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Analysis of climate change influences on the wind characteristics in Hungary

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Abstract—Due to intense human presence and various anthropogenic activities, global climate change has been detected. Increasing temperature values and an overall warming are projected, which will certainly affect the global circulation patterns and regional climatic conditions throughout Europe. As an indirect consequence, global warming may also alter the wind conditions in the Carpathian Basin. In order to provide reliable projections for the future, the first task is to analyze wind climatology of the recent past using various tools from mathematical statistics.

In this paper, detailed analysis of observed wind fields, trends of different percentiles, return values, wind related climate indices, and their spatial distributions are discussed over Hungary using the homogenized Hungarian synoptic data sets and the homogenized and gridded CARPATCLIM database. Wind related climate indices are defined to evaluate the frequency occurrence and the trend of moderate and strong wind days at the stations in the last few decades. The annual daily maxima of wind speed and wind gust are determined on the basis of available time series fitted to the generalized extreme value distribution at every station and grid cell. 50-year and 100-year return values are estimated from these fitted distributions.

In addition, simulated wind climate variability is evaluated for the future periods of 2021–2050 and 2071–2100 relative to the 1961–1990 reference period. Since projected wind speed is highly overestimated by the simulation of the regional climate model RegCM for the reference period (1961–1990), a bias correction is necessary to apply to the raw simulated wind data using CARPATCLIM as a reference database. The bias correction method is based on fitting the empirical cumulative density functions of simulated daily time series to the observations for each gridcell using monthly multiplicative correction factors.

Key-words: Hungarian wind climate, extremes, homogeneity, CARPATCLIM, RegCM climate model

1. Introduction

Based on the observations, global climate change has reduced the Pole to Equator temperature gradient, which certainly affects the large scale circulation as well as regional climatic conditions. Besides the changes of mean climatic values, the entire distribution is changing, thus influencing intensity and frequency of climate extremes (*AghaKouchak et al*., 2012). Various physical processes in the atmosphere lead to extreme values of meteorological elements. Weather and climate extremes (e.g., heat waves, extreme cold/hot conditions, too little/excessive precipitation, extreme winds) may especially affect exposed and vulnerable human and natural systems, therefore, development of appropriate action plans need detailed information on the past and future changes of extremes. It is essential to understand how and why climate extremes have changed recently, and how they will likely to change in the future.

Mid-latitude wind climate can be mainly determined by considering cyclogenesis processes and track analysis of high and low pressure systems over the continent. The surface winds are often depending on local conditions such as topography, geographical location, distance from large water bodies, and differential surface heating (*Oliver*, 2005). Examples of specific local wind include land/sea breeze, mountain/valley breeze, foehn winds formed by pressure or temperature gradient force. Moreover, local wind and instability can also be originated from (dust) storms.

Regional and local wind climate have direct effects on human activity, for instance, on aviation, urban planning (via impact on building design and air pollution), industry, energy sector, military operations, etc. Therefore, researchers, engineers, architects, designers need information about local wind climate as fine as possible. In most of the cases, their tasks and duties are strongly connected to appropriate analysis of meteorological and climatic problems, or they need to apply results of the analysis of regional or local wind fields to more specific, further impact studies. Moreover, many practical and theoretical problems in meteorology and climatology require accurate measurements of wind speed, direction, and gust. In order to ensure high quality of meteorological measurement systems, standards of measurements have been set by the World Meteorological Organization (WMO). Wind speeds are measured as 10-minute averages, wind gusts are the maximum speeds recorded within the 10-minute averages' period (*WMO*, 2008). The standard exposure height is 10 meter.

Direct wind climatological analysis of changes is hampered by the lack of several-decades-long, good quality, and homogeneous surface wind observations. Homogeneity of climate data is especially important when analyzing extremes, especially, at fine spatial scale. A climatological time series can be considered homogeneous if its variability is solely caused by changes in weather and climatic conditions (*Aguilar et al*., 2005). However, wind as a meteorological element is especially sensitive to uncertainties caused by relatively small changes related to the measuring process, in the vicinity of the measuring equipment. For example, installation of a small building or changes in vegetation cover near the measuring equipment, or changes in instrumentation and measuring methods can produce bias in wind measurements (*Wan et al.,* 2010). When such a change occurs, it can result a discontinuity in the time series or a false trend (*Menne* and *Williams Jr*., 2009). Therefore, quality control and homogenizing of available daily wind speed and wind gust data sets (1975–2012) were completed (*Péliné et al*., 2014) in order to assess Hungarian wind climate trends, variability, frequency, and intensity of extreme wind events as reliable as possible. For this purpose, the MASH (Multiple Analysis of Series for Homogenization) procedure developed at the Hungarian Meteorological Service (*Szentimrey,* 1999) was applied to homogenize 19 Hungarian stations' daily wind speed and wind gust data sets.

The word "extreme" refers to many different issues in the climate research literature, so there is no unique, precise climatological definition of an extreme (*Stephenson*, 2008). For instance, extreme may be associated to a climate variable or an impact of specific climatic conditions. In the case of a climate variable (e.g., temperature, precipitation, wind speed, etc.), extremes can be well defined as a rarely occurring value, i.e., with small probability, in the tail of the probability density function ($f(x)$) of the given climate variable. In the case of an impact, an extreme can be less well defined, since quantity of impacts cannot be described in a unique way. It is important to mention that on one hand, rare events (e.g., tornado) may not necessarily cause damage, and their impact does not always lead to a disaster; on the other hand, non-extreme events (e.g., strong wind or regularly occurring storm) may cause devastating effects and severe damages in the environment. In this paper, we are focusing on the analysis of climate variables themselves.

Based on the Special Report on Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation (SREX) published by the International Panel on Climate Change (*IPCC*, 2012), extreme weather or climate events are the occurrence of a value of a weather or climate variable above (or below) a threshold value near the upper (or lower) ends of the range of observed values of the variable. For simplicity, both extreme weather events and extreme climate events are often referred to collectively as 'climate extremes' (*Seneviratne et al*., 2012). They can be defined quantitatively in two ways: (1) related to their probability of occurrence, e.g., percentiles and return frequencies, (2) related to a specific (possibly impact-related) threshold.

Although the wind speed value itself is rarely used to define extreme events (e.g., mesoscale convective complex, cyclone, thunderstorm, squall lines, etc.) (*Peterson et al*., 2008), wind speed thresholds may be used to characterize the severity of the phenomenon (e.g., the Saffir-Simpson scale for tropical cyclones). Changes in wind extremes may be resulted from changes in the intensity or location of their associated phenomena (e.g., change in local convective activity) or from other changes in the climate system such as the movement of large-scale circulation patterns (*IPCC*, 2012). Wind extremes may be described by a range of daily/monthly/yearly quantities such as high percentiles, maxima, or wind-related climate indices after checking data series for homogeneity.

Our main aim is to analyze the wind climate in Hungary, specifically, to estimate temporal and spatial distributions of mean and extreme wind speed. For this purpose, different percentile values and their trends are calculated, moreover, return values and wind-related climate indices are determined using observed (station and gridded) and projected (from climate model simulation) data sets.

2. Applied data and methodology

2.1. Applied statistical distributions

For the sake of practical simplicity and to reduce complex characteristics of time series during the analysis, data distributions are often estimated by mathematical functions that depend on a few parameters only, so the analysis task is simplified to estimation of these parameters.

The special cases of the three-parameter generalized extreme value (GEV) or Fisher-Tippet distribution (*Palutikof et al.*, 1999) is widely used in meteorology, which includes Gumbel (type 1), Frechet (type 2), and Weibull (type 3) distributions. Distribution of averaged wind speed (with averaging period of 10 min) may be estimated by the two-parameter Weibull distribution, whereas distribution of maximum wind speed during a given period can be described by Gumbel distribution (*Wilks*, 2006).

The Weibull distribution is governed by two parameters, i.e., a scale factor (λ [m/s], being proportional to the mean wind speed), and a form factor or shape parameter (k [dimensionless], describing the shape of the distribution).

The Weibull distribution function $F(u)$ can be written as follows:

$$F(u) = 1 - \exp\left(1 - \left(\frac{u}{\lambda}\right)^k\right), \tag{1}$$

where u is the wind speed with an averaging period of 10 min, λ is the scale factor, and k is the shape parameter.

From this, the Weibull probability density function $f(u)$ can be expressed as follows:

$$f(u) = k \cdot \left(\frac{u^{k-1}}{\lambda^k}\right) \cdot \exp\left(-\left(\frac{u}{\lambda}\right)^k\right). \tag{2}$$

Average wind speed $[\bar{u}]$ of the whole analyzed period can be described by the Weibull parameters using Gamma function (Γ) as follows:

$$[\bar{u}] = \lambda \cdot \Gamma\left(1 + \frac{1}{k}\right), \tag{3}$$

$$\Gamma(x) = \int_0^\infty e^{-u} u^{x-1}\, du. \tag{4}$$

For k=1 and 2, the Weibull distribution is identical to the exponential and Rayleigh distribution, respectively. For k=3.4, the Weibull distribution is similar to the Gaussian distribution (*Wilks*, 2006; *Emeis*, 2013).

Wind speed extremes can be characterized with estimation of high percentiles, wind speed related climate indices, and return values using different specific periods. The return value is a threshold value, which can be defined by a fitted model (*von Storch* and *Zwiers*, 1999). The value of the analyzed variable may occur or be exceeded once on average during the specific return period.

The probability of occurrence of extreme values can be described by a Gumbel distribution (*Gumbel*, 1958). Probability density function $f(x)$ and cumulative frequency distribution function $F(x)$ are expressed in Eqs. (5) and (6), respectively:

$$f(x) = e^{-x} e^{-e^{-x}}, \tag{5}$$

$$F(x) = e^{-e^{-x}}. \tag{6}$$

For estimation of return values, the inverse of Eq.(6) should be calculated (*Emeis*, 2013), which is the following percentile function $G(p)$:

$$G(p) = -\ln\left(-\ln(p)\right). \tag{7}$$

In practice, independent maxima of the time series (for example, yearly maxima of wind speed or wind gust) are sorted in ascending order, then, these sorted values are plotted against $G(p)$. Data, which follow a Gumbel distribution form a straight line, in conformity with its definition. Estimations of return values for specific return periods (e.g., 50 years or 100 years) are quite straightforward by using this graph. The extreme value expected to occur once in 50 years or 100 years can be calculated from the equation of the fitted extrapolated straight line ($u_{max} = a \cdot (-\ln(-\ln(p))) + b$). For example, if the return period $T = 100$ years then the probability of occurrence $p = \frac{1}{T} = 0.01$ in any particular year within this entire period, thus, $G(p = 0.99) = 4.6$, and the return value (u_{max}) can be calculated from the equation of the fitted linear line.

The probability for the 100-year return value to appear in a chosen 100-year period is $P = 1 - 0.99^{100} = 0.634$.

2.2. *Wind indices*

In order to analyze the extreme wind characteristics, climate indices can be used. Similarly to the widely used temperature and precipitation related climate indices (e.g., *Bartholy* and *Pongrácz*, 2007), wind related climate indices are defined in this study. They consider daily average wind speed as well as daily maximum wind gust values. Three types of indices are used here: (i) the number of days above or below a certain threshold value, (ii) the number of periods of consecutive days above or below these thresholds, and (iii) the maximum length of these periods. The applied time frame includes yearly, seasonal, and monthly basis. *Table 1* summarizes the indices evaluated in this paper.

Table 1. List of used wind related climate indices, their definitions and units.

No.	Index	Definition	Unit
1–3	wavgGTXX	Yearly/seasonal/monthly number of days with average wind speed exceeding XX m/s; v_{avg} > XX m/s, where XX = 15, 10, 8	days
4–6	wavgLTXX	Yearly/seasonal/monthly number of days with average wind speed below XX m/s; v_{avg} < XX m/s, where XX = 1, 3, 5	days
7–9	CwXXD	Yearly/seasonal/monthly number of periods of consecutive days with daily average wind speed exceeding XX m/s, where XX = 15, 10, 8	–
10–12	CwXXD	Yearly/seasonal/monthly number of periods of consecutive days with daily average wind speed below XX m/s, where XX = 1, 3, 5	–
13–15	CwXXDmax	Yearly/seasonal/monthly number of maximum consecutive days with daily average wind speed exceeding XX m/s, where XX = 15, 10, 8	days
16–18	CwXXDmax	Yearly/seasonal/monthly number of maximum consecutive days with daily average wind speed below XX m/s, where XX = 1, 3, 5	days
19–23	CgXXD	Yearly/seasonal/monthly number of periods of consecutive days with daily maximum wind gust exceeding XX m/s, where XX = 15, 20, 25, 30, 35	–
24–29	GustGTXX	Yearly/seasonal/monthly number of days with daily maximum wind gust exceeding XX m/s; v_{gust} > XX m/s, where XX = 15, 20, 25, 30, 35	days

2.3. *Bias corrected outputs of RegCM regional climate model*

In order to estimate the future changes in wind related climate extremes, regional climate model outputs serve as the basis. For this purpose, simulation of the RegCM regional climate model (*Torma et al*., 2008, 2011) is used in this paper. For the reference period (1961–1990), model outputs overestimate the average wind speed for the Carpathian Basin. The overestimation of the yearly average wind speed is about 2 m/s, and the seasonal overestimation is the highest in winter (2.6 m/s in the gridcell centering 47.5°N and 19°E, which represent the Budapest agglomeration area). Therefore, simulated wind data should be bias-corrected for assessing extreme wind conditions as realistic as possible.

The probability density function (PDF) or the cumulative density function (CDF) describe completely the statistical properties of a dataset. If two data sets results in the same PDF or CDF then they can be considered statistically identical. The applied correction method is based on the study of *Pongrácz et al*. (2014), which uses the differences of the monthly empirical CDFs of RegCM model outputs and CARPATCLIM gridded data sets for the reference period. First, multiplicative correction factors $f_{multiplicative}$ are calculated on a monthly basis for the past (i.e., 1961–1990):

$$f_{multiplicative} = \frac{F_{obs}^{-1}(y)}{F_{model}^{-1}(y)} = \frac{x_{obs}}{x_{model}}\,, \tag{8}$$

where the probability-quantile of observations is x_{obs} and the probability-quantile of raw simulated data is x_{model}. Thus, the raw model data with CDF value p is corrected, and it becomes equal to CDF value of the observations. Then, these calculated factors are applied to the future periods (2021–2050, 2071–2100).

3. Results

Homogenized wind speed (1975–2012) and wind gust (1975–2013) measurements, as well as homogenized and gridded data sets of the CARPATCLIM (1961–2010) database are analyzed in order to assess Hungarian wind climate trends, variability, frequency, and intensity of extreme wind events. Average yearly wind speed is modified significantly by a homogenization procedure (*Péliné et al*., 2014). Consequently, the fitted linear trends of average and different percentile values also changed at many stations compared to those before the homogenization. These differences emphasize that inhomogeneities in climatological time series may lead to false values and misinterpretations of detected changes.

The generalized extreme value distribution is fitted to the annual maxima of wind speed at every station and all the CARPATCLIM grid points, which were used to estimate 50-year and 100-year return values. *Fig. 1* summarizes these return values for 19 Hungarian synoptic stations based on the data sets during 1975–2012. The smallest and the largest return values are about 10 m/s and 25 m/s at Paks and Siófok, respectively.

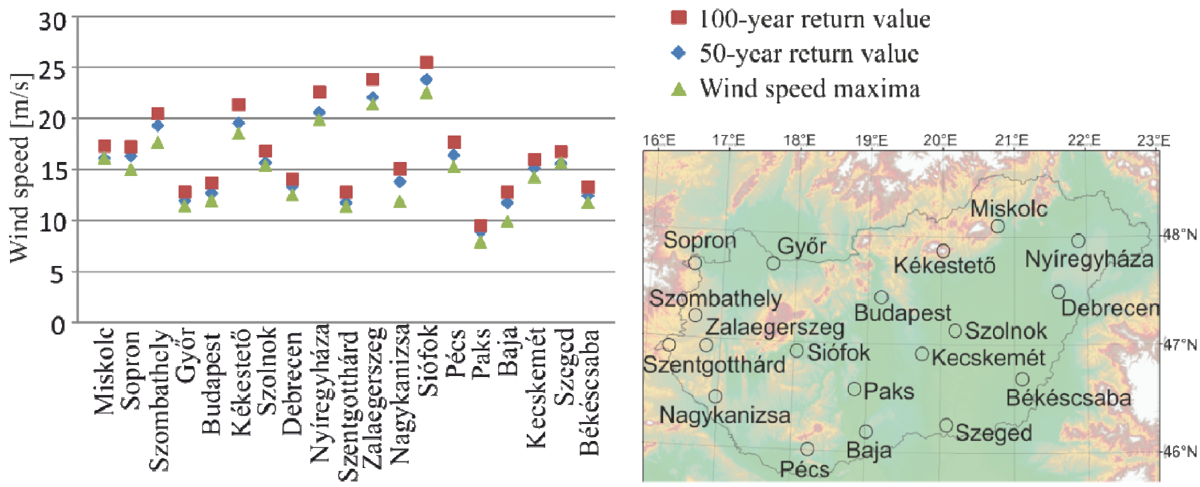

Fig. 1. Wind speed maxima and different return values [m/s] at the analyzed 19 stations calculated from 38-year time series (1975–2012).

In order to evaluate the spatial distributions of return values, gridded datasets can be used more efficiently. For this purpose, the quality-checked, homogenized, and interpolated gridded CARPATCLIM data series covering Hungary are used. *Fig. 2* shows both the 50-year and 100-year return values for the country, which result slight differences from the values calculated on the basis of station measurements. This is partially due to the fact, that daily wind speed of station data is calculated from at least eight measured data for a particular day, whereas CARPATCLIM daily 10-meter wind speed data sets have been created using three wind speed data (07, 14, and 21 UTC) from each day due to data availability for the whole period. (In the 1960's, data were recorded more rarely, in the 1960's than in the last few decades, so the night-time was less represented than nowadays).

Climate model experiments driven by gridded reanalysis fields (which are generated from measured and observed data) are essential, and provide important knowledge for modern climate research. However, the question arises how the different reanalysis data sets are reliable for estimation of wind climate parameters and validation of climate models. Global reanalysis data sets, i.e., ERA Interim, are used in our study, which is provided by the European Centre for Medium-Range Weather Forecasts (ECMWF) for researchers and climate modelers. ERA Interim is remarkably improved compared to the earlier ERA-40 reanalysis data sets (1957–2002) due to applied data assimilation methods and inclusion of more types of observations, e.g., satellite measurements (*Berrisford et al.*, 2009). In our study, datasets of wind components with fine resolution (0.50°) for the Carpathian Basin (45°–49.5°N and 15°–24°E) are analyzed for 1979–2012.

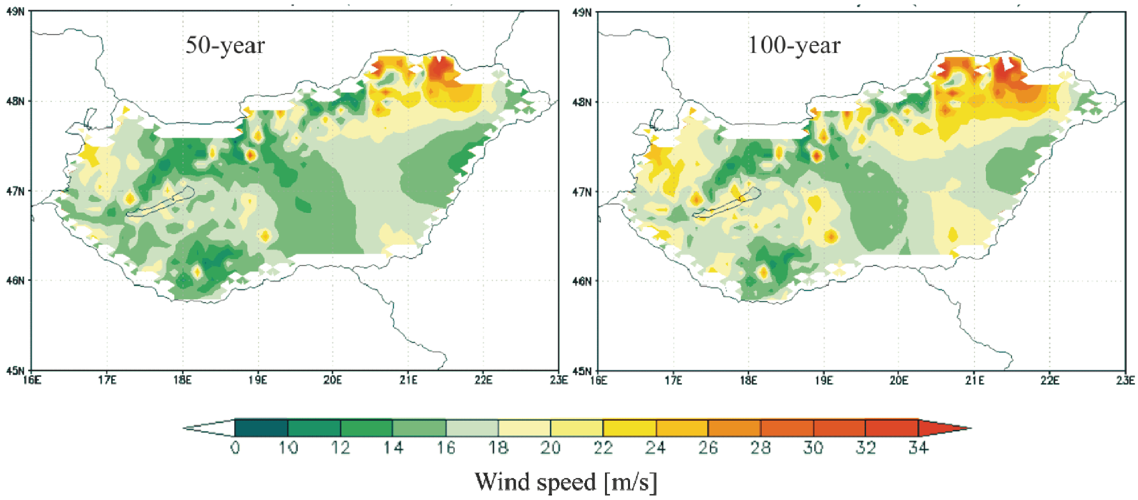

Fig. 2. 50-year and 100-year return values [m/s] calculated from CARPATCLIM data series (1961–2010).

Homogeneity of 10-meter daily average wind speed of 190 grid points of ERA Interim data sets is checked with MASH 3.03 software (*Szentimrey*, 2011) for the Carpathian Basin between 1979 and 2012. Results of homogenization proved that these gridded data series are homogeneous. Values of the applied test statistics for the characterization of inhomogeneity of time series were almost unchanged before and after homogenization and remained under the critical value (20.57; significance level: 0.05) at 72% of grid points. Values of yearly relative estimated inhomogeneity and yearly relative modification of time series differed from zero at 15% of all the grid points.

Weibull distributions are fitted in order to compare extremes of reanalysis and measured data series. Shape parameter (k) of the Weibull distribution describes frequencies of larger wind speeds. The larger the value of k, the smaller the variability of wind speed. Increasing scale parameter (λ) when constant shape parameter is assumed occurs as an elongation of the probability density function (pdf) along the abscissa with decrease and right-shift of the maxima of pdf (*Wilks*, 2006). Variability of scale parameter is smaller in ERA Interim grid points (3.06–3.83) compared to the synoptic stations (2.13–4.51). Values of the Weibull shape parameters of the reanalysis grid points are between 2.10 and 2.65, which are clearly larger than that is found in case of the stations data (1.38–2.16). This overestimation of the Weibull shape parameters reduces the variability of wind climatic conditions and the probability of extreme wind speed (*Rodrigo et al.*, 2013).

The main disadvantage of homogeneous gridded reanalysis data series is that spatial difference cannot be reproduced by reanalysis data unlike in case of station measurements. Monthly scale parameters of both station and gridded data averages are close in spring and summer, when regional differences are relatively small. The monthly average shape parameters are almost equal in June, however, in all the other months, overestimations are found at ERA Interim grid points compared to the station data.

Shape parameters are shown in *Fig. 3* as a function of scale parameter of the fitted Weibull distributions. Smaller shape parameter can occur in winter due to higher cyclone activity. Larger scale parameter was found in spring, when both the value and variability of monthly average wind speed are the largest. Average station shape parameters are generally overestimated by the average gridpoint shape parameters, similar conclusion is valid for the scale parameter. The only exception occurs in spring, when average station scale parameters are underestimated by the average gridpoint scale parameters. Because the scale parameter depends on wind speed, that is why the wind speed is overestimated, except in spring. The smallest differences (biases) of calculated parameters are observed in June and July.

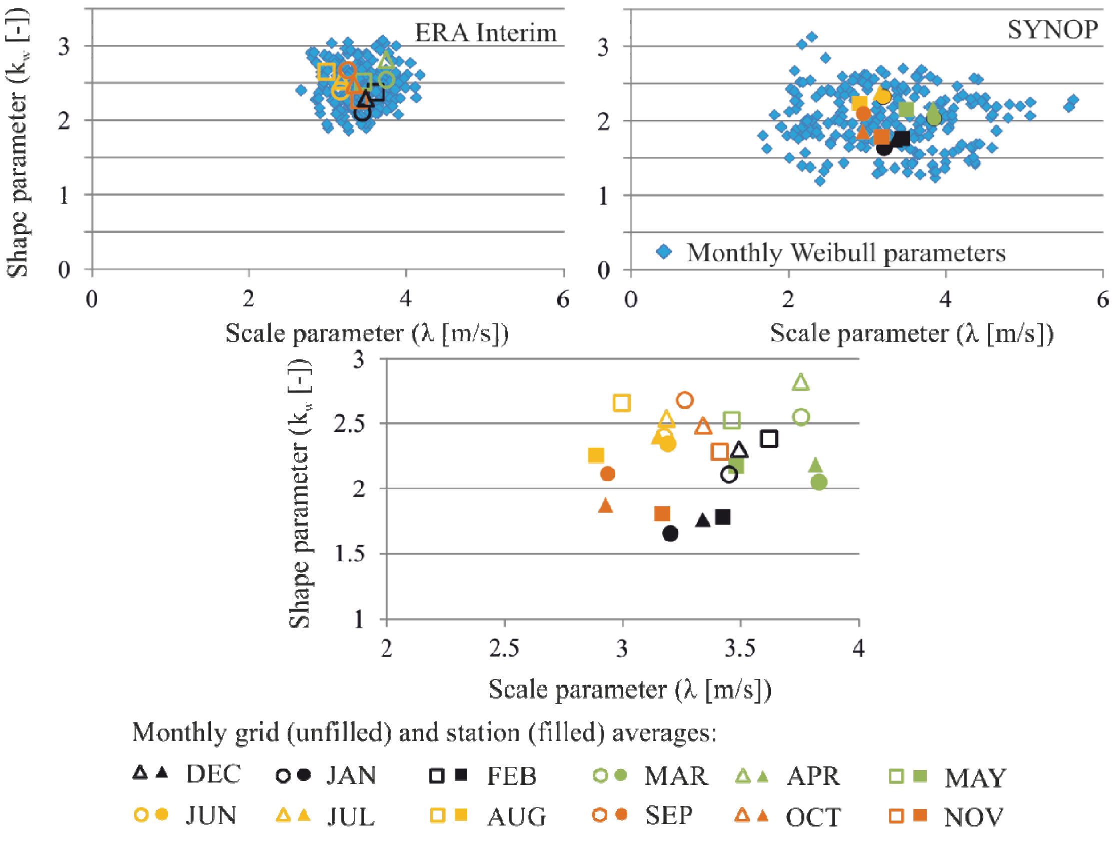

Fig. 3. Parameters of the Weibull distribution fitted to daily wind speed data series of grid points (upper left) and stations (upper right) in every month (blue) and in different seasons (winter – black, spring – green, summer – yellow, autumn – brown). Monthly grid (empty symbols) and station (filled symbols) averages are plotted in the lower diagram.

From the results discussed above, it can be concluded that significant differences exist between the statistical distributions of ERA Interim and synoptic station data, therefore, the further analysis of frequency occurrence, trend of moderate and strong wind days, and wind related indices are all based on more reliable measured data sets for Hungary.

Analysis of the indices listed in *Table 1* can answer whether the frequencies of windy, gusty days and calm periods have increased or decreased in the recent past. This is especially important from urban aspects, since air pollution in cities is a major environmental issue leading to many potential health problems.

Yearly number of days with average daily wind speed below 1 m/s, 3 m/s, and 5 m/s has increased during the analyzed period at most of the stations. Changes are statistically significant (on 0.05 confidence level) in all stations in case of 5 m/s (wavgLT5), and most of the stations in case of smaller thresholds (wavgLT1, wavgLT3). Yearly number of days with average wind speed exceeding 8 m/s has significantly decreased at every station, however, declining of the yearly number of stormy days (wind speed exceeding 15 m/s) is significant at four stations only (Szombathely, Szolnok, Zalaegerszeg, and Siófok).

Yearly number of periods of consecutive days (lasting 1–10 days) with daily average wind speed below 1 m/s (Cw1D) is shown in Fig. 4. These wind related climate indices decreased in Siófok for periods with different lengths, the longest recorded period lasted 10 days, which occurred in 1982. Increasing trends are found in Győr, which is in good agreement with the results of our previous analysis (*Péliné et al.*, 2014) concluding that the average wind speed declined at this station.

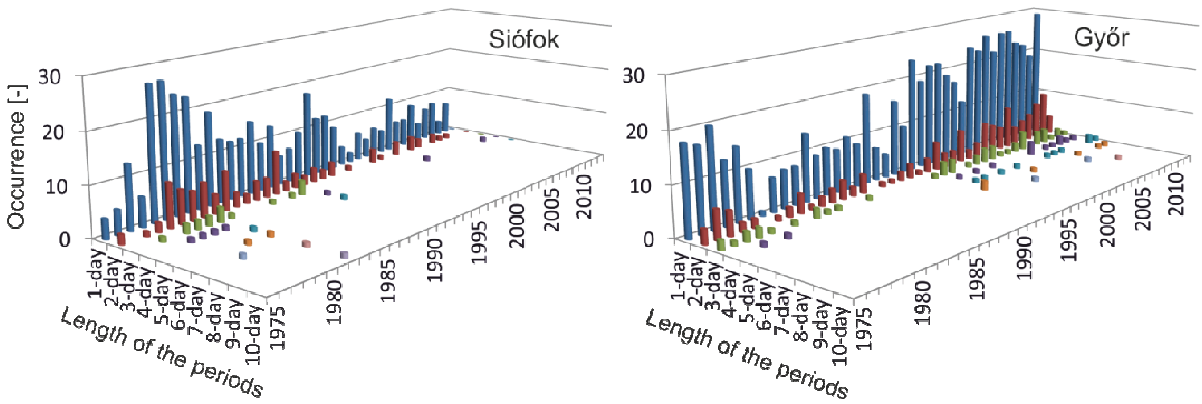

Fig. 4. Yearly Cw1D wind speed indices in Siófok and Győr calculated from homogenized data series.
Trend coefficients of the significant (confidence level: 0.05) changes are the following:
Siófok : 1-day: -0.31, 2-day: -0.12, 3-day: -0.04
Győr : 1-day: +0.41, 2-day: +0.12

Yearly numbers of maximum consecutive days below or above a certain daily average wind speed (below 1 m/s and 3 m/s, or above 8 m/s) are summed for all stations and for all years. Temporal changes of these cumulative indices are plotted in *Fig. 5*. Summed yearly numbers of maximum consecutive days below 3 m/s (above 8 m/s) wind speed, Cw3Dmax (Cw8Dmax) have increased (decreased) significantly, unlike Cw1Dmax, where the detected change is not significant.

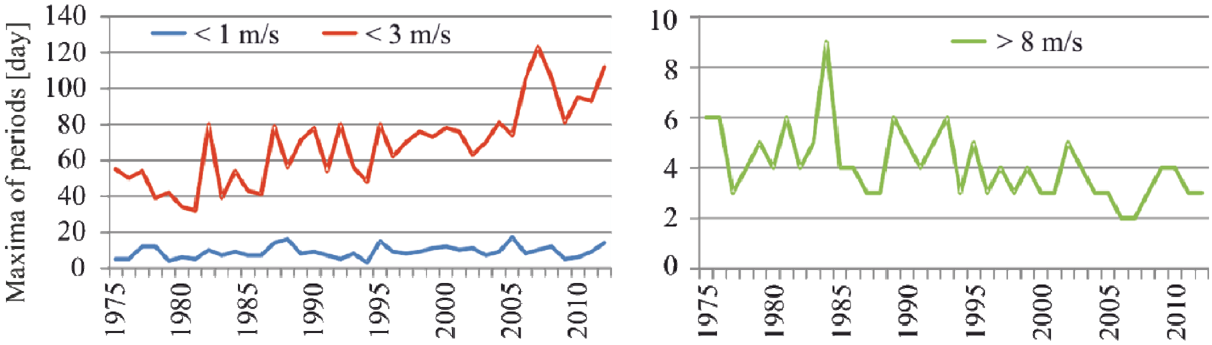

Fig. 5. Temporal changes of yearly Cw1Dmax, Cw3Dmax, and Cw8Dmax wind speed indices summed for all stations and calculated from homogenized data series.

Yearly and monthly number of days with daily maximum wind gust exceeding 15, 20, 25, 30, 35 m/s are calculated for every station from homogenized wind gust time series covering the time period 1975–2013. The temporal changes are estimated by fitting linear trends, for which the calculated trend coefficients are summarized in *Fig. 6*. Yearly trend coefficients of GustGT15 and GustGT20 indices are all negative in all stations, the decreasing trends are statistically significant (at 0.05 level). Due to the more rare occurrences of higher wind gusts, the trend coefficients tend not to be significant in case of GustGT25, GustGT30, and GustGT35. For instance, in case of the highest analyzed wind gust threshold (GustGT35), significant changes are found only at two stations (Miskolc and Zalaegerszeg).

In most of the months (from June to January, and also in April), decreasing trends can be detected at all the stations, similarly to the annual trends. Besides the general decreasing monthly trend coefficients, increasing monthly trends are also found at some stations in March. The lower graph of *Fig. 6* summarizes the linear trend coefficients for March. Overall, significant changes (with confidence level of 0.05) are found only at a few stations (Miskolc, Szentgothárd, Szolnok, Nyíregyháza, and Szombathely in case of different indices). Monthly trends are mostly small and not significant in February and May. However, all these results should be evaluated as a complex issue in the context of other wind-related climate indices. For instance, although the values of the rarely occurring GustGT25 index show increasing trend in March in Szombathely, most of the other wind-related indices (e.g., wavgGT8, wavgGT10, and wavgGT15) calculated from the daily average wind speed at this station have decreased significantly.

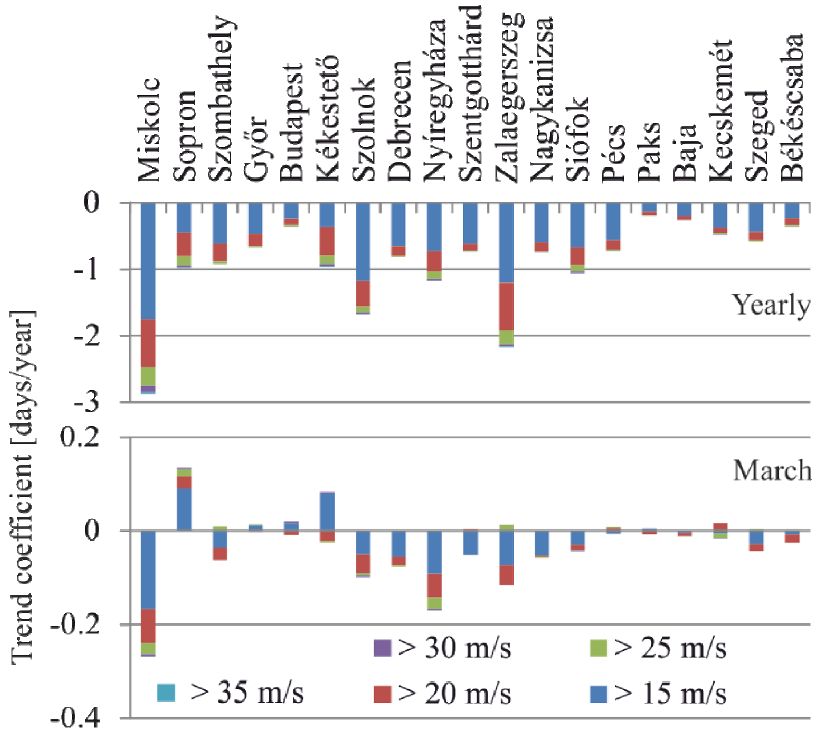

Fig. 6. Fitted linear trend coefficients of yearly (upper graph) and monthly (March, lower graph) number of days with daily maximum wind gust exceeding 15 m/s, 20 m/s, 25 m/s, 30 m/s, and 35 m/s wind gust at the analyzed stations calculated from homogenized data series (1975–2013).
Significant changes (confidence level: 0.05) are found in March as follows:

decreasing trend:	GustGT15: Miskolc, Szentgotthárd
	GustGT20: Miskolc, Szolnok
	GustGT25: Miskolc, Nyíregyháza
increasing trend:	GustGT25: Szombathely

In addition to the analysis of the recent past wind fields, the projected changes in the future are also important for possible impact analysis. For this purpose, simulated wind data are evaluated for the future periods of 2021–2050 and 2071–2100 relative to the 1961–1990 reference period.

First, validation of simulated data is illustrated for a selected gridpoint, located at 47.5°N and 19.0°E, which represents Budapest. Similarly to the other gridpoints within Hungary, the monthly mean wind speed calculated from CARPATCLIM data is overestimated substantially by the RegCM simulation in the 1961-1990 reference period (*Fig. 7*). The maximum and minimum bias of the monthly mean wind speed at this selected location is 2.7 m/s in January, and 0.8 m/s in June, respectively. The range of monthly wind speed biases changes with percentiles, in some months it reaches 4 m/s (*Fig. 8*). Percentile differences are the smallest in May and June, when small averaged differences (biases) of the calculated Weibull parameters have also been found between ERA Interim and observed data.

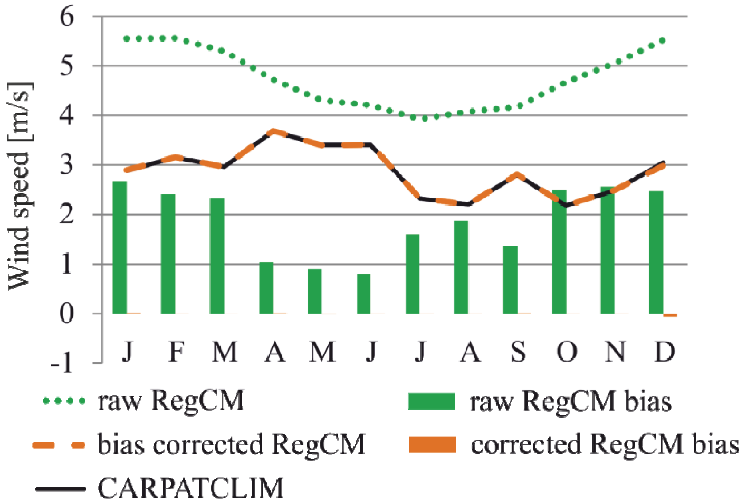

Fig. 7. Comparison of RegCM simulation and CARPATCLIM data: annual distribution of monthly mean wind speed (lines) and monthly mean wind speed bias (columns), for the gridpoint 47.5°N and 19.0°E, for the period 1961–1990.

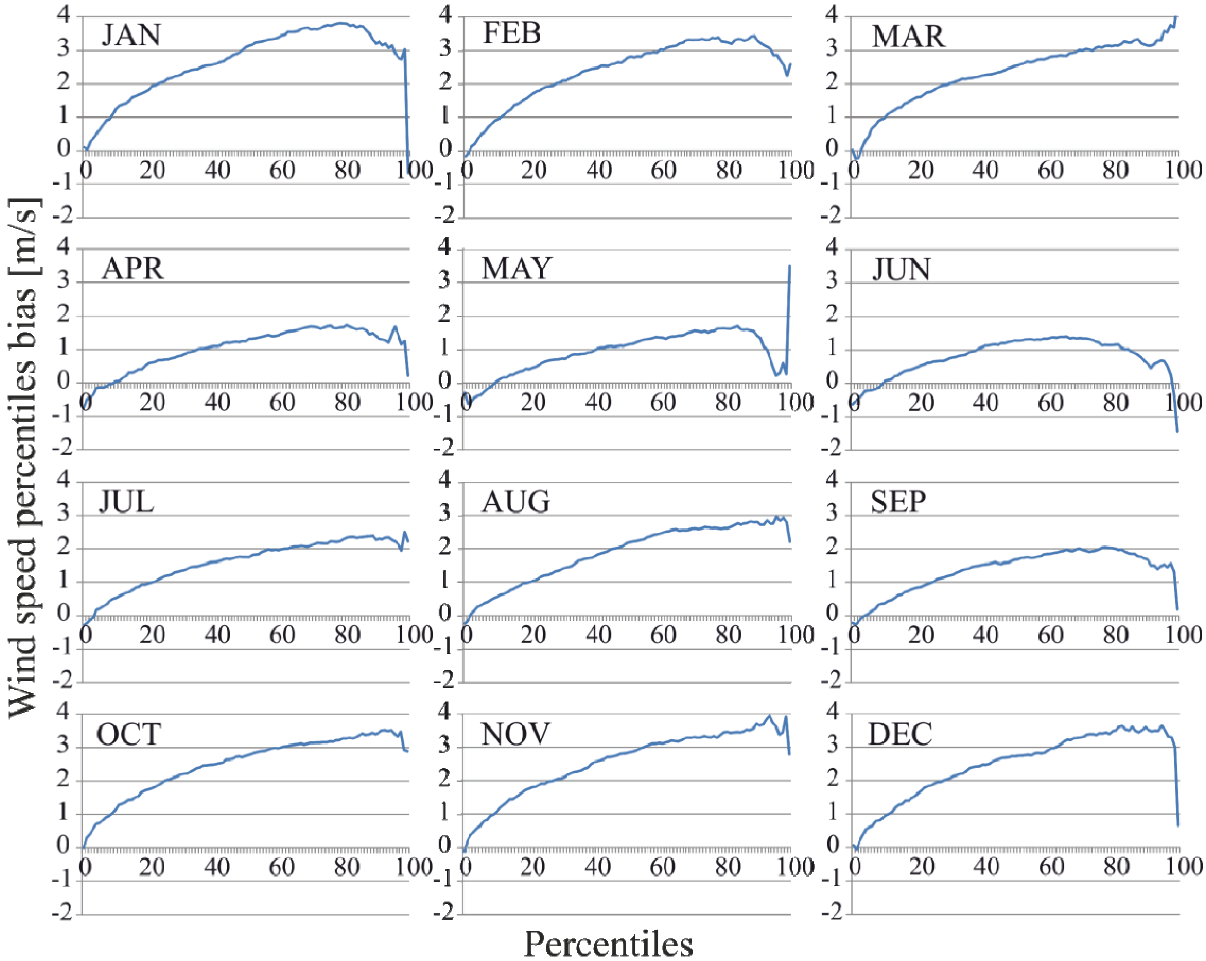

Fig. 8. Wind speed monthly percentiles biases calculated from differences of raw RegCM outputs (i.e., before completing any bias-correction) and CARPATCLIM for the gridpoint 47.5°N and 19.0°E covering the period 1961–1990.

Since projected wind speed is highly overestimated by the simulation of the regional climate model RegCM in the reference period (1961–1990), a bias correction is certainly necessary to apply to the raw simulated wind data using CARPATCLIM as a reference database. The bias correction method is based on fitting the empirical cumulative density functions of simulated daily time series to the observations for each gridcell using monthly multiplicative correction factors.

Fig. 9 compares the distributions of RegCM model outputs (raw and bias-corrected simulated wind data) to the CARPATCLIM wind data for the gridpoint 47.5°N and 19.0°E (representing Budapest) over the period 1961–1990. The charts clearly demonstrate that the differences between the two wind fields' distributions can be eliminated using the bias correction technique. (Similar good agreements are reached for each gridpoint.)

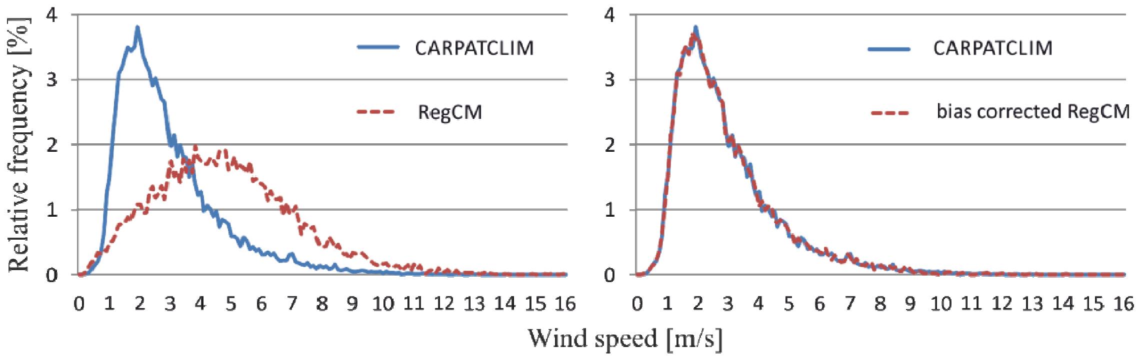

Fig. 9. Effect of bias correction of the simulated wind data. Comparison of relative frequencies of wind fields of CARPATCLIM to RegCM experiment for the period 1961–1990, for the gridpoint 47.5°N and 19°E, for raw simulated data (left) and bias-corrected data (right).

After determining the multiplicative correction factors on a monthly basis that correct the simulated wind speed of RegCM experiments, spatial distributions of the differences between the bias-corrected RegCM outputs and the CARPATCLIM wind speed data are calculated and mapped for different percentile values (0.50, 0.90, and 0.99) for the reference period 1961–1990, and for the projected periods (2021–2050 and 2071–2100). In case of the median and the upper decile (i.e., 0.50 and 0.90 percentiles, respectively), the difference in the reference period is less than 0.1 m/s in every gridcell for the whole year except in December, when the bias is between 0.1 m/s and 0.2 m/s. In the tail of the distribution larger differences can be found, for example, in case of the 0.99 percentile, the difference is reaching 1 m/s in some gridpoints (the monthly average difference value for all the percentiles is –0.04 m/s in the selected gridpoint in December).

For the evaluation of the projected climate change, bias-corrected RegCM outputs are used. Projected mean and extreme changes of wind conditions are analyzed. Differences between the future and past bias-corrected RegCM wind speed fields are mapped (*Fig. 10*) for different percentile values (0.90 and 0.99) for both analyzed future periods.

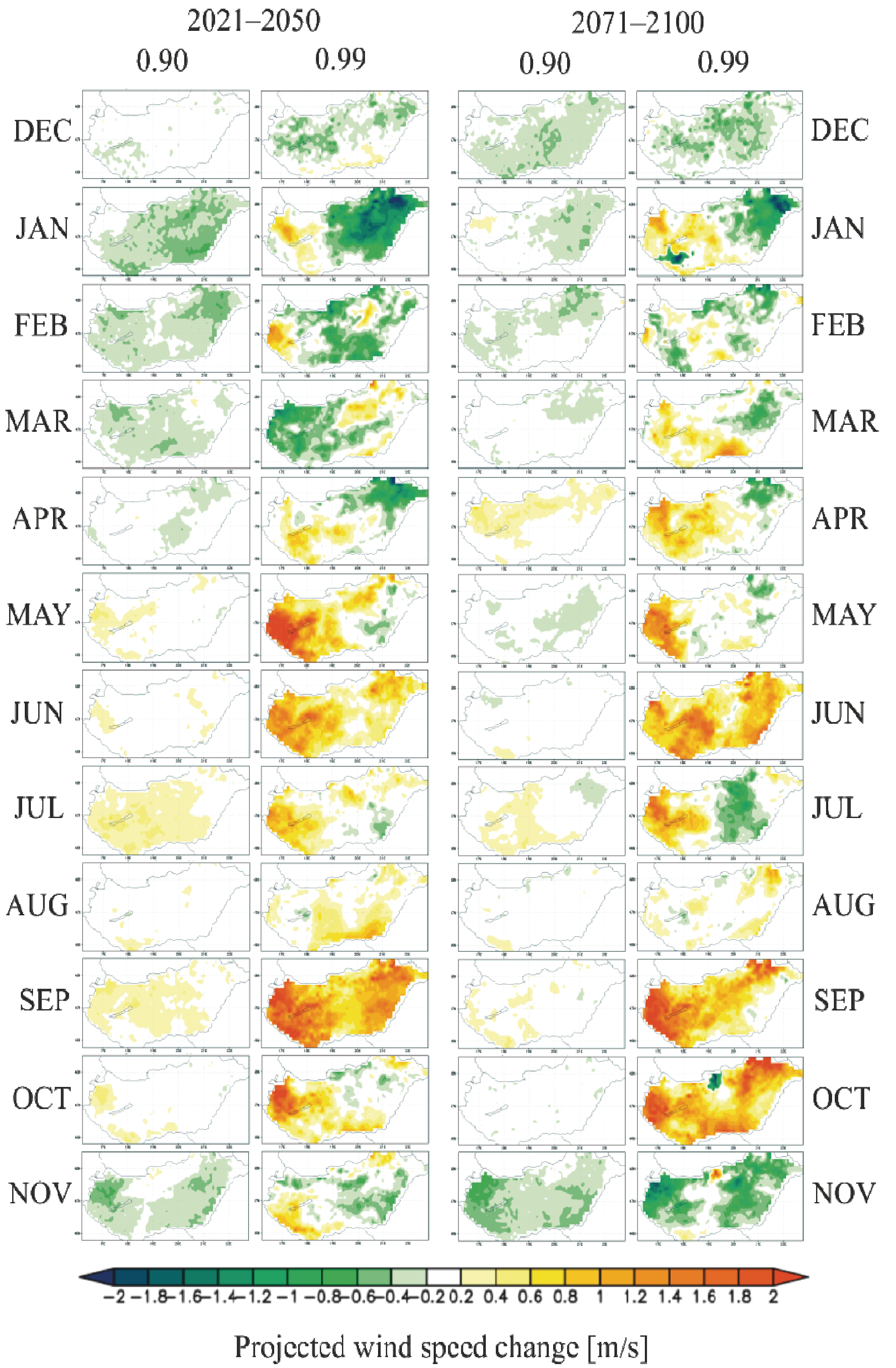

Fig. 10. Spatial distributions of the projected monthly mean changes of the 0.90 and 0.99 percentile values calculated from the bias-corrected RegCM wind speed data for the future periods (2021–2050 and 2071–2100).

Projected monthly changes in the 0.90 percentile are relatively small (the maximum is 0.6 m/s) for both periods, whereas changes in the 0.99 percentile values are projected to exceed 2 m/s in several regions in the country. Differences of the medians do not exceed 0.4 m/s.

4. Summary and conclusions

Our analysis of homogenized observed station and gridded wind data show overall decrease in the annual mean wind speed, which is consistent with the reduced Pole to Equator meridional temperature gradient in a warmer globe. Similar decreasing trend is also concluded by *Spinoni et al*. (2014) using CARPATCLIM data sets wind speed decrease in every season in Hungary.

Our results can be summarized as follows.

(1) Comparison of the raw and homogenized wind speed (1975–2012) and wind gust (1975–2013) measurements leads to different results, which highlight that inhomogeneities may mislead our conclusions.

(2) Wind climate extremes can be described by a range of daily/monthly/ yearly quantities such as high percentiles, maxima, return values, and wind indices. For instance, overestimation of the Weibull shape parameters in ERA Interim reanalysis data (1979–2012) compared to synoptic stations reduces the variability of wind conditions and the probability of extreme wind speed. That is why the use of homogenous, quality-controlled, and reliable (measured) data series are essential when completing a reliable wind climatological analysis with special focus on extremes.

(3) GEV distributions are fitted to the annual daily maxima of wind speed at all the measuring stations and all the grid points of CARPATCLIM (1961–2010) database, which are used to estimate 50-year and 100-year return values. The return values are generally in the interval between 14 m/s and 20 m/s in most of Hungary, however, they exceed 26 m/s in the northeastern region of the country (in Nyíregyháza among the stations). The differences can partially be explained by the different calculation method of daily wind speed.

(4) Regarding the wind speed indices, yearly occurrence of days with small average wind speed has become more frequent, and the yearly number of days with average wind speed exceeding the larger thresholds has decreased. These negative trends are generally significant. Yearly number of periods of consecutive days with daily average wind speed below 3 m/s has also decreased significantly. Wind gust related indices has also decreased in general.

(5) Since simulated wind speed time series (using RegCM) highly overestimate the measurements in the reference period (1961–1990), and thus, do not reproduce the distribution of the CARPATCLIM daily wind speed values, a bias correction is applied to the simulated wind data using CARPATCLIM as a reference. Differences of the percentile values (between

raw simulated data of RegCM and the CARPATCLIM wind) are the smallest during months May and June. Similarly, the smallest biases of ERA Interim data compared to the station measurements are found in June and July. These results indicate that the larger bias values may be associated with winds resulted by winter storms.

(6) The application of bias correction substantially reduced the average monthly bias (practically to zero). The differences of the percentiles in the reference period are generally small, except in the tail of the distribution, where it can reach 1 m/s in some gridpoints in case of the 0.99 percentile value.

(7) Projected monthly changes in the median and the 0.90 percentile are relatively small (below 0.4 m/s and 0.6 m/s, respectively) for both future periods (2021–2050 and 2071–2100), however, estimated monthly changes of the 0.99 percentile may reach 2 m/s.

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