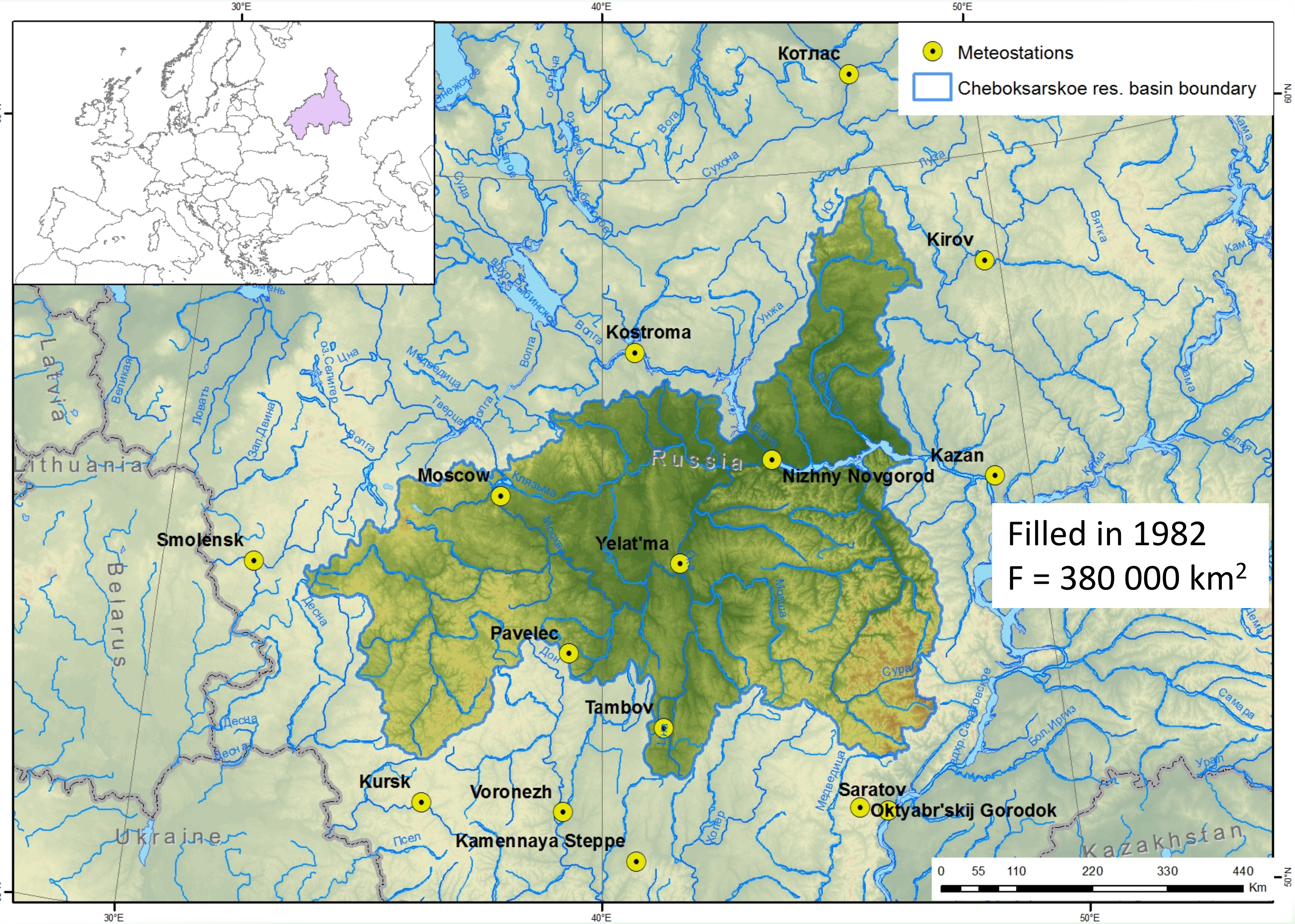
Daily air temperature (T)

Daily air humidity (D)

9 Methods & models

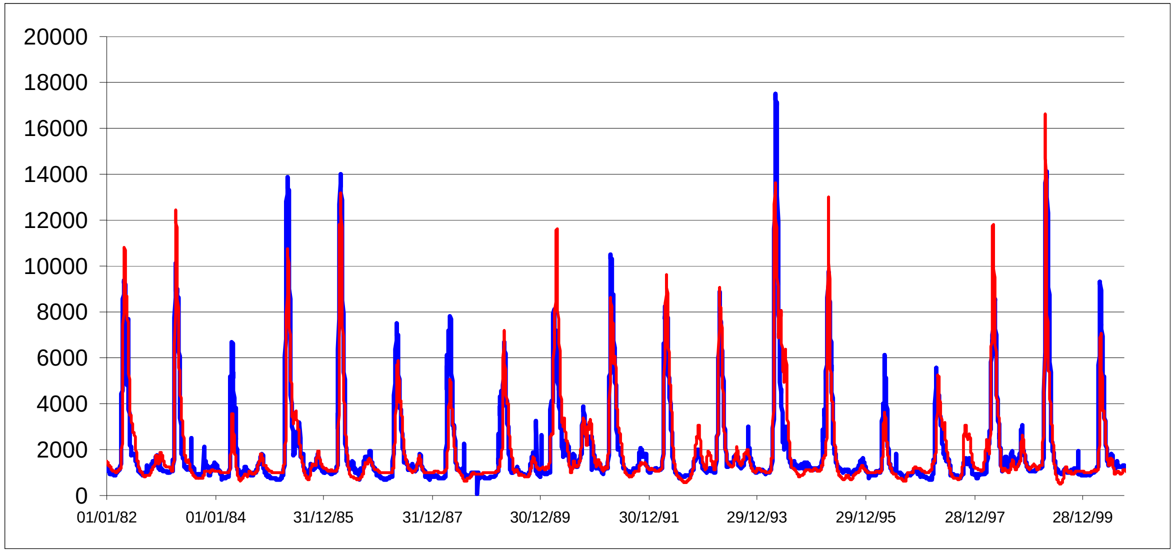


10 Case study: forecasting the spring inflow into Cheboksarskoe water reservoir



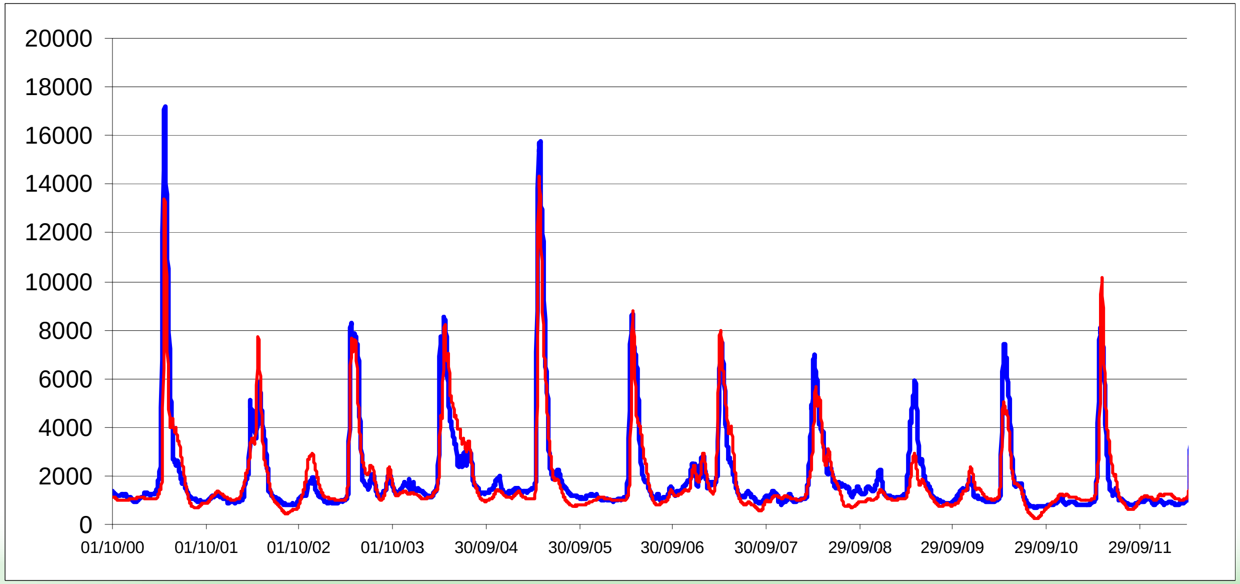
Filled in 1982
$F = 380\ 000\ km^2$

The model was calibrated and validated against the observed data for 1982-2010



Calibration period (1982-1999)

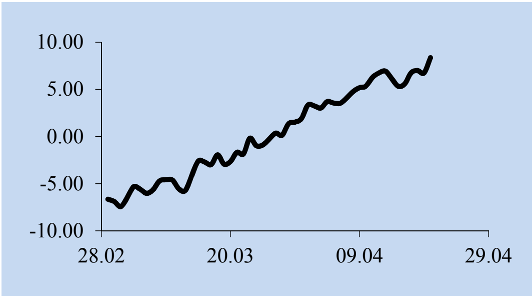
Validation period (2000-2010)

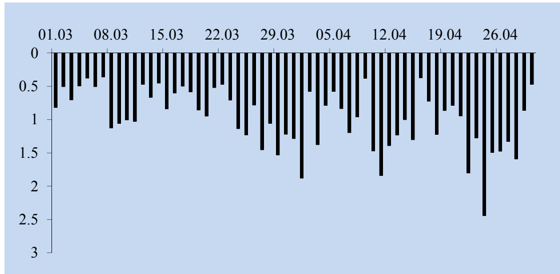


12 Deterministic long-term forecast

Simulated characteristics of snow and basin conditions on the forecasting date (March, 1)

Mean (climatology) time series of meteorological variables for the lead-time period (1 March-31 May)





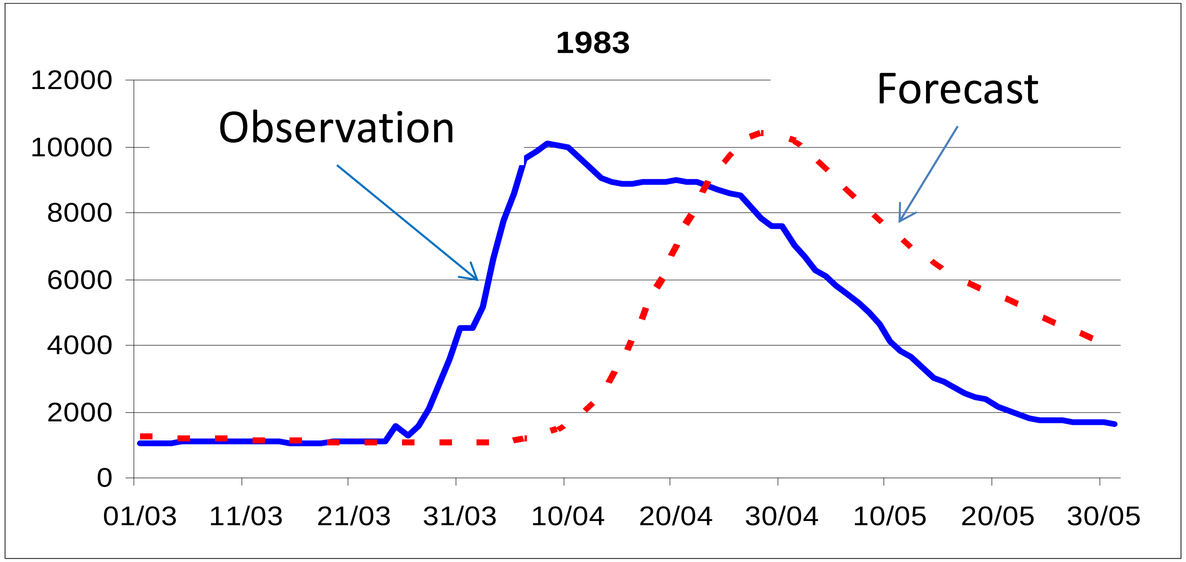
ECOMAG

Deterministic Forecast of flood characteristics

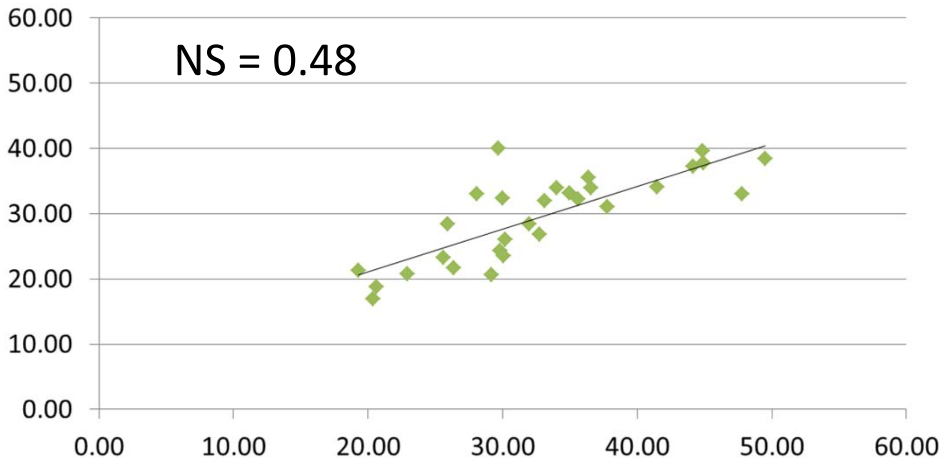
Climatic mean

- **15 locations**
- **daily T, P and D**
- **March1 – May 31**

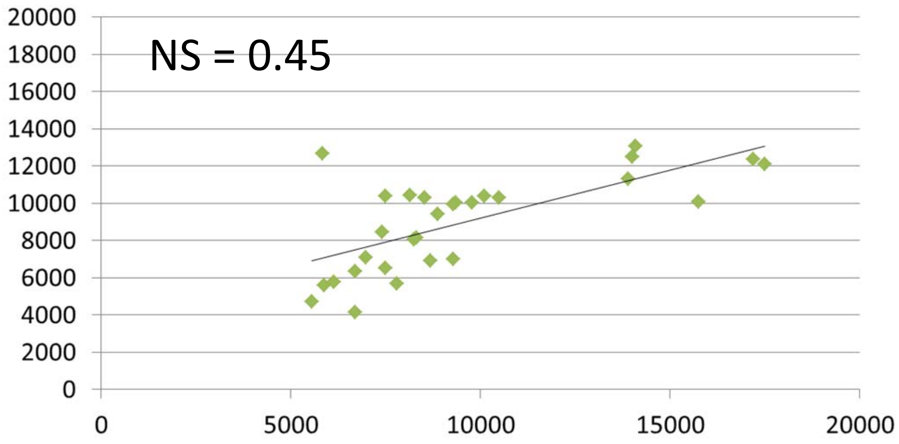
(1950 – 2010)

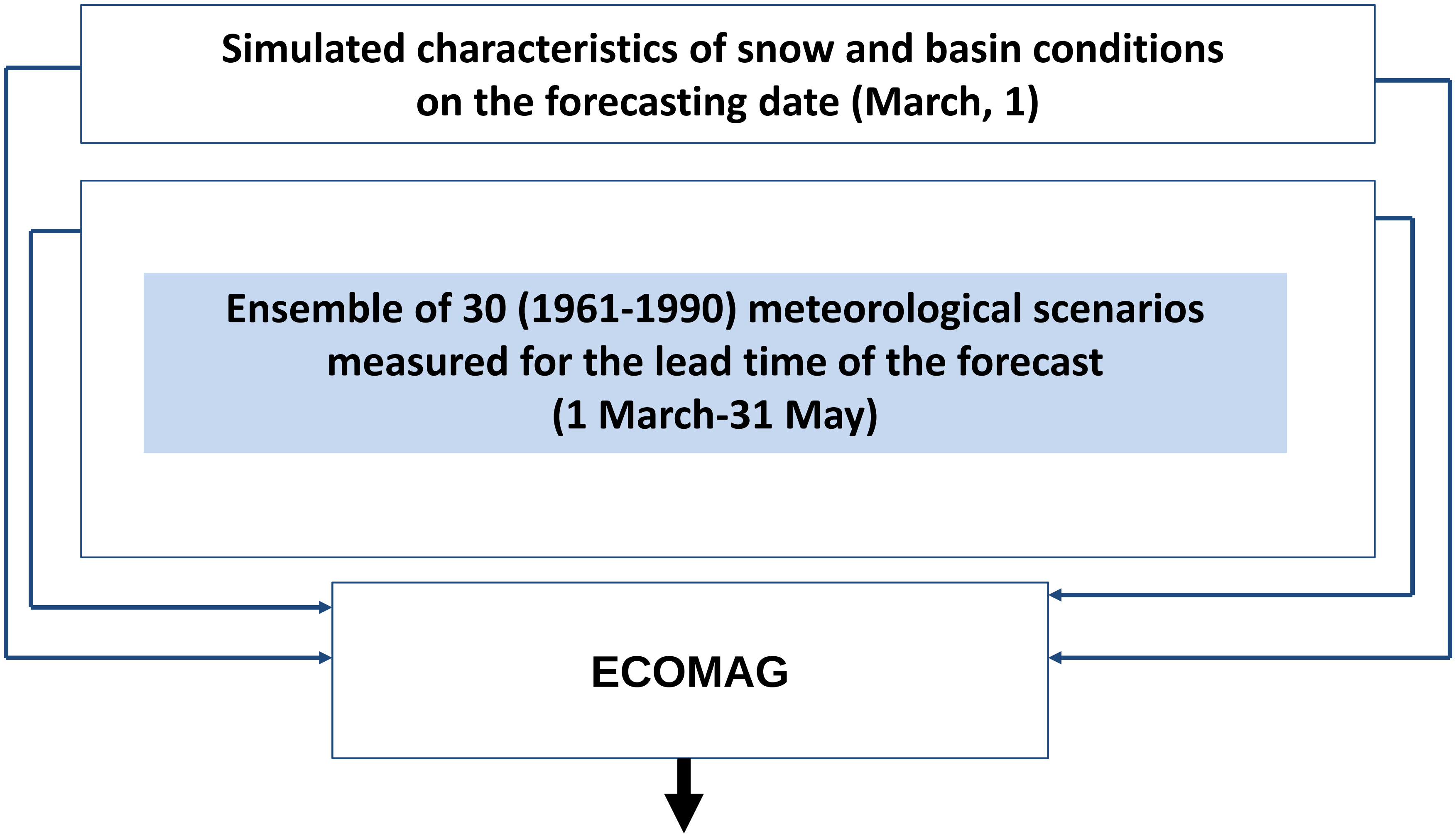


Total inflow volume during March – May



Maximum discharge (cu.m*s^{-1})



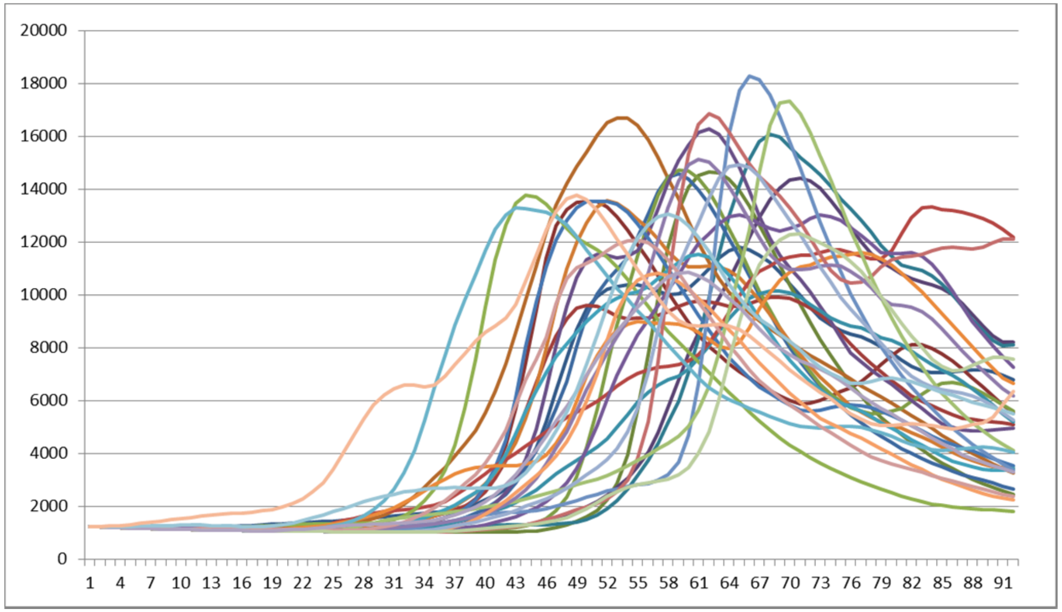


Probability distributions of flood characteristics

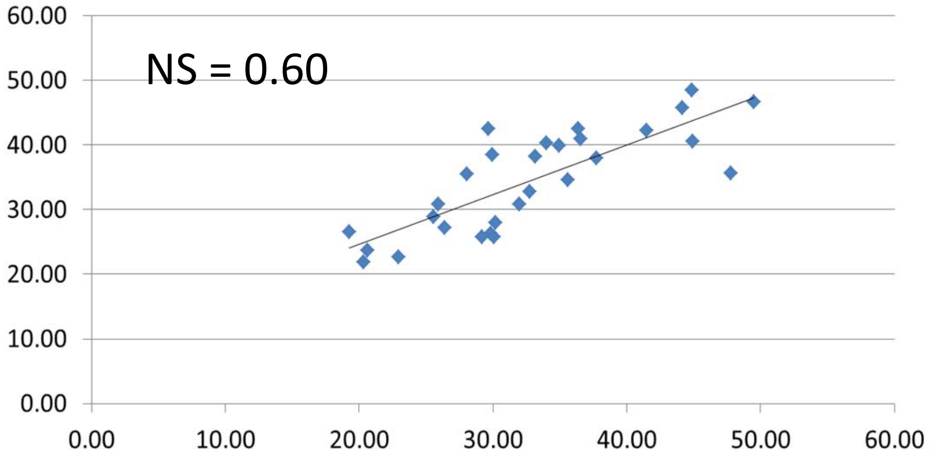
Observed weather ensembles

- **15 locations**
- **daily T, P and D**
- **March1 – May 31**

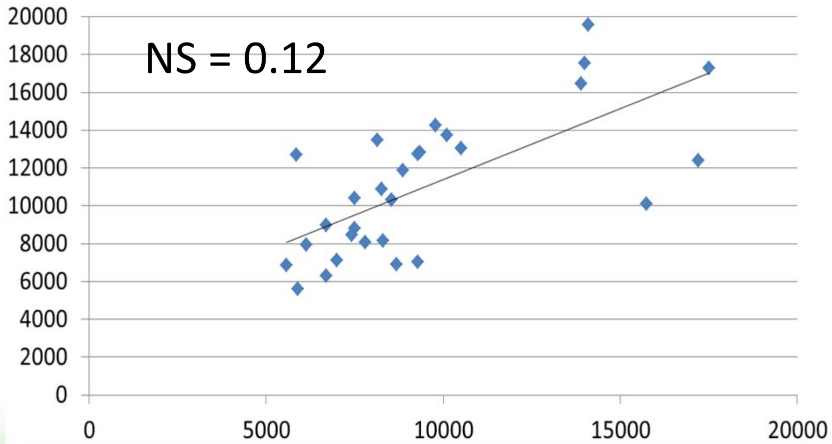
(1950 – 2010)



Mean total inflow volume during March – May



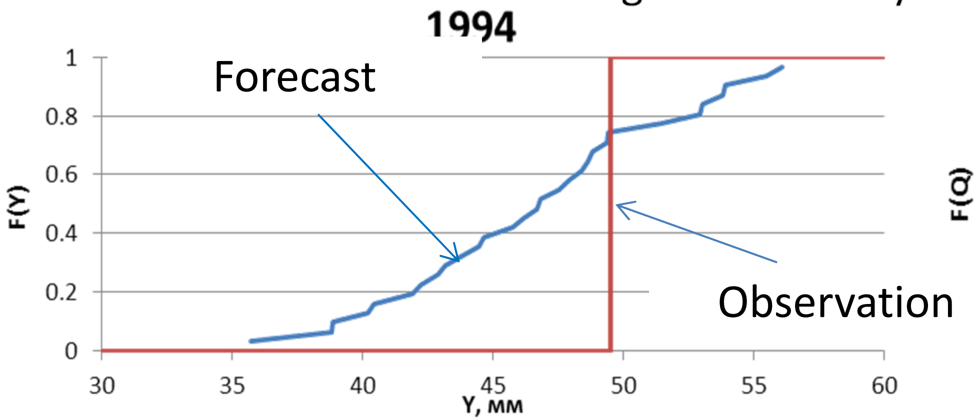
Mean maximum discharge (cu.m*s^{-1})

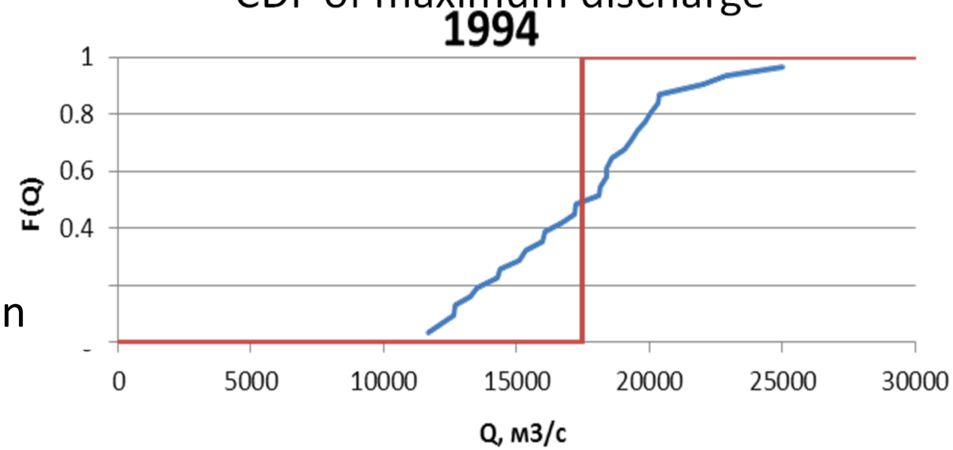


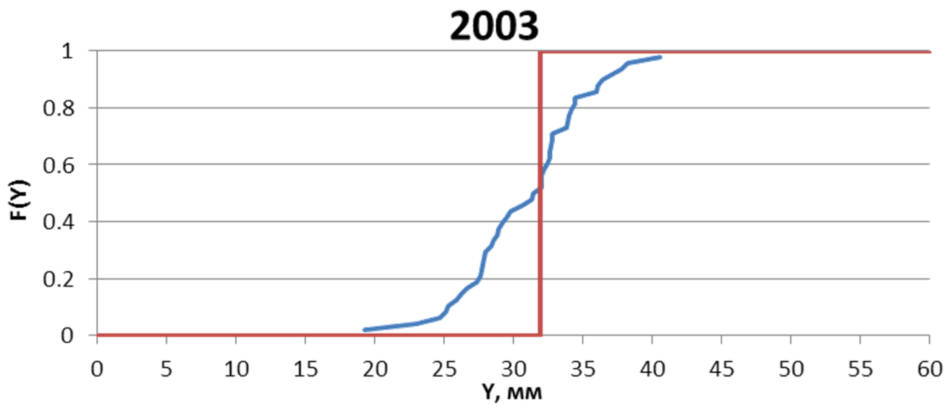
16 Probabilistic long-term forecast 2

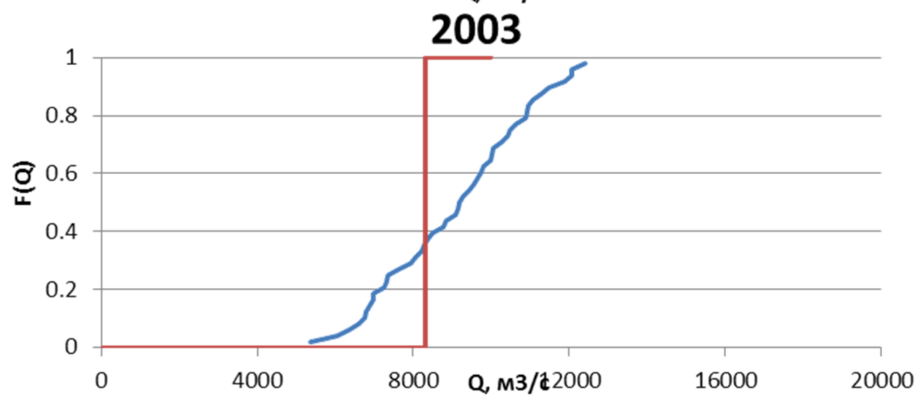
CDF of inflow volume during March – May

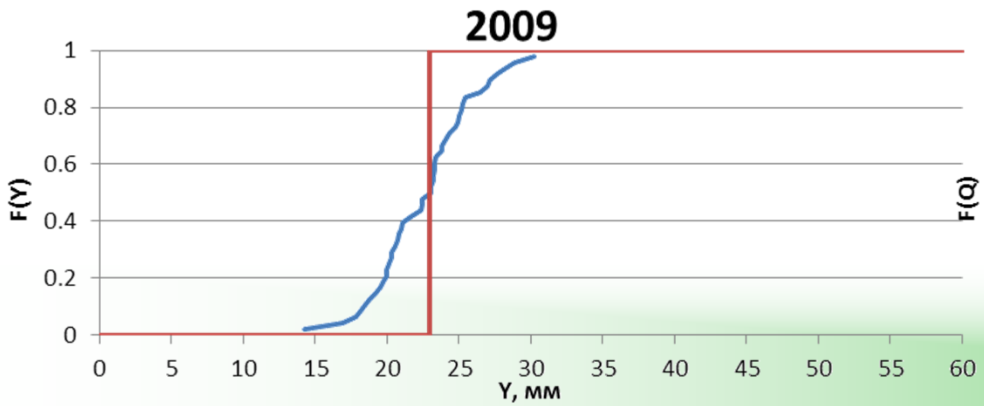
CDF of maximum discharge

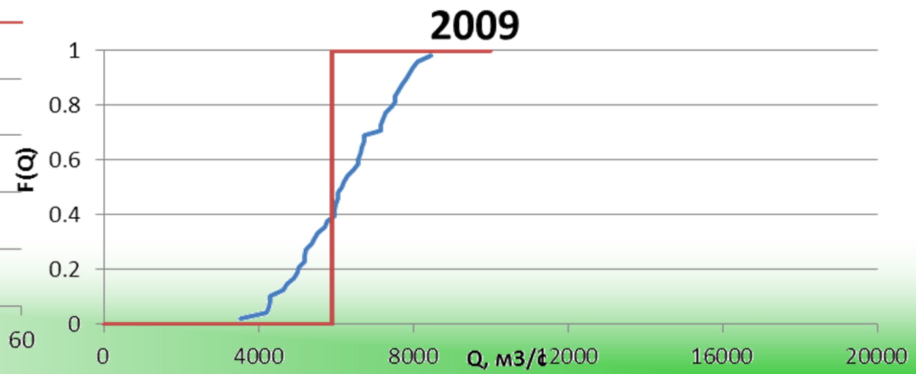


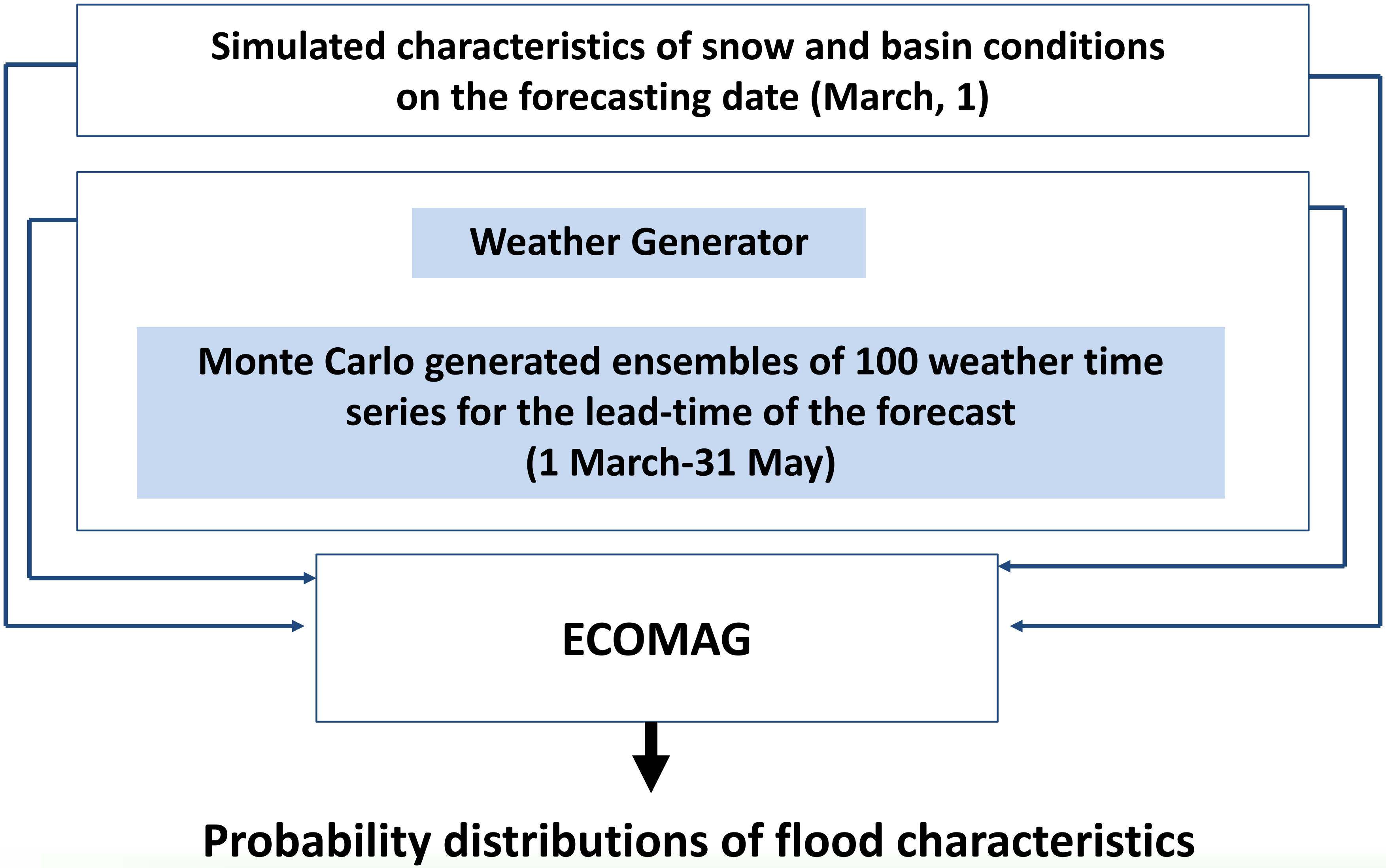











Simulated characteristics of snow and basin conditions on the forecasting date (March, 1)
Weather Generator
Monte Carlo generated ensembles of 100 weather time series for the lead-time of the forecast (1 March-31 May)
ECOMAG
Probability distributions of flood characteristics

Nested Weather Generator - NeWGEN (Gelfan, Moreido, 2014[1])

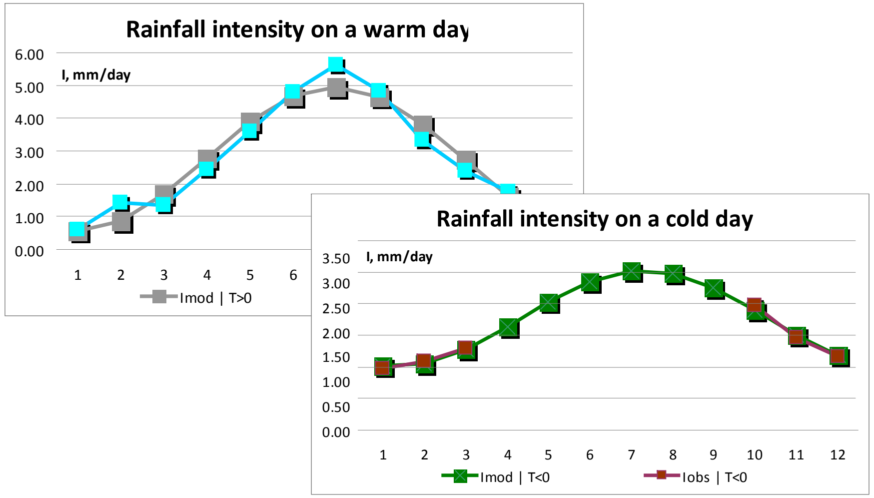
Precipitation model

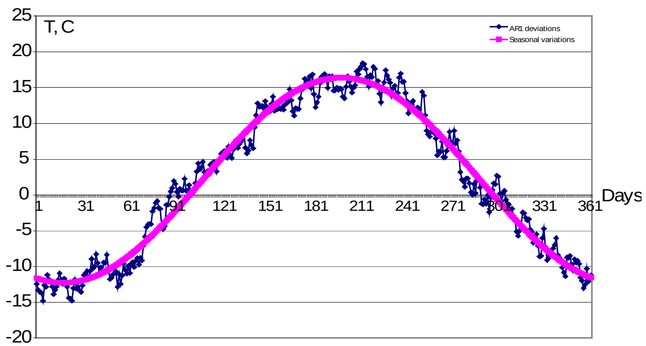
- Daily dry/wet state – 1st-order Markov chain
- Precipitation amount on a wet day - intensity-dependent gamma-distributed value with seasonal variability described by Fourier series

$$P_{ij} = \Pr[J_n = j \mid J_n\text{-}1 = i] \qquad P_1 = \frac{P_{01}}{P_{10} + P_{01}}$$

$$\pi_i = \Pr[J_0 = i],$$

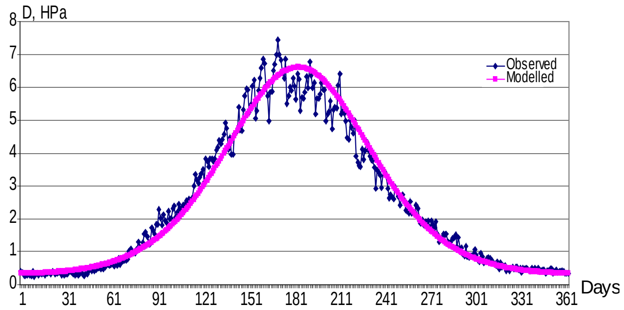
$$i,j = 0,1;\ n = 1,2\ldots \qquad r_1 = P_{11} - P_{01}$$





Temperature model

- Mean annual air temperature – normally distributed random value. Daily temperature - Fourier series with daily deviations described by AR(1) model



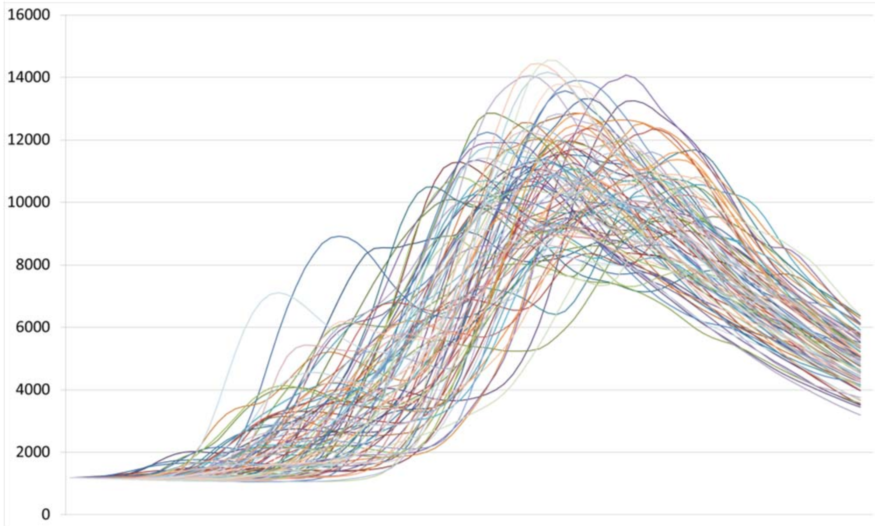
Air humidity deficit

- Mean annual humidity deficit – normally distributed random value. Seasonal variability of the daily humidity deficit on a wet day is described by Fourier series.

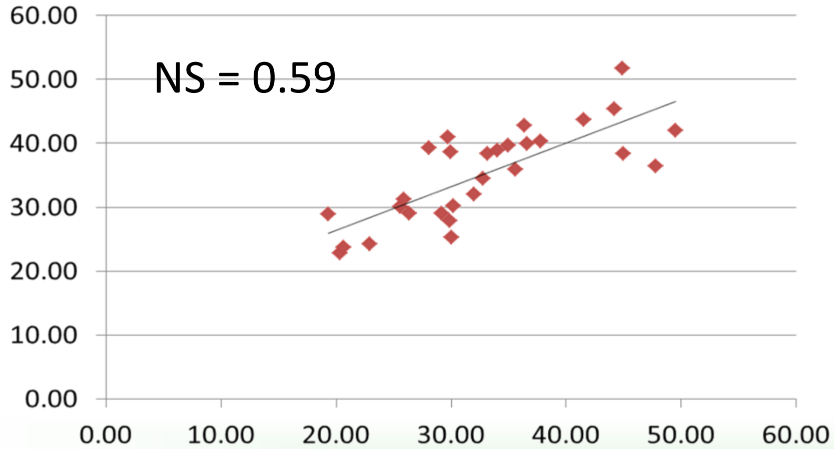
[1] Russian Ice and Snow Journal, 2014, vol. 2

100 generated climate ensembles
- **15 stations**
- **daily T, P and D**
- **March1 – May 31**

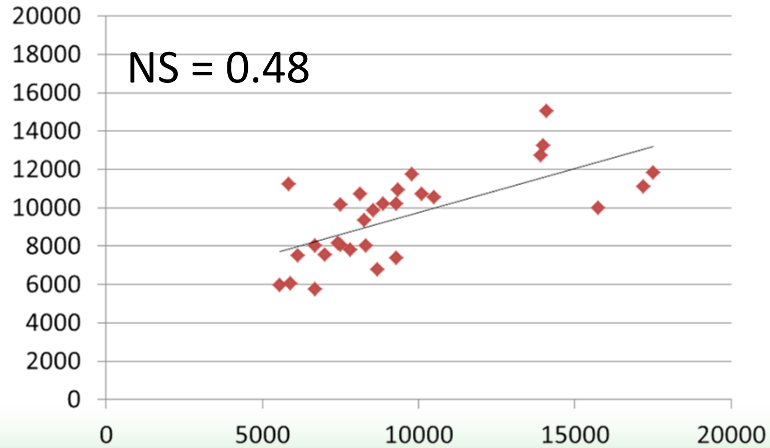
(1950 – 2010)



Mean total inflow volume during March – May



Mean maximum discharge (cu.m*s^{-1})



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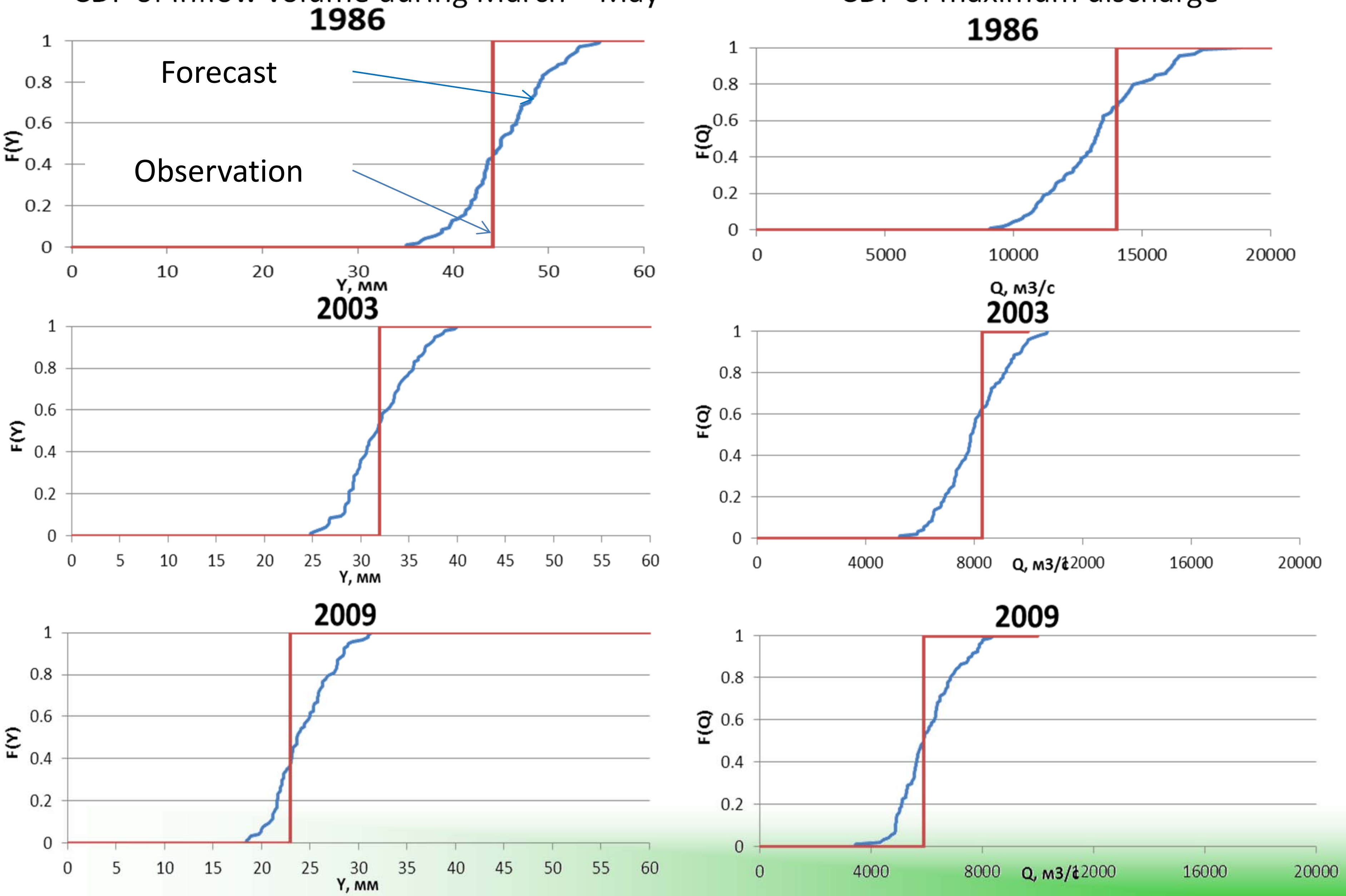
CDF of inflow volume during March – May

CDF of maximum discharge



Meteorological scenarios for lead-time period	Nash-Sutcliffe efficiency for total inflow volume	Nash-Sutcliffe efficiency for maximum discharge
Deterministic forecast		
Climatic mean	0.48	0.45
Ensemble forecast (average)		
Observed weather	0.60	0.12
Generated weather	0.59	0.48

- An approach for model-based forecast of spring inflow into a large reservoir has been developed employing two types of model forcing for the lead-time period
  - Use of the historical, observed weather patterns (assumed to be equally likely) to drive the model, starting at the forecast date
  - Use of artificial weather patterns, generated by a stochastic model ("weather generator"), persisting the probabilistic properties of observed weather variables

- Ensemble forecast allows for significant improvement in total inflow volume prediction
- Incorporation of stochastic weather generator allows for estimation of the events of larger return period as compared to the observed weather ensemble

Thank you for your attention!