Large scale simulation experiments for the assessment of one-step ahead forecasting properties of stochastic and machine learning point estimation methods

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Background information

- The scientific literature includes a large number of studies assessing the **one-step ahead forecasting performance** of stochastic and/or machine learning methods when applied to geophysical processes within **case studies**, e.g.:

Lambrakis et al. (2000); Ballini et al. (2001); Yu et al. (2004);
Yu and Liong (2007); Hong (2008); Koutsoyiannis et al. (2008);
Papacharalampous et al. (2017b)

- However, **generalized information** about the forecasting methods cannot be extracted from case studies.
- **Makridakis and Hibon (2000)** presented the results of the M3-Competition. In the latter the one- and multi-step ahead forecasting performance of several methods were assessed on 3 003 real-world time series.
- Recently, **Papacharalampous et al. (2017a)** compared several stochastic and machine learning methods regarding their multi-step ahead forecasting properties when applied to **stationary stochastic processes**. The methods were tested on 48 000 simulated time series.
- In a similar vein, **Tyralis and Papacharalampous (2017)** compared several random forests methods regarding their one-step ahead forecasting performance on 16 000 simulated time series. The aim was to suggest an optimal set of time lags to be used in the fitting phase.

The present study

- We have focused on **one-step ahead forecasting in geoscience**.
- We have conducted **12 large scale simulation experiments**.
- Additionally, we have conducted a **real-world multiple-case study**.
- We have compared **20 forecasting methods**.

Time series

✓ 12 x **2 000 time series** of **100 values**, resulted from the simulation of ARMA and ARFIMA processes (see **4**), which are widely used for the modelling of geophysical processes

✓ **135** mean annual time series of temperature, which contain **100 continuous observations** (see **5**)

Forecasting methods (see **6**)

✓ **11 stochastic methods** originating from the families: simple, ARMA, ARIMA, ARFIMA, exponential smoothing, state space

✓ **9 machine learning methods** originating from the families: neural networks, random forests, support vector machines

- The comparative assessment of the methods has been based on the **error** and the **absolute error** of the forecast of the last value.

Simulated stochastic processes

Simulation experiment	Stochastic process	Parameters of the stochastic process
SE_1	AR(1)	$\varphi_1 = 0.7$
SE_2	AR(1)	$\varphi_1 = -0.7$
SE_3	AR(2)	$\varphi_1 = 0.7$, $\varphi_2 = 0.2$
SE_4	MA(1)	$\theta_1 = 0.7$
SE_5	MA(1)	$\theta_1 = -0.7$
SE_6	ARMA(1,1)	$\varphi_1 = 0.7$, $\theta_1 = 0.7$
SE_7	ARMA(1,1)	$\varphi_1 = -0.7$, $\theta_1 = -0.7$
SE_8	ARFIMA(0,0.45,0)	
SE_9	ARFIMA(1,0.45,0)	$\varphi_1 = 0.7$
SE_10	ARFIMA(0,0.45,1)	$\theta_1 = -0.7$
SE_11	ARFIMA(1,0.45,1)	$\varphi_1 = 0.7$, $\theta_1 = -0.7$
SE_12	ARFIMA(2,0.45,2)	$\varphi_1 = 0.7$, $\varphi_2 = 0.2$, $\theta_1 = -0.7$, $\theta_2 = -0.2$

Simulation of the ARMA processes

- **R package stats** (R Core Team 2017)

Simulation of the ARFIMA processes

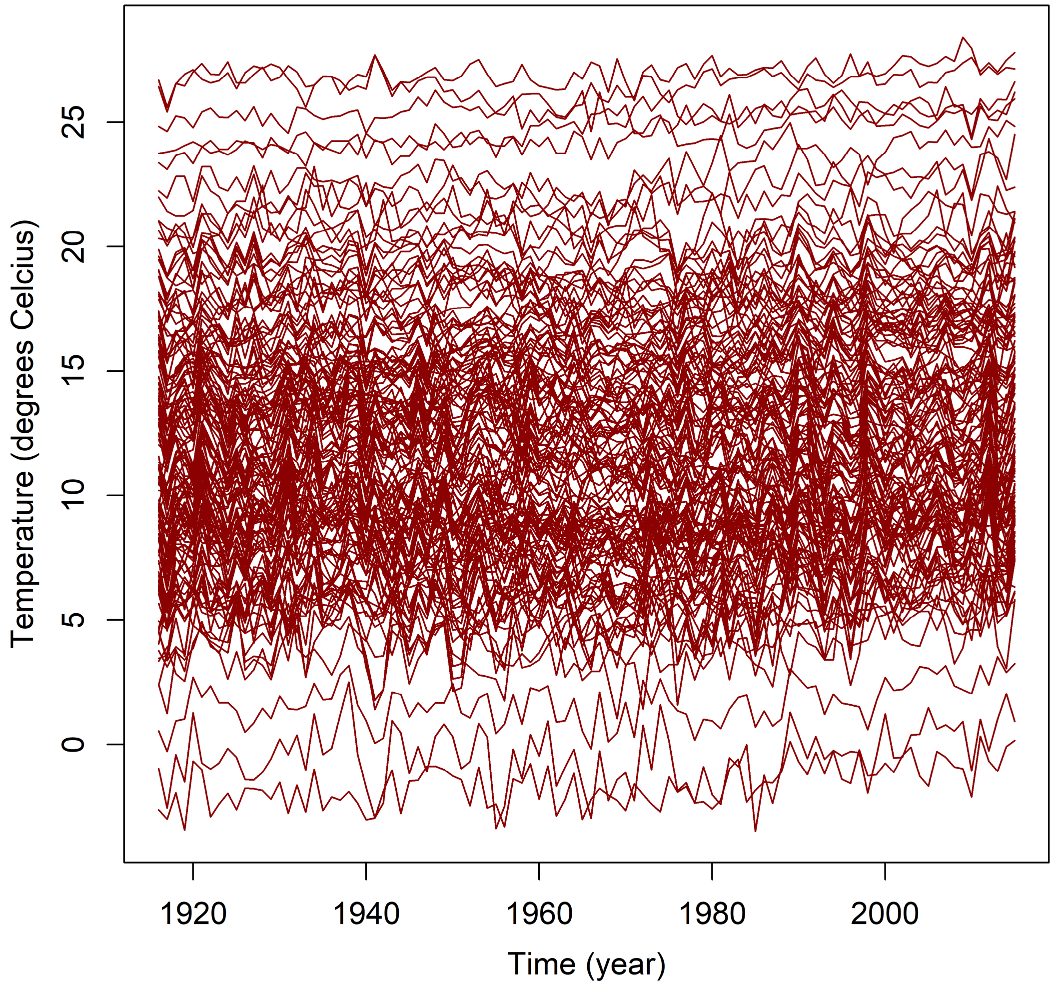
- **R package fracdiff** (Fraley et al. 2012)

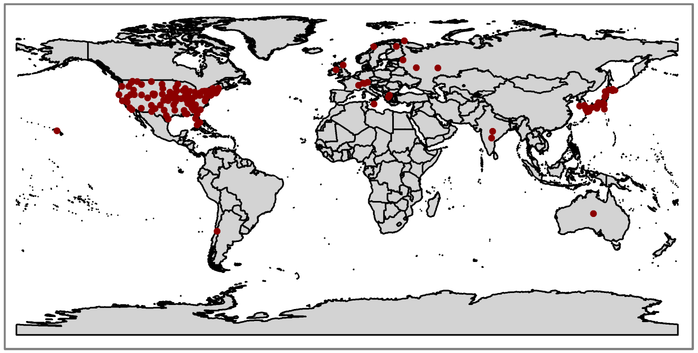
The simulations were performed with zero mean and standard deviation of 1.

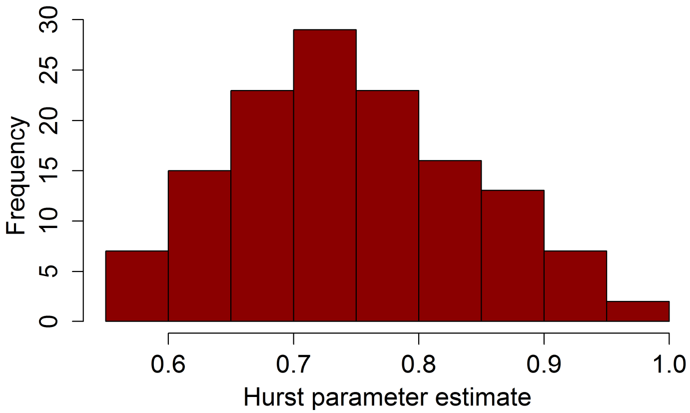
The definitions of the ARMA and ARFIMA stochastic processes can be found in Wei (2006).

Real-world time series

135 mean annual time series of temperature







Hurst parameter estimation

- **R package HKprocess** (Tyralis 2016, see also Tyralis and Koutsoyiannis 2011)

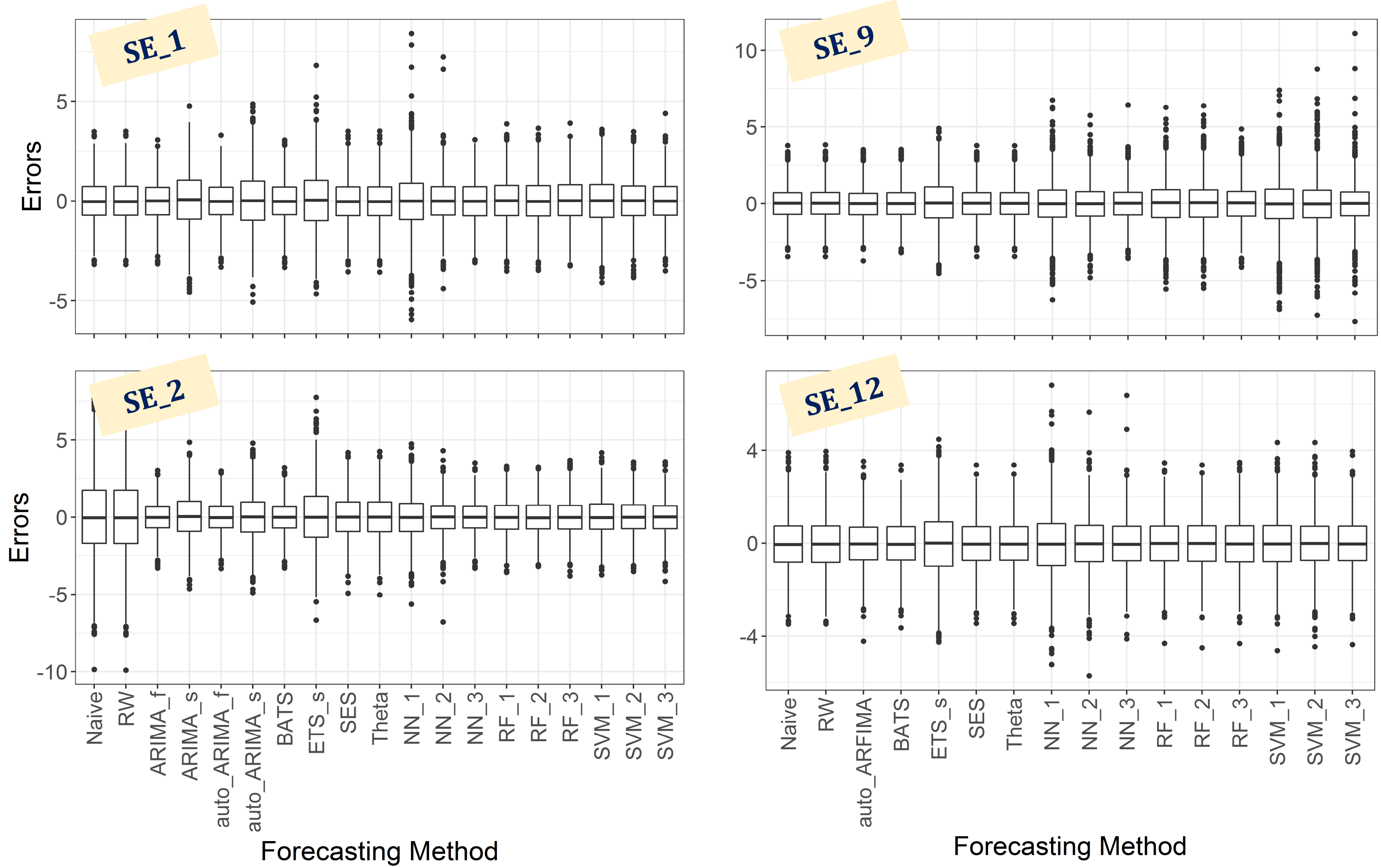
Forecasting methods

Naive *simple*	**RW** *simple*	**ARIMA_f** *ARMA*	**ARIMA_s** *ARMA*	**auto_ARIMA_f** *ARIMA*
auto_ARIMA_s *ARIMA*	**auto_ARFIMA** *ARFIMA*	**BATS** *state space*	**ETS_s** *state space*	**SES** *exponential smoothing*
Theta *exponential smoothing*	**NN_1** *neural networks*	**NN_2** *neural networks*	**NN_3** *neural networks*	**RF_1** *random forests*
RF_2 *random forests*	**RF_3** *random forests*	**SVM_1** *support vector machines*	**SVM_2** *support vector machines*	**SVM_3** *support vector machines*

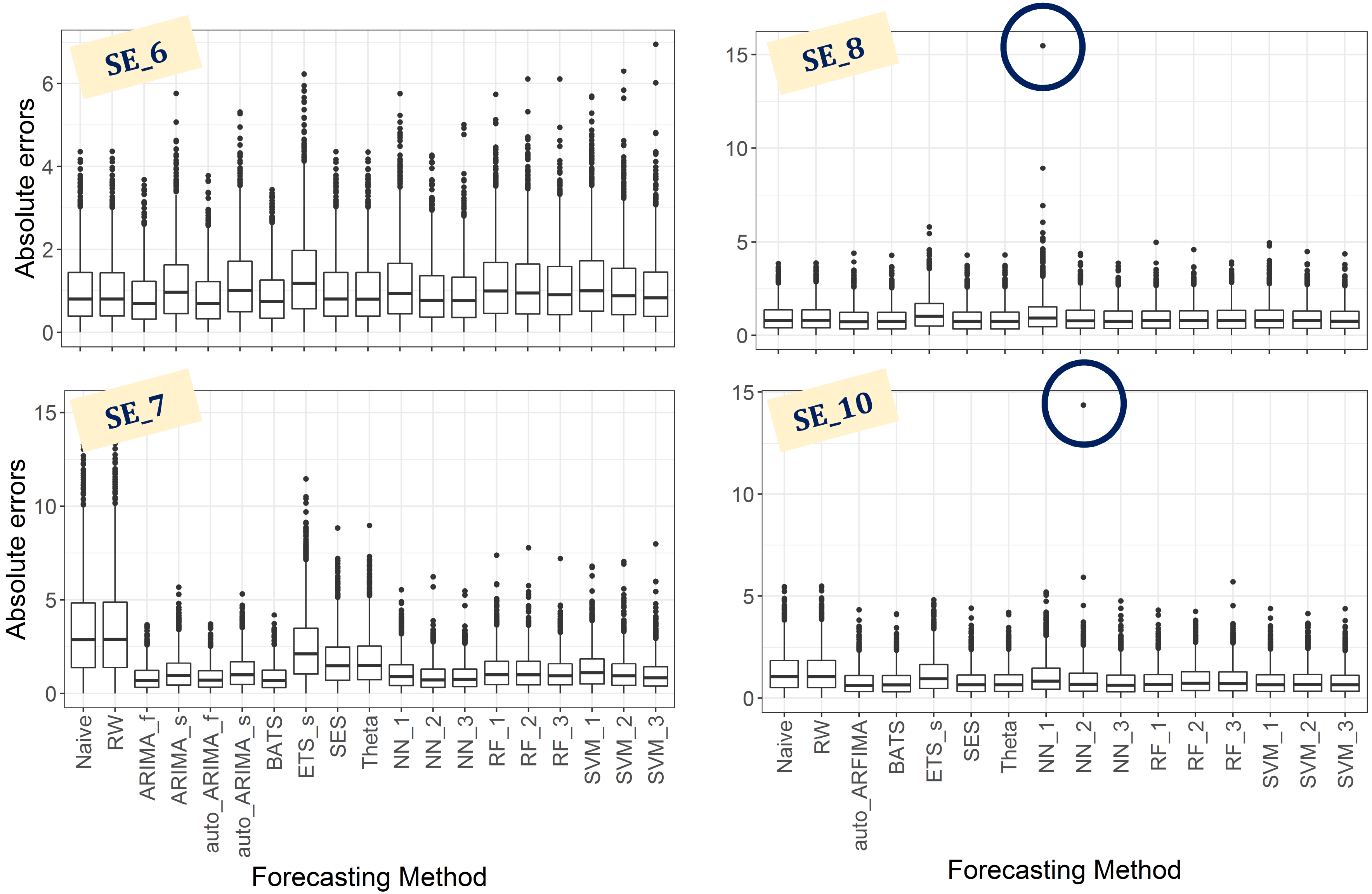
Implementation of the forecasting methods

- **R package forecast** (Hyndman and Khandakar 2008, Hyndman et al. 2017)
- **R package kernlab** (Karatzoglou et al. 2004)
- **R package nnet** (Venables and Ripley 2002)
- **R package randomForest** (Liaw and Wiener 2002)
- **R package rminer** (Cortez 2010, 2016)

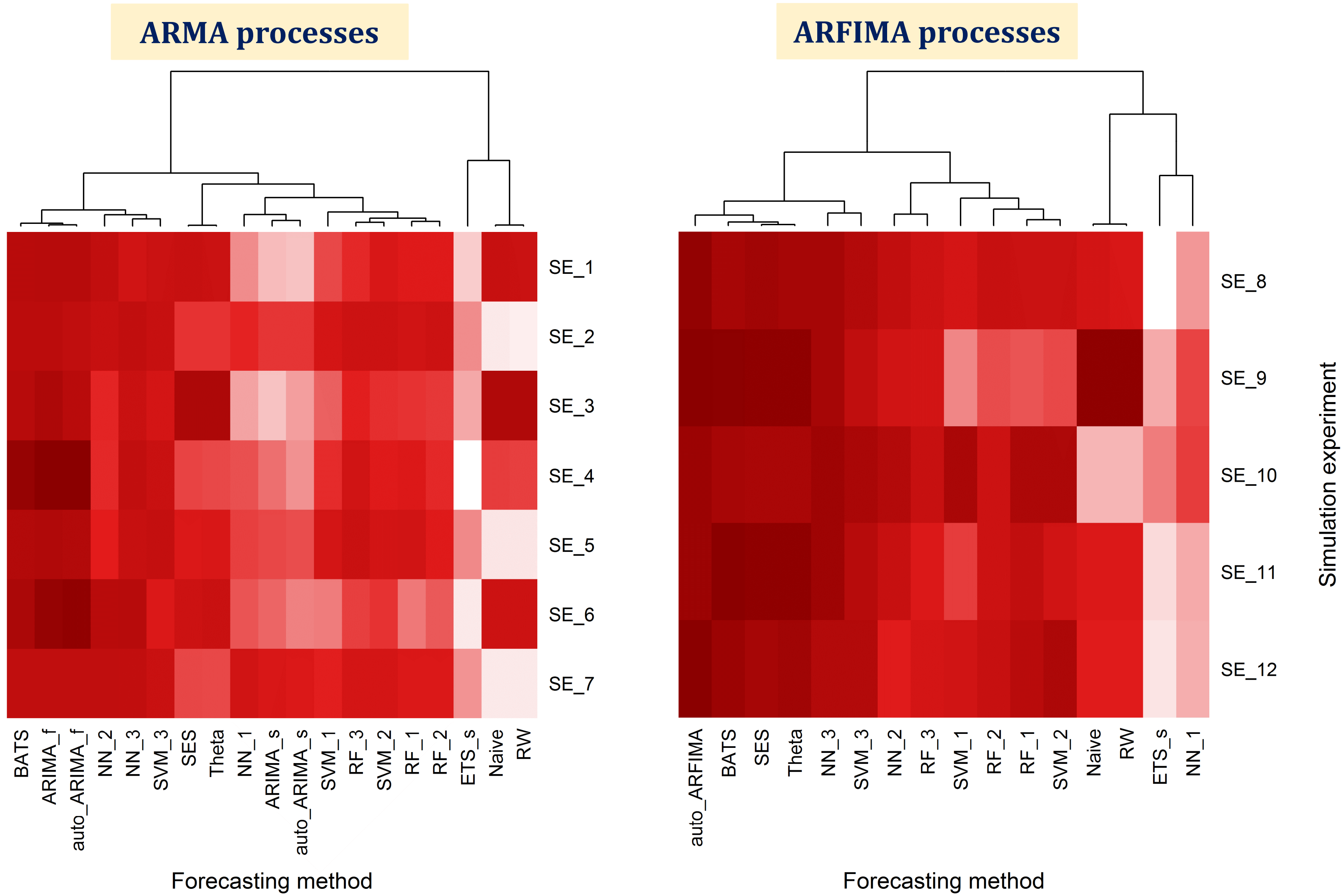
Simulation experiments: Errors



Simulation experiments: Absolute errors

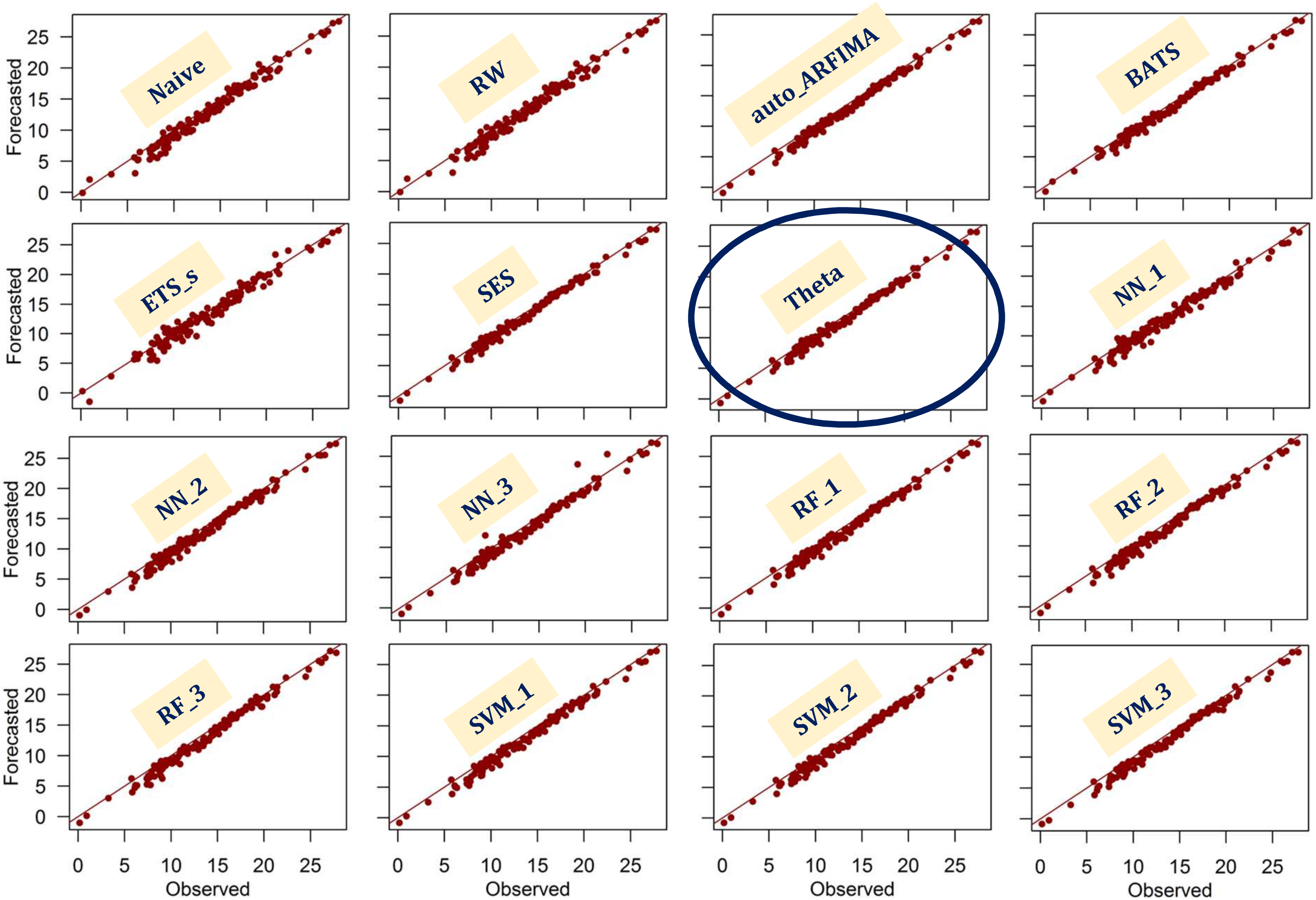


Simulation experiments: Average-case performance

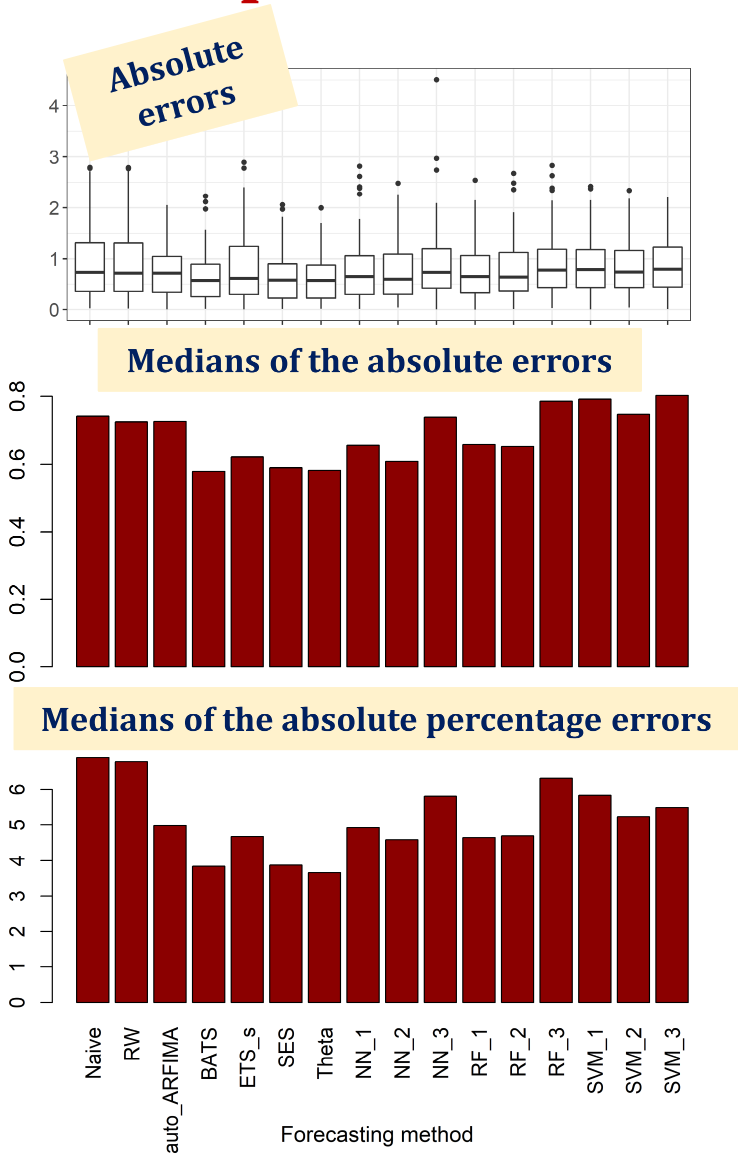


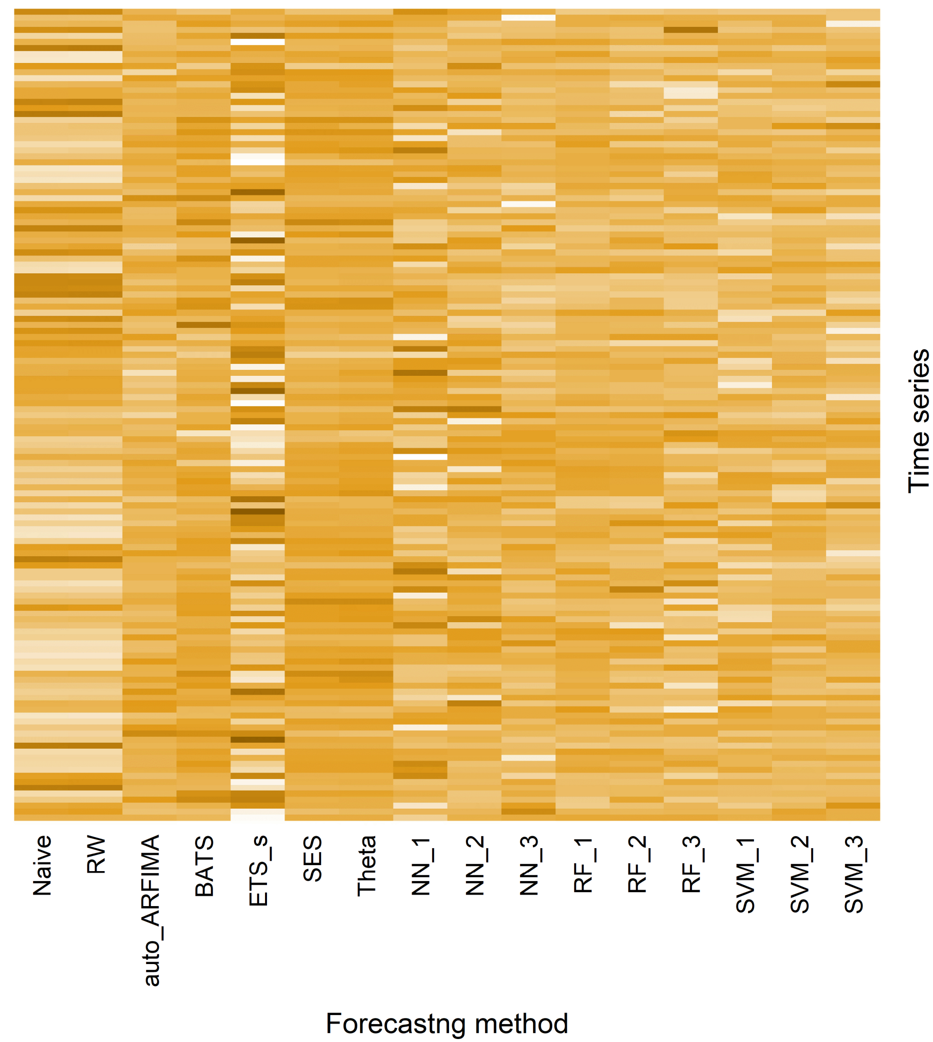
The darker the colour the better the forecasts.

135 temperature time series: Forecasted vs observed



135 temperature time series: Performance assessment





The darker the colour the better the forecasts.

Summary and conclusions

- We have conducted **large scale simulation experiments** for the assessment of the one-step ahead forecasting properties of several stochastic and machine learning point estimation methods.
- Our findings indicate that **the results can vary significantly** across the different simulation experiments and across the different time series.
- ARIMA_f, auto_ARIMA_f and BATS were proven to be the most accurate forecasting methods on the ARMA processes. The same applies to auto_ARFIMA, BATS, SES and Theta on the ARFIMA processes.
- The simple forecasting methods (Naive and RW) are also competent.
- Most of the observed **far outliers** were produced by neural networks.
- We have additionally applied our methodology to 135 mean annual time series of temperature.
- The **Theta** method, presented by Assimakopoulos and Nikolopoulos (2000), exhibited the best performance whithin this real-world case study being slightly better than BATS and SES.

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