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# Statistical modelling of agrometeorological time series by exponential smoothing

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A b s t r a c t. Meteorological time series are used in modelling agrophysical processes of the soil-plant-atmosphere system which determine plant growth and yield. Additionally, long-term meteorological series are used in climate change scenarios. Such studies often require forecasting or projection of meteorological variables, *eg* the projection of occurrence of the extreme events. The aim of the article was to determine the most suitable exponential smoothing models to generate forecast using data on air temperature, wind speed, and precipitation time series in Jokioinen (Finland), Dikopshof (Germany), Lleida (Spain), and Lublin (Poland). These series exhibit regular additive seasonality or non-seasonality without any trend, which is confirmed by their autocorrelation functions and partial autocorrelation functions. The most suitable models were indicated by the smallest mean absolute error and the smallest root mean squared error.

K e y w o r d s: exponential smoothing, meteorological time series, statistical forecasting,

## INTRODUCTION

Meteorological time series are an important source of information for agricultural planning. Basically, every farm operation and the process of plant growth and development as well as the yield of a crop are strongly affected by weather conditions (Porter and Semenov, 2005; Pirttioja *et al*., 2015). Therefore, meteorological time series are essential for crop modelling while forecasting of meteorological quantities is indispensable for scheduling agrotechnical measures such as fertilizer application (Asseng *et al*., 2012), irrigation (Magno *et al*., 2014), harvesting (Toscano *et al*., 2014; Trnka *et al*., 2014). Modelling and forecasting of meteorological time series improve our understanding of the variation of climatic conditions at varying scales in order to assess the effects of climate change on crop production (Smith *et al*., 2007). For instance, forecasts can be used to assess or to anticipate potentially hazardous weather extremes such as frosts, droughts, high winds (Schlenker and Roberts, 2006).

Two distinct approaches exist in forecasting and projection of meteorological elements: dynamical-physical models based on the laws of physics, including global circulation models (GCMs) used for long-term climate projections, and statistical models estimated directly from observations that are used for short-term predictions (McSharry, 2011). The first group of models facilitates projection of the effects of climate change. However, these models are based on understanding the interactions between mass and energy exchange between oceans, atmosphere, and biosphere, which are still not sufficiently acknowledged. On the other hand, the quality of forecasts based on statistical models strongly depends on the extent to which the future resembles the past. Representative historical data are therefore crucial for proper construction of such models.

Key meteorological time series are air temperature, humidity and pressure, wind speed, precipitation, and solar radiation, which are automatically measured within meteorological stations with relatively high frequency and accuracy. Long-term meteorological records from around the world are available nowadays, giving a good background for testing various statistical forecasting methods that try to build a model of the process that is to be predicted. While the idea of forecasting is to use an elaborated model on the values of the series to predict future ones, the meteorological forecasting techniques further depend on the time scale in question and the type of the series (Baranowski *et al*., 2015; Meehl *et al*., 2009; Smith *et al*., 2007).

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Methods used in statistical forecasting of meteorological time series include analyses of simple exponential smoothing, random walk, moving average, autoregressive integrated moving average (ARIMA), and artificial intelligence techniques such as Fuzzy Logic, Multi-Layered Perceptrons, Radial Basis Functions, Logistic Regression, and Recurrent Neural Networks (Bilgili, 2007; Chan *et al.*, 2006; Dong *et al.*, 2013; Ghiassi *et al.*, 2005; Reikard, 2009). Additionally, the hybrids of different methods are used to improve the forecasting accuracy. Although some of these methods represent a very sophisticated level of complexity, it was shown during model comparisons that statistically sophisticated or complex methods did not necessarily provide more accurate forecasts than simpler ones (Makridakis and Hibon, 2000).

The exponential smoothing methods play a special role in forecasting of meteorological time series and they are still being developed and improved (Gardner, 2006). A total of fifteen methods can be distinguished as the main framework of the family of the exponential smoothing methods. Additionally, a state space framework was elaborated, which can be applied to all the exponential smoothing models and which allows computation of prediction intervals, likelihood, and model selection criteria (Hyndman and Khandakar, 2008; Hyndman *et al.*, 2002).

The aim of this paper is to compare statistical short-time forecasting of air temperature, precipitation and wind speed using exponential smoothing on the basis of 31 years time series originating from four different locations in Europe.

## MATERIALS AND METHODS

Four study sites were selected according to the following criteria in order to offer a cross-section of climatic conditions in Europe as well as their shifts under climate change. In order to represent the contrasting climatic conditions with a minimum number of sites, it was decided to choose sites for northern, central, and southern Europe. Jokioinen in Finland was chosen for northern Europe and Lleida in Spain for southern Europe. For central Europe, two sites were chosen: Dikopshof located in the west part of Germany and Lublin in the east part of Poland. The four sites represent boreal, Atlantic central, continental, and Mediterranean south climates. The principal characteristics of these sites and their agro-climatic conditions are summarised in Table 1.

Jokioinen site has a subarctic climate that has severe winters, no dry season, cool, short summers, and strong seasonality (Köppen-Geiger classification: Dfc). Lleida has a semi-arid climate with Mediterranean-like precipitation patterns (annual average of 369 mm), foggy and mild winters, and hot and dry summers (Köppe-Geiger classification: BSk). Dikopshof represents a maritime temperate climate (Köppen-Geiger climate classification: Cfb). There is significant precipitation throughout the year in the German site. Lublin site has a warm summer continental climate (Köppen-Geiger climate classification: Dfb). The weather time series in all sites were measured with standard equipment, comparable for all stations. Three variables were considered in the present study: air temperature, precipitation, and wind speed. Datasets were collected on a daily basis from January 1st 1980 to December 31st 2010 (11 322 days). For Jokioinen, wind speed was measured at 10 m height and was converted to a height of 2 m assuming the logarithmic wind profile of Allen *et al*. (1998, their eq. 47). For Lleida, the wind speed time series had gaps of 82 days in autumn 1986 and global radiation data had gaps of 48 days (11 days in September 1988 and 37 days in spring 1990). These gaps were filled by taking the absolute values of the associated grid cell in the ERA-interim dataset.

The descriptive statistics of the meteorological time series are presented in Table 2. The highest mean and median values of air temperature in the period of 31 years were observed at Lleida station and the lowest at Jokioinen station. The parameters of skewness and kurtosis of the analysed time series give information about differences in their statistical distributions. Air temperature is characterized by negative skewness and small kurtosis, which inform us that this distribution is left-tailed and has a more rounded peak and thinner tails compared to the wind speed distribution, characterized by positive skewness and larger kurtosis. Completely different distribution shape can be observed for precipitation, with higher positive skewness and very large kurtosis values for all the stations. This means that this distribution is strongly right-tailed and has a very sharp peak and fat tail.

**T a b l e 1.** The principal characteristics of sites and their agro-climatic conditions

| Site | Jokioinen | Dikopshof | Lublin | Lleida |
|---|---|---|---|---|
| Country | Finland (FI) | Germany (DE) | Poland (PL) | Spain (ES) |
| Latitude (°N) | 60°48’ | 50°48’29’’ | 51°14’55’’ | 41°42’ |
| Longitude (°E) | 23°30’ | 6°57’7’’ | 22°33’37’’ | 1°6’ |
| Altitude (meters) | 104 | 60 | 194 | 337 |
| Environmental zone | Boreal | Atlantic Central | Continental | Mediterranean South |

**T a b l e 2.** Descriptive statistics of the whole daily 31 years meteorological time series from 6 stations in Germany (DE), Finland (FI), Poland (PL), and Spain (ES)

| Meteorological variable | Site | Mean | Min | Max | Std | Median | Skewness | Kurtosis |
|---|---|---|---|---|---|---|---|---|
| Precipitation (mm day$^{-1}$) | Jokioinen (FI) | 1.7 | 0.0 | 79.1 | 3.9 | 0.1 | 5.0 | 49.3 |
| | Dikopshof (DE) | 1.7 | 0.0 | 75.4 | 3.8 | 0.0 | 4.5 | 38.1 |
| | Lublin (PL) | 1.5 | 0.0 | 61.6 | 3.9 | 0.0 | 5.7 | 49.7 |
| | Lleida (ES) | 0.9 | 0.0 | 83.6 | 3.8 | 0.0 | 7.2 | 75.7 |
| Wind speed (m s$^{-1}$) | Jokioinen (FI) | 2.3 | 0.0 | 7.7 | 1.0 | 2.6 | 0.5 | 3.5 |
| | Dikopshof (DE) | 2.6 | 0.2 | 9.4 | 1.3 | 2.4 | 1.1 | 4.8 |
| | Lublin (PL) | 3.0 | 0.0 | 17.4 | 1.8 | 3.1 | 1.5 | 6.5 |
| | Lleida (ES) | 2.6 | 0.3 | 17.8 | 1.7 | 2.2 | 2.0 | 9.2 |
| Air temperature (°C) | Jokioinen (FI) | 4.6 | -33.4 | 25.0 | 9.3 | 4.7 | -0.4 | 2.8 |
| | Dikopshof (DE) | 10.2 | -16.8 | 28.9 | 6.8 | 10.5 | -0.2 | 2.5 |
| | Lublin (PL) | 8.7 | -22.8 | 28.3 | 8.8 | 9.1 | -0.2 | 2.4 |
| | Lleida (ES) | 15.0 | -8.3 | 33.1 | 7.6 | 14.7 | 0.0 | 2.1 |

Mean, min, max, standard deviation (Std) and median have units corresponding to the units of meteorological variable, skewness and kurtosis are non-dimensional.

A time series is an ordered sequence of values of a variable at equally spaced time intervals, *eg* hourly temperatures at weather stations. The main aim of time series modelling is to carefully collect and rigorously study the past observations of a time series to develop an appropriate model which describes the inherent structure of the series. This allows explaining the data in such a way allowing prediction, monitoring, or control. A common method used to study time series is the exponential smoothing. The idea of exponential smoothing is to smooth the noise out of the original series and to use the smoothed series in forecasting future values of the variable of interest. The exponential smoothing is a smoothing technique used to reduce irregularities such as a long-term direction and random fluctuations with known periodicity in time series data, thus providing a clearer view of the true underlying behaviour of the series. It also provides an effective means of predicting future values of the time series (forecasting). In exponential smoothing, forecasts are weighted combinations of past observations, with recent observations given relatively more weight than older observations. The name 'exponential smoothing' reflects the fact that the weights decrease exponentially as the observations get older. The main advantage of the exponential smoothing methods is their robustness that allows a fast and efficient implementation of the technique together with the descriptive and the inferential statistics.

Exponential smoothing was introduced and developed by Brown (1959, 1963). Independently, Holt (2004) developed a similar exponential smoothing method with a different approach for smoothing seasonal data. Since then, several authors (Gardner, 1985; Hyndman *et al.*, 2002, 2008; Muth, 1960; Winters, 1960) have worked to develop exponential smoothing within a statistical framework.

Taking into account the pattern of the time series considered in this paper, we focus on two models: the simple exponential smoothing and the exponential smoothing with no-trend and with seasonality which are denoted as the (N,N) model and the (N,A) model, respectively (Hyndman *et al.*, 2008), where the pair (*,*) stands for a possible trend and seasonal combinations. It should be noted that in the (*,*) notation A stands for the additive component and N stands for none.

The (N,N) model is used for data patterns without cyclic variation or pronounced trend. This model for a given time series $y_1, ..., y_n$ is given by the equation:

$$l_t = \alpha\, y_t + (1-\alpha)\, l_{t-1}, \tag{1}$$

where: $l_t$ denotes an exponential smoothed value of the series at time $t$ and $\alpha$ is a smoothing weight. The method of simple exponential smoothing (N,N) takes the forecast for the previous period and adjusts it using a forecast error. Hence, the new forecast is simply the old forecast plus an adjustment for the error that occurred in the last forecast.

The (N,A) model is used for data which do not indicate any trend and experience regular changes repeated with nearly the same pace and intensity. This model for given time series $y_1$, ..., $y_n$ is well described by the system of equations:

$$l_t=\alpha y_t - s_{t-m}+(1-\alpha)\, l_{t-1}, \quad (2)$$

$$s_t = \delta(y_t - l_{t-1})+(1-\delta)\, s_{t-m}, \quad (3)$$

where: $s_t$ denotes a smoothed seasonal component of the series at time $t$, $m$ is the length of seasons, and $\delta$ is a seasonal weight. The smoothing Eqs (1), (2), and (3) determine how the smoothing value changes as time progresses. The smoothing weights determine the contribution of the previous smoothing value to the current smoothing value.

At the beginning, the smoothing process computes the smoothing value for time $t=1$. However, this computation requires an initial estimate of the smoothing value at time $t=0$. An appropriate choice for the initial smoothing state $S_0$ is computed as the mean for all values included in complete seasonal cycles.

Smoothing weight $\alpha$ and seasonal weight $\delta$ take values between zero and one. If $\alpha$=1, then the previous observations are ignored entirely. If $\alpha$=0, the current observation is ignored entirely, and the smoothed value consists entirely of the previous smoothed value. Values of $\alpha$ in-between produce intermediate results.

If $\delta=0$, then the seasonal component for a particular point in time is predicted to be identical to the predicted seasonal component for the respective time during the previous seasonal cycle, which in turn is predicted to be identical to that from the previous cycle, and so on. Thus, a constant unchanging seasonal component is used to generate the one-step-ahead forecasts. If $\delta = 1$, then the seasonal component is modified ‘maximally’ at every step by the respective forecast error.

Suppose we have observed data up to and including time $t$-1 and we want to forecast the next value $y_t$ of our time series. If the forecast is denoted by $\hat{y}_{t+h|t}$, then the forecast error $e_t$ is found to be $y_t$-$\hat{y}_{t+h|}$. The forecast for the next period is $\hat{y}_{t+h|t}=l_t$ for the (N,N) model and $\hat{y}_{t+h|h}= l_t+s_{t-m+h}$ for the (N,A) model.

A visual check of the accuracy of forecasts is often the most powerful method for determining whether or not the current exponential smoothing model fits the data. We can also examine autocorrelation function (ACF) and partial autocorrelation function (PACF) plots. The ACF plot is a bar chart of the coefficients of correlation between a time series and lags of itself. The PACF plot is a plot of the partial correlation coefficients between the series and lags of itself.

To determine the optimum parameters of the chosen model, we use the mean absolute error (*MAE*) and the root mean squared error (*RMSE*):

$$MAE = \frac{1}{n}\sum_{t=1}^{n} |e_t\,|, \quad (4)$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n} e_t^2}\,, \quad (5)$$

where: $n$ is the number of periods of time.

The *MAE* and the *RMSE* can be used together to diagnose the variation in the errors in a set of forecasts. The *MAE* is the average over the verification sample of the absolute values of the differences between forecast and the corresponding observation. The *RMSE* is the square root of the average squared values of the differences between the forecast and the corresponding observation. Those errors have the same units of measurement and depend on the units in which the data are measured.

The chosen model was run by using computer software STATISTICA, Stat Soft Inc., USA. The implementation of the exponential smoothing methods in STATISTICA follows closely the survey of techniques presented by Gardner (1985), who proposed a ‘unified’ classification of exponential smoothing methods. The parameters $\alpha$ and $\delta$ of the (N,A) model and the parameter $\alpha$ of the (N,N) model were selected by a grid search of the parameters space and the accuracy was chosen as a criterion for determination thereof. The values of the parameters were systematically evaluated by starting with value $\alpha=0.1$ and $\delta=0.1$ with increments of 0.1. Then $\alpha$ and $\delta$ were chosen to produce the smallest *MAE* and *RMSE* for the residuals (*ie* observed values minus one-step-ahead forecasts).

The majority of plots and the basic statistics of the time series were completed with the use of RStudio integrated development environment for R version 0.97.551 (R Core Team, 2014).

## RESULTS AND DISCUSSION

The visual analysis of the air temperature time series and their decomposition plots (not shown) do not indicate any long-term trends, but they have regular fluctuations which are repeated from year to year with about the same timing and level of intensity. The ACF and PACF plots indicate seasonal temperature patterns without trends at all four sites (Fig. 1). A seasonal character with no trend was also observed for wind speed (Fig. 2). This implies that the best exponential smoothing model for air temperature and wind speed is the additive seasonal model (N,A).

The results obtained for air temperature series are presented in Table 3. It can be observed that the best-fitting model for the temperature series from each of the considered sites was characterized by the same pair of parameters $\alpha$=0.9 and $\delta=0.1$. This means that changes in air temperature time series have the same nature and pattern for the considered sites. Similarly, we obtained $\delta=0.1$ for all the wind speed models, but the $\alpha$ value for Dikopshof, Lublin, and Lleida wind speed time series that generates the smallest *MAE* is different from the $\alpha$ value that produces the

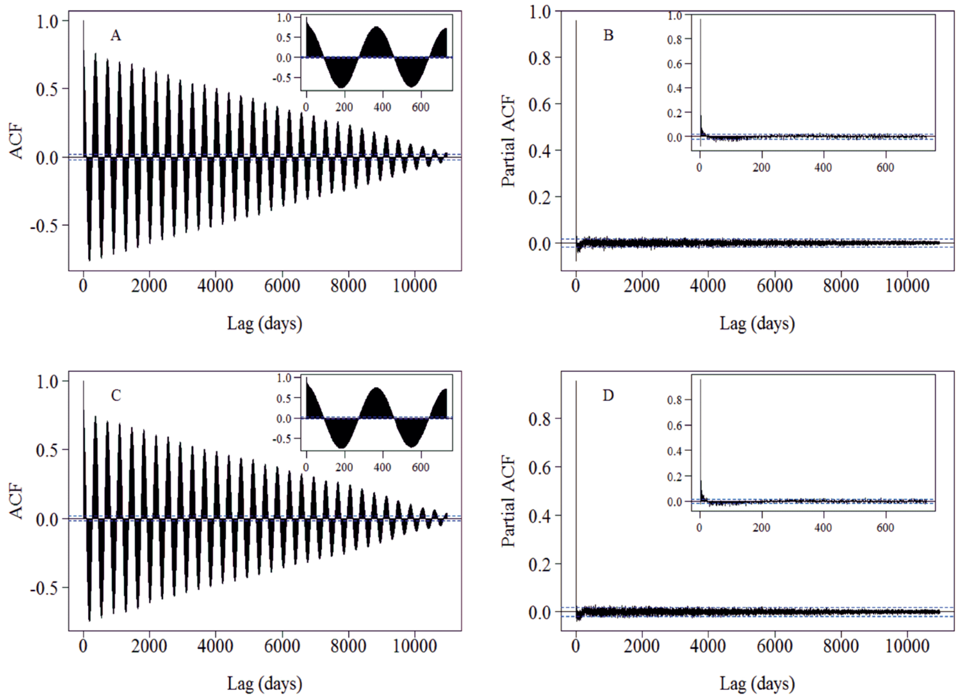


**Fig. 1.** ACF and partial ACF plots for air temperature time series from: A and B – Lleida, Spain; C and D – Jokioinen, Finland; stations.

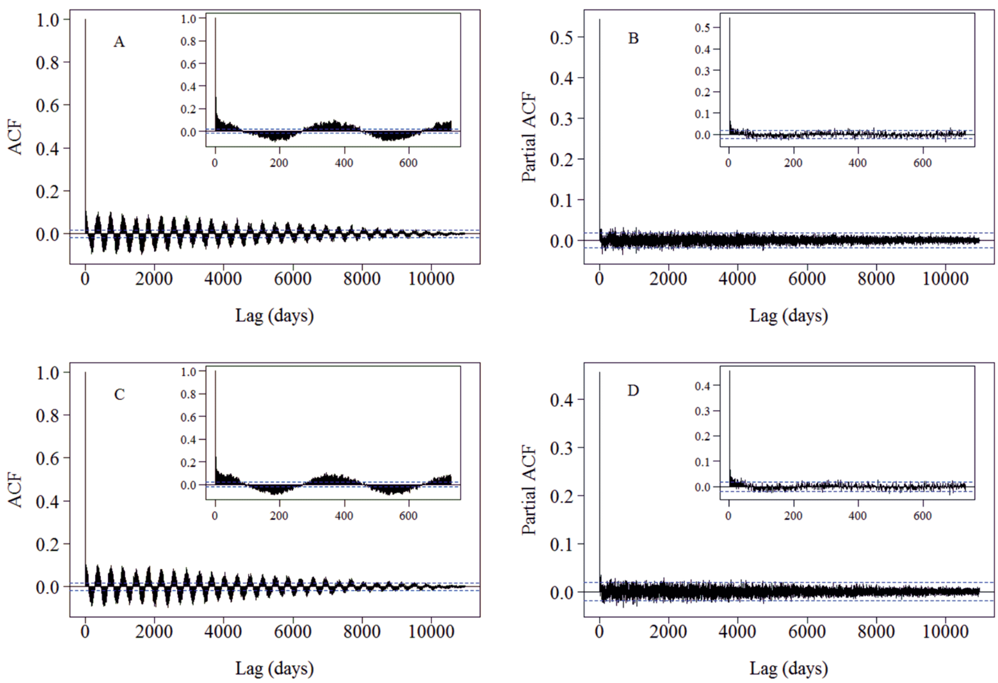


**Fig. 2.** ACF and partial ACF plots for wind speed time series from: A and B – Dikopshof, Germany; C and D – Lublin, Poland; stations.

smallest *RMSE* (Table 4). This low value of the seasonal parameter $\delta$ suggests that the air temperature and wind speed data are not strongly affected by seasonal factors. The high value of the smoothing parameter $\alpha$ indicates that the fluctuation of the air temperature is large and the low values of $\alpha$ show small variablity in wind speed data. The smoothed value calculated for the final period in each of the finally selected models can be used for forecasting future statistics. Figure 3 presents the comparison between real and annual forecast of the air temperature in Jokioinen and Lleida, respectively, obtained using the (N,A) model with parameters $\alpha=0.9$ and $\delta=0.1$. The real values and annual forecast of the wind speed in Dikopshof and in Lublin are shown in Fig. 4.

**T a b l e 3.** Exponential smoothing parameters for mean air temperature ((N,A) model)

| Site | $S_0$ | $\alpha$ | $\delta$ | *MAE* (°C) | *RMSE* (°C) |
|---|---|---|---|---|---|
| Jokioinen | 4.657 | 0.9 | 0.1 | 2.0482 | 2.7626 |
| Dikopshof | 10.250 | 0.9 | 0.1 | 1.7113 | 2.1932 |
| Lublin | 8.670 | 0.9 | 0.1 | 1.9117 | 2.4877 |
| Lleida | 15.050 | 0.9 | 0.1 | 1.5772 | 2.0230 |

**T a b l e 4.** Exponential smoothing parameters for wind speed ((N,A) model)

| Site | $S_0$ | $\alpha$ | $\delta$ | *MAE* (m s$^{-1}$) | *RMSE* (m s$^{-1}$) |
|---|---|---|---|---|---|
| Jokioinen | 4.657 | 0.9 | 0.1 | 2.0482 | 2.7626 |
| Dikopshof | 10.250 | 0.9 | 0.1 | 1.7113 | 2.1932 |
| Lublin | 8.670 | 0.9 | 0.1 | 1.9117 | 2.4877 |
| Lleida | 15.050 | 0.9 | 0.1 | 1.5772 | 2.0230 |

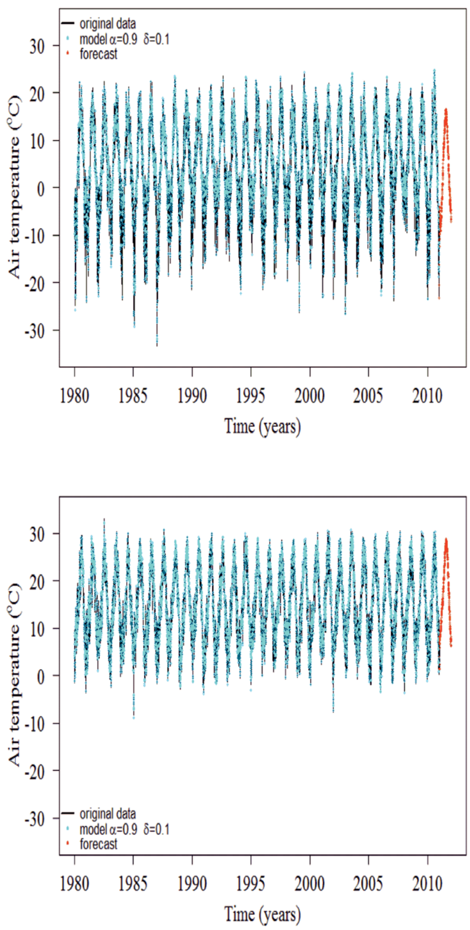


**Fig. 3.** Smoothed time series and annual forecasting of air temperature ((N,A) model) in Jokioinen (upper plot) and Lleida (lower plot).

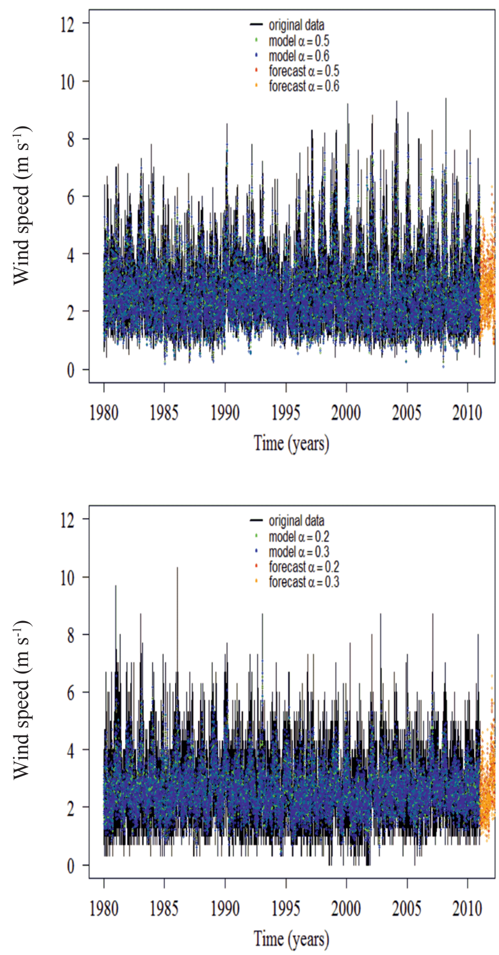


**Fig. 4.** Smoothed time series and annual forecasting of wind speed ((N,A) model) in in Dikopshof (upper plot) and Lublin (lower plot).

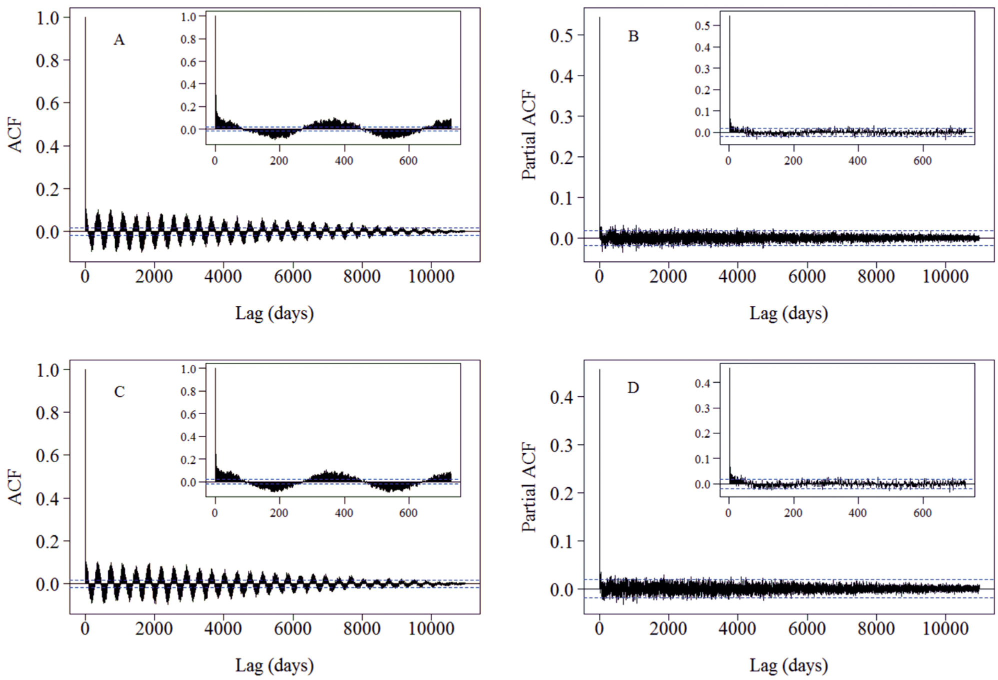


**Fig. 5.** ACF and partial ACF for precipitation time series from: A and B – Dikopshof, Germany; C and D – Jokioinen, Finland; stations.

**T a b l e 5.** Exponential smoothing parameters for precipitation (N,N) and (N,A) models

| Site | $S_0$ | $\alpha$ | δ | *MAE* | *RMSE* |
|---|---|---|---|---|---|
| | | | | (mm day$^{-1}$) | |
| | | (N,N) model | | | |
| Dikopshof | 1.719 | 0.1 | – | 2.228 | 3.809 |
| | | 0.4 | – | 2.185 | 4.015 |
| Lleida | 0.932 | 0.1 | – | 1.504 | 3.808 |
| | | 0.5 | – | 1.465 | 4.150 |
| | | (N,A) model | | | |
| Jokioinen | 1.720 | 0.1 | 0.1 | 2.263 | 3.929 |
| Lublin | 1.470 | 0.1 | 0.1 | 2.109 | 4.038 |

A quite different situation was found for precipitation time series. The analysis of the time series courses and the ACF and PACF plots revealed that the (N,N) model should be applied to Dikopshof and Lleida time series, which do not demonstrate a trend or seasonality, and the (NA) model should be applied to Lublin and Jokioinen time series, which do not demonstrate a trend but show seasonality (Fig. 5). The parameters that produced the smallest *MAE* or *RMSE* are presented in Table 5.

For the Dikopshof and Lleida precipitation time series, the value of $\alpha$ that yields the smallest *MAE* differs from the $\alpha$ value that generates the smallest *RMSE*. While $\alpha = 0.1$ gives the smallest *RMSE* for both sites, the smallest *MAE* is generated by different values of $\alpha$. The smallest *MAE* and *RMSE* values for Lublin and Jokioinen precipitation time series are generated using $\alpha$=0.1 and $\delta = 0.1$. These low values of the $\alpha$ and $\delta$ parameters suggest that the precipitation

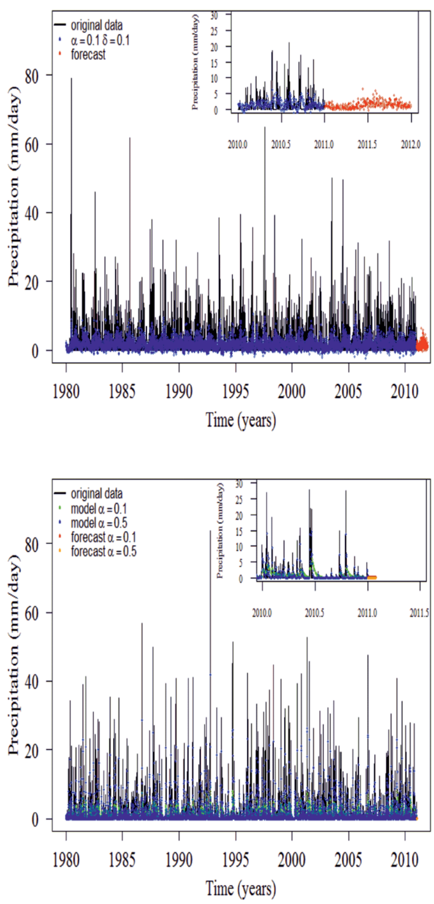


**Fig. 6.** Smoothed time series and annual forecasting of precipitation in Jokioinen (upper plot, (N,A) model) and Lleida (lower plot, (N,N) model).

data from Lublin and Jokioinen have small variability and seasonality. Figure 6 displays the actual values and the forecast of the precipitation in Jokioinen and Lleida.

The results indicate that the use of exponential smoothing to weather time series analysis is a valuable tool to get information about analysed data structures and their components, being a good basis for successful future predictions. Considerable differences exist between the selected models of air temperature, wind speed, and precipitation and their parameters ($\alpha$ and $\delta$) for the particular sites. Comparable results were obtained earlier by (Cadenasa and Rivera, 2010; Niu *et al.*, 2015; Yusof and Kane, 2012). The presented results suggest that structures of the time series of particular quantities obtained in various climatic zones differ substantially. This is in agreement with results obtained by Baranowski *et al.* (2015), who analyzed multifractal properties of meteorological time series coming from different climatic zones and noticed large differences in the multifractal spectra and sources of multifractality for series in different climatic zones. Earlier studies (Bartos and Jánosi, 2006; Lin and Fu, 2008; Trnka *et al.*, 2014) also indicated that the analysis of temporal scaling properties is fundamental for transferring locally measured fluctuations to larger scales and vice-versa. which should be included in forecasting models.

The presented study have delivered quite promising results of short term forecasting of weather time series using the simple exponential smoothing method, however further comparative analyses are planned, especially with the use of more elaborate models such as seasonal ARIMA models or artificial neural networks ANN. The development of short term forecasting of meteorological time series is fundamental for crop modelling, creating precision irrigation systems, and can help decision makers establish strategies for proper planning of agriculture (Pinson *et al.*, 2010).

## CONCLUSIONS

1. The exponential smoothing method applied to analized metorological time series belonging to diffrent climatic zones enabled to get short time forecasting with good prediction power.

2. To predict air temperature and wind speed, the model of seasonal exponential smoothing with no-trend should be preferably used. In contrast, precipitation series exhibit site-specific model parameters.

3. It has been proven that for obtaining reasonable knowledge about the overall forecasting error, more than one measure should be used in practice.

4. The results highlight the importance of considering the seasonality in forecasting of air temperature or wind speed in Europe, contrasting to forecasting precipitation. A best-fitting model for precipitation depends on the site. The Boreal and Continental sites are better described by additive seasonal exponential smoothing, while simple exponential smoothing is a better model for Atlantic Central and Mediterranean South sites.

5. Because of its simplicity and exactness, the exponential smoothing method has proved to be very useful for air temperature, precipitation, and wind speed forecasting.

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