HIC 2018

ERROR EVOLUTION PATTERNS IN MULTI-STEP AHEAD STREAMFLOW FORECASTING

G. A. Papacharalampous[1] / H. Tyralis[2] / D. Koutsoyiannis[3]

[1] National Technical University of Athens, Iroon Polytechniou 5, 157 80 Zografou, Greece, papacharalampous.georgia@gmail.com

[2] National Technical University of Athens, Iroon Polytechniou 5, 157 80 Zografou, Greece, montchrister@gmail.com

[3] National Technical University of Athens, Iroon Polytechniou 5, 157 80 Zografou, Greece, dk@itia.ntua.gr

Available online at: itia.ntua.gr/1851

13TH INTERNATIONAL HYDROINFORMATICS CONFERENCE HIC 2018

1-6 JULY 2018 | PALERMO | ITALY

1. Introduction

- The major consideration in the hydrological time series forecasting literature is to present point forecasts as accurate as possible, probably because of their practical value (Krzysztofowicz 2001).
- Quantification of the forecast uncertainty is also essential (Krzysztofowicz 2001; Koutsoyiannis 2010; Montanari and Koutsoyiannis 2012) and strongly connected with the construction of confidence intervals.
- Simulation experiments can constitute a highly promising approach to uncertainty quantification (Montanari 2007), since this quantification can be achieved through the estimation of the variance of the forecast errors.
- The latter cannot be avoided; therefore, it is important to increase the understanding on how they may occur (Lange 2005). This understanding can facilitate their proper modelling, which is currently an open challenge.
- Herein, we examine the error evolution in multi-step ahead forecasting with an emphasis on monthly streamflow processes.

2. Methodology

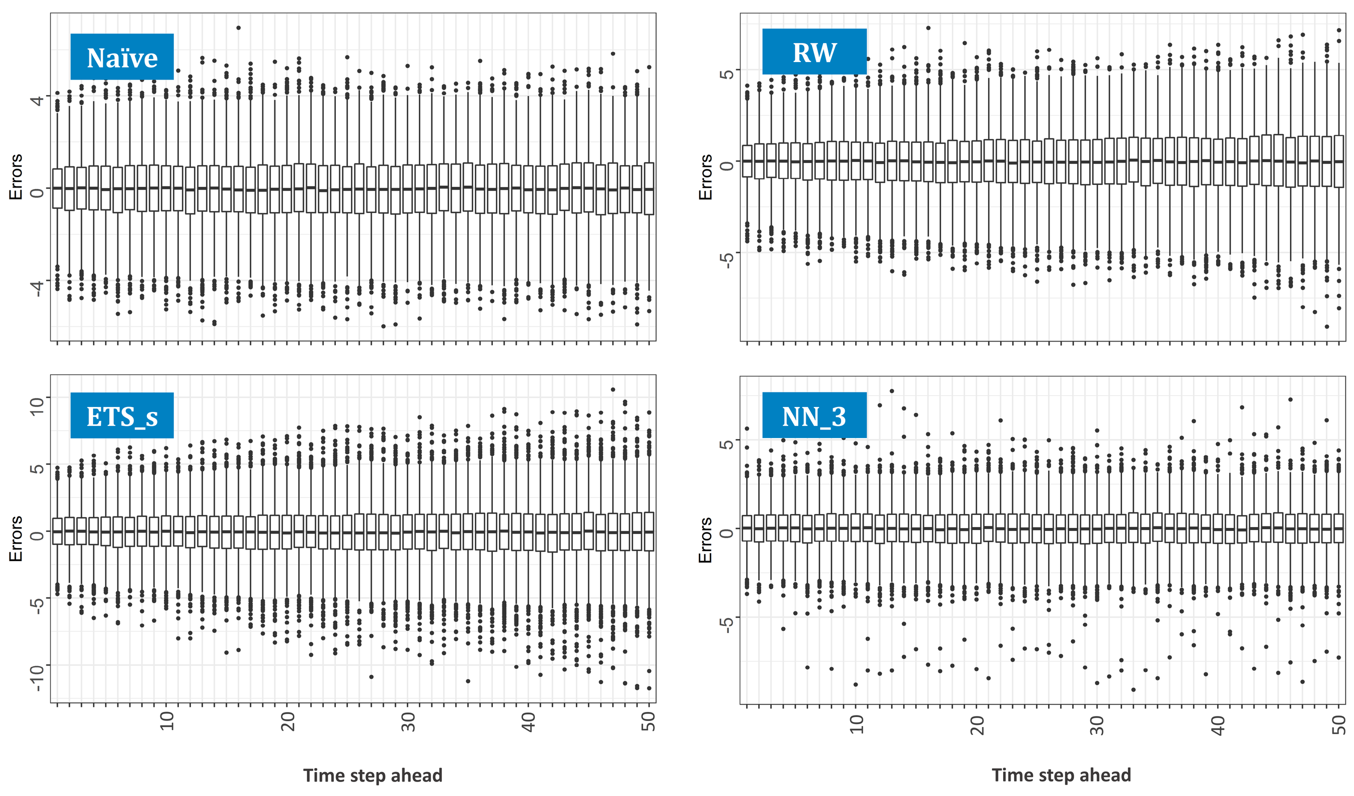
- We conduct 6 large-scale simulation experiments.
- Within each of these experiments we simulate 2 000 time series according to the following table:

Simulation experiment	Simulated process	Time series length
SE_1a	ARFIMA(0,0.30,0)	150
SE_1b		350
SE_2a	ARFIMA(1,0.30,0)	150
SE_2b		350
SE_3a	ARFIMA(0,0.30,1)	150
SE_3b		350

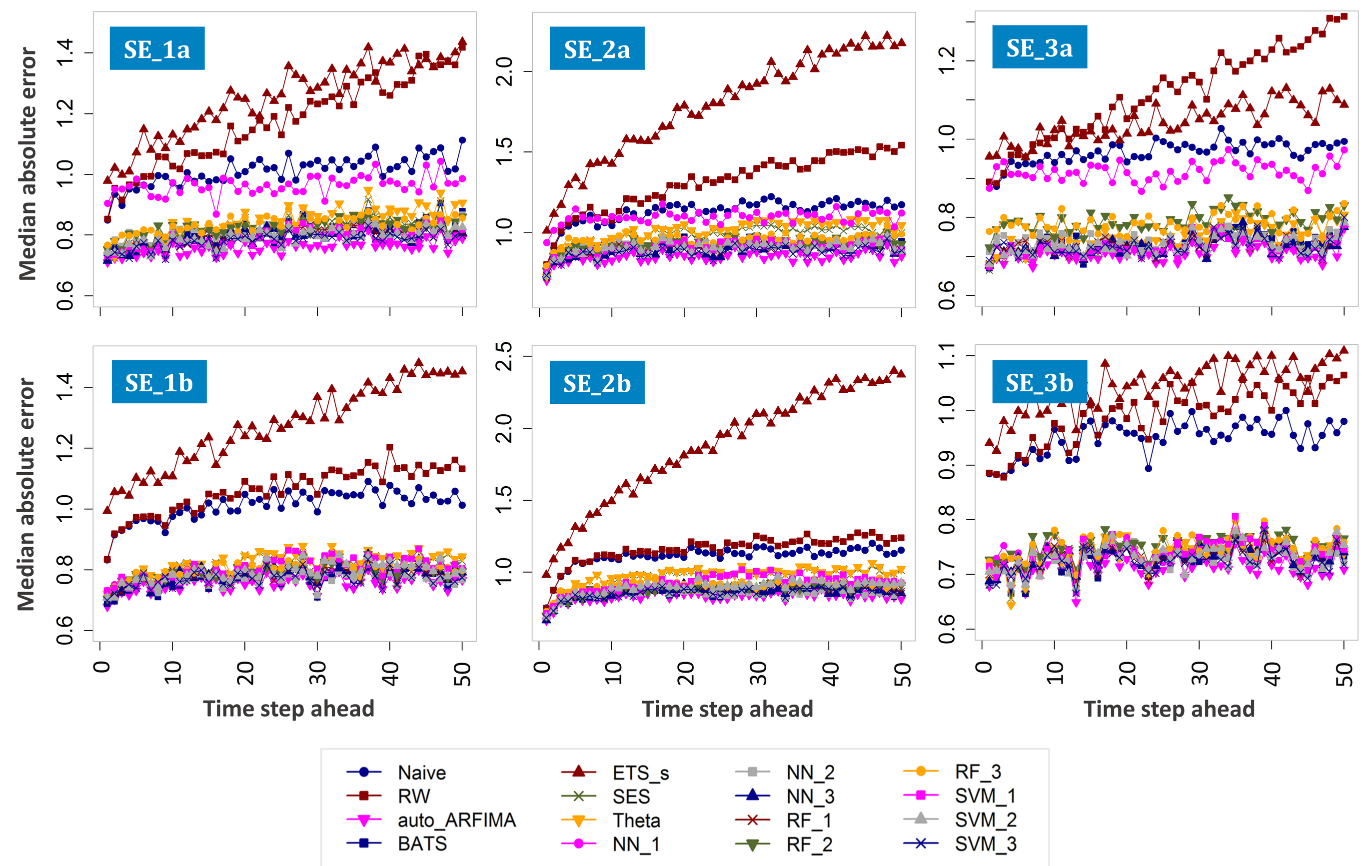
- We additionally conduct a comparative case study using 92 time series of monthly streamflow. These time series originate from catchments in Australia and are extracted form a larger dataset (Peel et al. 2000).
- To describe the long-term persistence of the deseasonalized real-world time series we estimate their Hurst parameter *H* using the mleHK algorithm of the HKprocess R package (Tyralis 2016), which implements the maximum likelihood method (Tyralis and Koutsoyiannis 2011).
- The *H* estimates range between 0.56 and 0.99 with a mean value of 0.78.
- We compare 16 forecasting methods (Naïve, RW, auto_ARFIMA, BATS, ETS_s, SES, Theta, NN_1, NN_2, NN_3, RF_1, RF_2, RF_3, SVM_1, SVM_2, SVM_3).
- For their implementation we use the forecast (Hyndman and Khandakar 2008, Hyndman et al. 2017), rminer (Cortez 2010, 2016), nnet (Venables and Ripley 2002), randomForest (Liaw and Wiener 2002) and kernlab (Karatzoglou et al. 2004) R packages , as well as several built in R algorithms (R Core Team 2017).
- Before applying the forecasting methods, we split each time series into a fitting and a testing set. The latter is the last 50 values for the simulation experiments and the last 12 values for the comparative case study.
- We fit the models to the fitting set and make predictions corresponding to the testing set using the recursive multi-step ahead forecasting method. Next, we calculate the errors and the absolute errors at each time step of the forecast horizon.
- Within the simulation experiments we carry out a statistical analysis on the formed data sets and we present the results accordingly.
- For the real-world time series, the fitting set is used after deseasonalization, which is performed using a multiplicative model of time series decomposition, while the seasonality is subsequently added to the forecasted time series.
- We present the results of the comparative case study in a qualitative form to facilitate the detection of systematic patterns.

3. Results

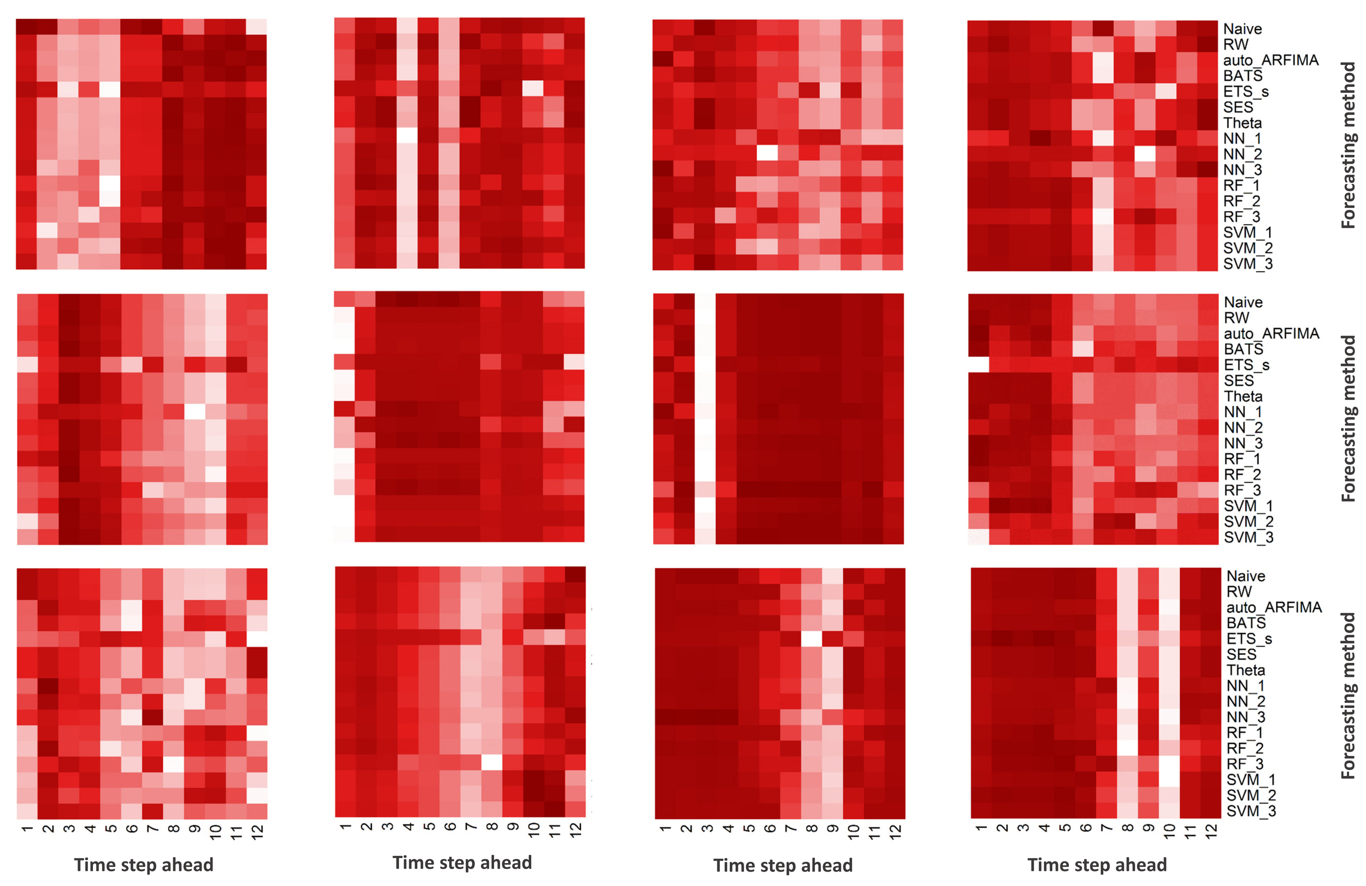
- We subsequently present the side-by-side boxplots of the errors computed for the Naïve, RW, ETS_s and NN_3 forecasting methods within SE_1a.



- The error evolution can differ to a great extent from the one forecasting method to the other. However, all the error boxplots tend to be approximately symmetric around zero.
- At the first few time steps ahead we observe an apparent increase of the median and iqr values. This increase is followed by a stabilization of the error distributions for most of the forecasting methods (e.g. Naïve and NN_3).
- On the contrary, when using the RW and ETS_s forecasting methods the errors seem to keep increasing until the last time step of the forecast horizon.
- The outliers are more frequent and lay farther from the median values when using specific forecasting methods (e.g. NN_3).
- Furthermore, the following figures present the medians of the absolute errors computed at each step of the forecast horizon:



- The results vary from the one simulation experiment to the other to an extent depending on the forecasting method.
- Some forecasting methods are more useful than others.
- Finally, we present 12 of the heatmaps produced within the comparative case study.



The darker the colour the smallest the absolute forecast error.

- The relative magnitude of the errors seems to strongly depend on the individual case examined and can be either small or large, regardless the forecasting method used and the time step of our interest.

4. Contribution

- Our findings indicate that the error evolution can differ to a great extent from the one forecasting method to the other.
- This specific information can be used to decide on a forecasting method, since some methods are more useful than others.
- Nevertheless, the errors computed at each time step of a forecast horizon within a specific case study strongly depend on the case examined.
- This fact is illustrated with a comparative case study.

References

Cortez, P., 2010. Data Mining with Neural Networks and Support Vector Machines Using the R/rminer Tool. In: P. Perner, eds. Advances in Data Mining. Applications and Theoretical Aspects. Springer Berlin Heidelberg, pp 572–583. doi:10.1007/978-3-642-14400-4_44

Cortez, P., 2016. rminer: Data Mining Classification and Regression Methods. R package version 1.4.2. https://cran.r-project.org/web/packages/rminer/index.html

Hyndman, R.J., and Khandakar, Y., 2008. Automatic time series forecasting: the forecast package for R. *Journal of Statistical Software*, 27 (3), 1–22. doi:10.18637/jss.v027.i03

Hyndman, R.J., O'Hara-Wild, M., Bergmeir, C., Razbash, S., and Wang, E., 2017. forecast: Forecasting functions for time series and linear models. R package version 8.0. https://cran.r-project.org/web/packages/forecast/index.html

Karatzoglou, A., Smola, A., Hornik, K., and Zeileis, A., 2004. kernlab - An S4 Package for Kernel Methods in R. *Journal of Statistical Software*, 11 (9), 1–20

Koutsoyiannis, D., 2010. HESS Opinions "A random walk on water". *Hydrology and Earth System Sciences*, 14, 585–601. doi:10.5194/hess-14-585-2010

Krzysztofowicz, R., 2001. The case for probabilistic forecasting in hydrology. *Journal of Hydrology*, 249 (1–4), 2–9. doi:10.1016/S0022-1694(01)00420-6

Lange, M., 2005. On the uncertainty of wind power predictions-Analysis of the forecast accuracy and statistical distribution of errors. *Journal of Solar Energy Engineering*, 127 (2), 177–184. doi:10.1115/1.1862266

Liaw, A., and Wiener, M., 2002. Classification and regression by randomForest. *R News*, 2 (3), 18–22

Montanari, A., 2007. What do we mean by 'uncertainty'? The need for a consistent wording about uncertainty assessment in hydrology. *Hydrological Processes*, 21 (6), 841–845. doi:10.1002/hyp.6623

Montanari, A., and Koutsoyiannis, D., 2012. A blueprint for process-based modeling of uncertain hydrological systems. *Water Resources Research*, 48 (9), W09555. doi:10.1029/2011WR011412

Peel, M.C., Chiew, F.H.S., Western, A.W., and McMahon, T.A., 2000. Extension of unimpaired monthly streamflow data and regionalisation of parameter values to estimate streamflow in ungauged catchments. Report prepared for the National Land and Water Resources Audit

R Core Team, 2017. R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria

Tyralis, H., 2016. HKprocess: Hurst-Kolmogorov Process. R package version 0.0-2. https://cran.r-project.org/web/packages/HKprocess/index.html

Tyralis, H., and Koutsoyiannis, D., 2011. Simultaneous estimation of the parameters of the Hurst–Kolmogorov stochastic process. *Stochastic Environmental Research and Risk Assessment*, 25 (1), 21–33. doi:10.1007/s00477-010-0408-x

Venables, W.N., and Ripley, B.D., 2002. Modern Applied Statistics with S, fourth edition. New-York: Springer-Verlag. doi:10.1007/978-0-387-21706-2