Wind under Microscope

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Annotation

We investigated the scaling behaviour of hourly wind speed and wind records from ten sites located in Slovakia for the period 2006-2016. We used the Fast Fourier Transform (FFT) and the Continuous Wavelet Transform (CWT) to study the scaling behaviour of wind speed data. From spectral slope of power spectra were investigated an correlation of wind speed data and was identified an breakpoint of two regime for meteorological scale. From CWT were identify cycle of the wind for different range.

Keywords: scaling, wind, velocity, FFT, CWT

Abstract

It is hard to look closer at wind as itself and sometimes average speed and direction of the wind it's not enough for investigating its behaviour. In such situations, we can use a powerful tool for our purpose, mathematics.

We investigated the scaling behaviour of hourly wind speed and wind records from ten sites located in Slovakia for the period 2006-2016. We used the Fast Fourier Transform (FFT) and the Continuous Wavelet Transform (CWT) to study the scaling behaviour of wind speed data. The analysis was done through MATLAB software, which provides very useful functions.

Results shows that wind speed fluctuates persistently with long term correlations, as indicated by the average spectral slope of β_1 = 0.886 for wind speed within mesoscales. In speed records were identified two scaling regimes (mesoscale and synoptic) described by distinct spectral slope changing at the crossover periods. Was found that the crossover period occurs earlier in the case of wind speed on average at 3,5 days. At synoptic scales longer than the crossover periods, the power spectra of the analysed records show properties of white noise, i.e. the time series are almost uncorrelated in time. Finally, by means of the Continuous Wavelet Transform we show that there is a daily scales but that wind speed data exhibit intermittent diurnal cycles chiefly from spring to autumn, which can be explained by more a pronounced convective heating of the ground. A spectral gap between the diurnal cycles and the synoptic scales is clearly visible in the wavelet spectrograms.

Introduction

In order to look closer at the wind we need to perform careful statistical analysis of wind speed and its frequency distribution (de Araujo Lima and Bezerra Filho, 2010; Pimenta et al., 2008; Shipkovs et al. 2011). For many theoretical and practical problems it is important to know whether the energy of wind at the various scales of motion extends uniformly over all the scales, or whether there are stronger scales separated by gaps (Fiedler et al., 1970). Therefore, apart from the probability distribution of wind speed and the duration of individual windy episodes, investigating the dynamics and the scaling behaviour of wind provide valuable insight into the underlying stochastic processes governing the temporal variability of wind.

Meteorologists usually differentiate between three types of scales of atmospheric systems: microscale; mesoscale and synoptic scale, although there is no general agreement in terms of the limits of these scales (Fiedler et al, 1970; Vinnichenko, 1970). Nevertheless, for the sake of clarity we adopt here the definition of Fiedler et al. (1970) according to which the synoptic scale includes of all scales of motion that can be analysed on the basis of weather maps (periods > 2 days). This synoptic scale includes both the cyclone-scale and the planetary scales. The range of microscales is defined here as all systems in which the vertical and horizontal velocities are within the same order of magnitude (periods < 1 hr). These scales are usually brought by mechanically driven eddies such as convective cells caused by vertical temperature gradients (e.g. thunderstorm cells). And finally, the mesoscale fills in the interval between the microscale and synoptic scales. The mesoscale is represented by e.g. strong diurnal variations (e.g. mountain-valley flows). The mesoscale covers period between 1 to 48 hours.

Using two different methods: Fast Fourier Transform and the Continuous Wavelet Transform there is a possibility to describe the scaling properties of wind speed in the surface boundary layer of the atmosphere at ten sites in Slovakia

Materials and Methods

Data

Thanks to SHMÚ we were able to processed data which were measured at ten sites in Slovakia during the time period from January 2006 to December 2016. The time series used here are hourly averages. The spectral and wavelet analyses were done in the Matlab environment.

Fourier power spectra

Fourier spectrum analysis generally provides frequency information about the energy content of measured, and presumed stationary, time-series data,
First, we examined the power spectra density as a function of frequency according to:

$$S(f) \propto 1/f^{\beta} \qquad \text{Eq. 1}$$

where *S(f)* is the power spectrum; *f* is the spectral frequency (day^{-1}), and β is the power-law scaling (or spectral) exponent. *S*(*f*) shows the strength of the energy variations as a function of frequency. Computation of S(f) can be done by FFT algorithm, where power spectrum density shows a noise behaviour (Fortuna et al, 2014). If any short- or long-term memory exists in the analysed time series, the spectral power should be related to frequency according to Eq. 1. As one of the oldest spectral analyses, the fast Fourier analysis is based on decomposing a signal into its frequency components with varying amplitudes (Onderka et al., 2011; Fleming et al. 2002). The log-log power spectrum of a $1/f^{\beta}$ process is a linear with slope β.

If a time series has a similar amount of variance across all time scales, and when successive observations are independent on the previous observations, there is no short-term nor long-term autocorrelation. Its power spectra exhibit "white noise" {$S(f) \propto 1$}, where the spectral slope β is close or equal to zero. For white noise, energy is equally distributed for all frequencies and thus the power spectrum is flat, while a random walk (i.e. differences between consecutive samples represents a white noise) shows a slope of β = 2 (the Brownian or red noise). Noise with a spectral slope between 1 and 2 is often referred to as the pink noise. The $1/f^{\beta}$ process is that it is self-similar, i.e. the statistical properties of the time series are the same regardless of the scale of measurement, and hence the process lacks a characteristic time scale (Fortuna et al., 2014).

Wavelet Transforms

Wavelet methodology is capable of revealing aspects of data that other signal analysis techniques lack, aspect like trends, break down points, discontinuities in higher derivatives and self-similarity (Siddiqi, 2005).

The wavelet transform can be used to analyse time series that contain nonstationary power at many different frequencies (Daubechies 1990). The wavelet transform of a function *f*(*t*) is defined as the integral transform.

$$Wf(\lambda,t)=\int_{-\infty}^{\infty} f(u)\bar{\psi}_{\lambda,t}(u)du \qquad \lambda>0, \qquad \text{Eq. 2}$$

where:

$$\psi_{\lambda,t}(u)\equiv\frac{1}{\sqrt{\lambda}}\psi\left(\frac{u-t}{\lambda}\right), \qquad \text{Eq. 3}$$

represents a family of functions called wavelets. A scale parameter λ determines the oscillatory frequency and the lenght of the wavelet, and *t* is a time parameter determines its shifting position (Avdakovic, 2011).

$\bar{\psi}_{\lambda,t}(u)$ is the complex conjugate of $\psi_{\lambda,t}(u)$. Changing the value of λ has the effect of dilating ($\lambda > 1$) or contracting ($\lambda < 1$) the function ψ(*t*), and changing *t* has the effect of analysing the function *f*(*t*) around different points *t* (Kumar 1997).

Decreasing the parameter λ, the wavelet becomes more shrink and takes only short time behaviour of *f*(*t*) into account and vice versa. Therefore the wavelet transform allow a flexible time-scale window image. The wavelet transform Eq. 2 is called the continuous wavelet transform (abbreviated CWT) because the scale and time parameters λ and *t* assume continuous values (Kumar 1997). It is important to note that $\psi_{\lambda,u}(t)$ has the same shape for all values of λ and also assume that a wavelet function $\psi_0(t)$ depends on a non-dimensional time parameter *t*. For accepting $\psi_0(t)$ as a wavelet, this function must have zero mean and be localized in both time and frequency space (Farge 1992). The Morlet wavelet, consisting of a plane wave modulated by a Gaussian (Torrence, 1997):

$$\psi_0(t)=\pi^{-1/4}e^{i\omega_0\eta}e^{-\eta^2/2}, \qquad \text{Eq. 4}$$

where ω_0 is the non-dimensional frequency, here taken to be 6 to satisfy the admissibility condition and η is dimensionless time. (Farge 1992).

Principle of CWT is to apply the wavelet as a band-pass filter to the time series. The wavelet is stretched in time by varying its scale (s), so that $\eta=s\cdot t$, and normalizing it to have unit energy (Grinsted et al, 2004).

Fourier transform determined only which frequency appear within signal, but in some time series for example like wind speed time series it is very improbable that one frequency endure whole time of measurement. Wavelet transform allows time-frequency localization in time series by producing coefficients represents properties of a signal in time. Matrix of coefficients creates a spectrum of certain frequencies located in time. By examine the spectrum it is possible to identify regular variation of event. The spectrum provides wide-range view of frequencies and its duration localized in time.

However, a bias naturally occurs at the beginning and at the end of the wavelet power spectrum because the wavelet is not completely localized in time (Grinsted et al., 2004; Torrence and Compo, 1998). Therefore, a cone of influence (COI) has been proposed to ignore the edge effects. The COI is an area in which the wavelet power caused by the poorly localized wavelet near the beginning and end of a time-series has dropped to e^{-2} of the wavelet power at the edge. This COI is visualized in the wavelet power spectra in Figure 2. are areas with faded intensity of colour.

Results

In power law scaling a change in slope indicated different scaling regimes in the analysed time series. Identifying scale regimes in wind speed was reached by Fourier spectral power. In log-log scale were observed two regimes, therefore the spectrum were fitted by two-line regression and calculated the spectral slope for the two scaling regimes. In Table 1. are listed spectral slopes β_1 and β_2, elevation and breakpoints for certain sites. Spectral slopes were estimated by Monte Carlo means for the certain power spectra. The breakpoint is crossover period of two slopes of the spectra. The standard deviation of the estimated slopes is indicated next to the spectral slope estimates.

The mesoscale slope for period below breakpoint is $\beta_1 \pm st.\ dev_1$ while above breakpoint the power spectra become more uncorrelated with a spectral slope $\beta_2 \pm st.\ dev_2$. which means the data above breakpoint are likely white noise. The average spectral slopes are 0.876 for the first spectral region (below the breakpoint at 4.4 days) and 0.133 periods above 4.4 days. Since station Kuchyňa – Nový Dvor has very high deviation from other values was excluded from other calculation. After the adjustment, the results are: average β_1 = 0.886, average β_2 = 0,142 and average breakpoint 3,5 days.

Table1. Full-scale Monte Carlo means for the spectral slopes β_1, β_2 and the breakpoint. The associated standard deviations are indicated ± st. dev.

Site	Elevation (m a.s.l.)	Breakpoint (days)	β_1		st.dev$_1$	β_2		st.dev$_2$
Tisínec	216	2,6	0,934	±	0,132	0,188	±	0,022
Telgárt	901	4,6	0,847	±	0,125	0,024	±	0,038
Liesek	692	3,2	0,865	±	0,103	0,172	±	0,025
Chopok	2005	2,8	1,070	±	0,088	0,269	±	0,025
Gánovce	703	3,1	0,794	±	0,147	0,144	±	0,031
Piešťany	163	4,9	0,838	±	0,166	0,024	±	0,046
Jaslovské Bohunice	176	2,3	0,902	±	0,286	0,256	±	0,040
Bratislava-airport	133	4,9	0,849	±	0,065	0,067	±	0,023
Kuchyňa-Nový Dvor	206	12,4	0,783	±	0,347	0,051	±	0,077
Bratislava - FMFI	250	3,1	0,880	±	0,110	0,136	±	0,028
Mean	**549,5**	**4,4**	**0,876**			**0,1331**		

There is no evidence of statistic significant relationship between the spectral slopes and elevation of sites or period of breakpoints and elevation of sites. But on the other hand only 10 sites were included in calculation so we cannot rule out the possibility the apparent positive relationship. More sites data are needed to be analysed for outcome with high degree of certainty.

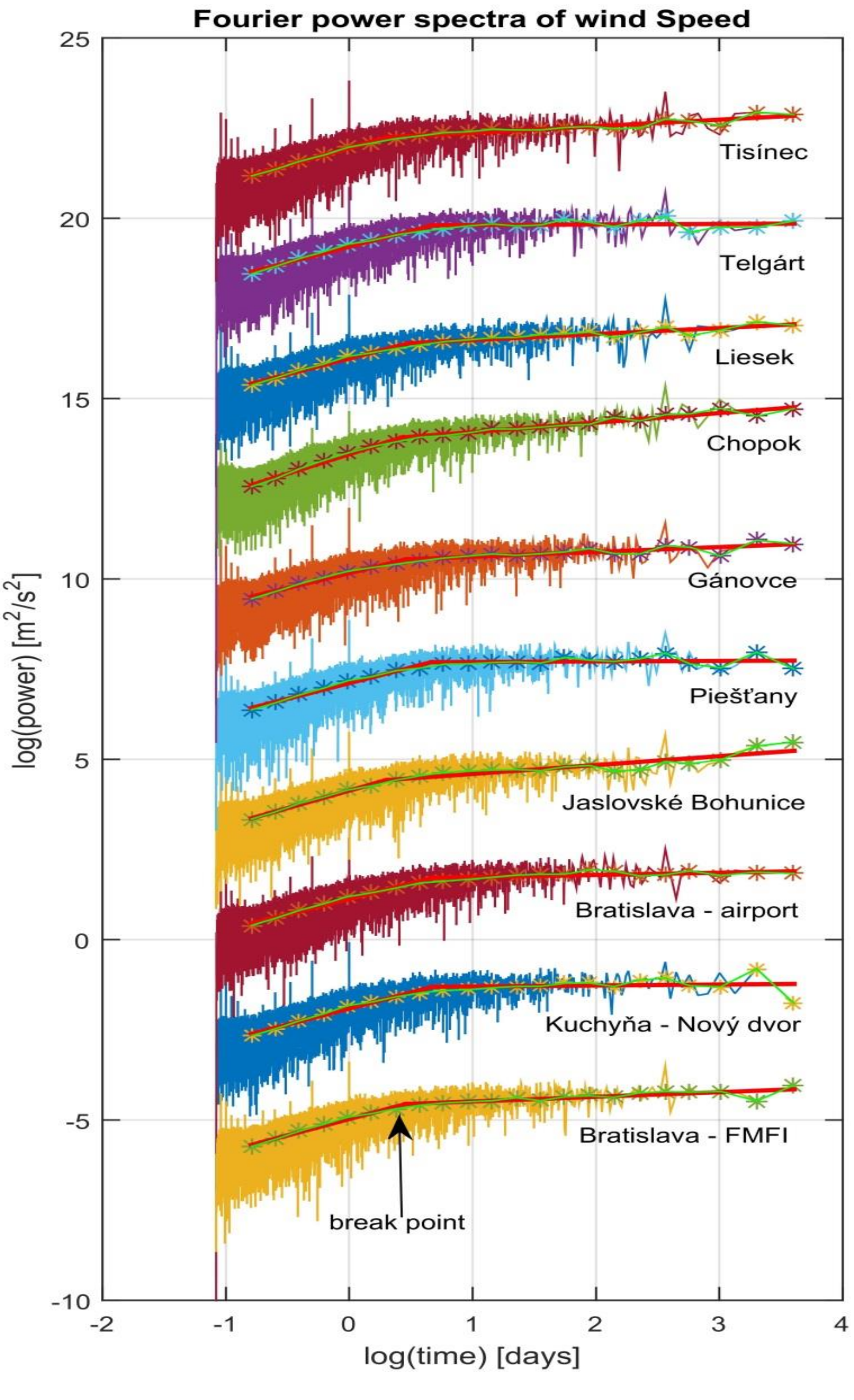
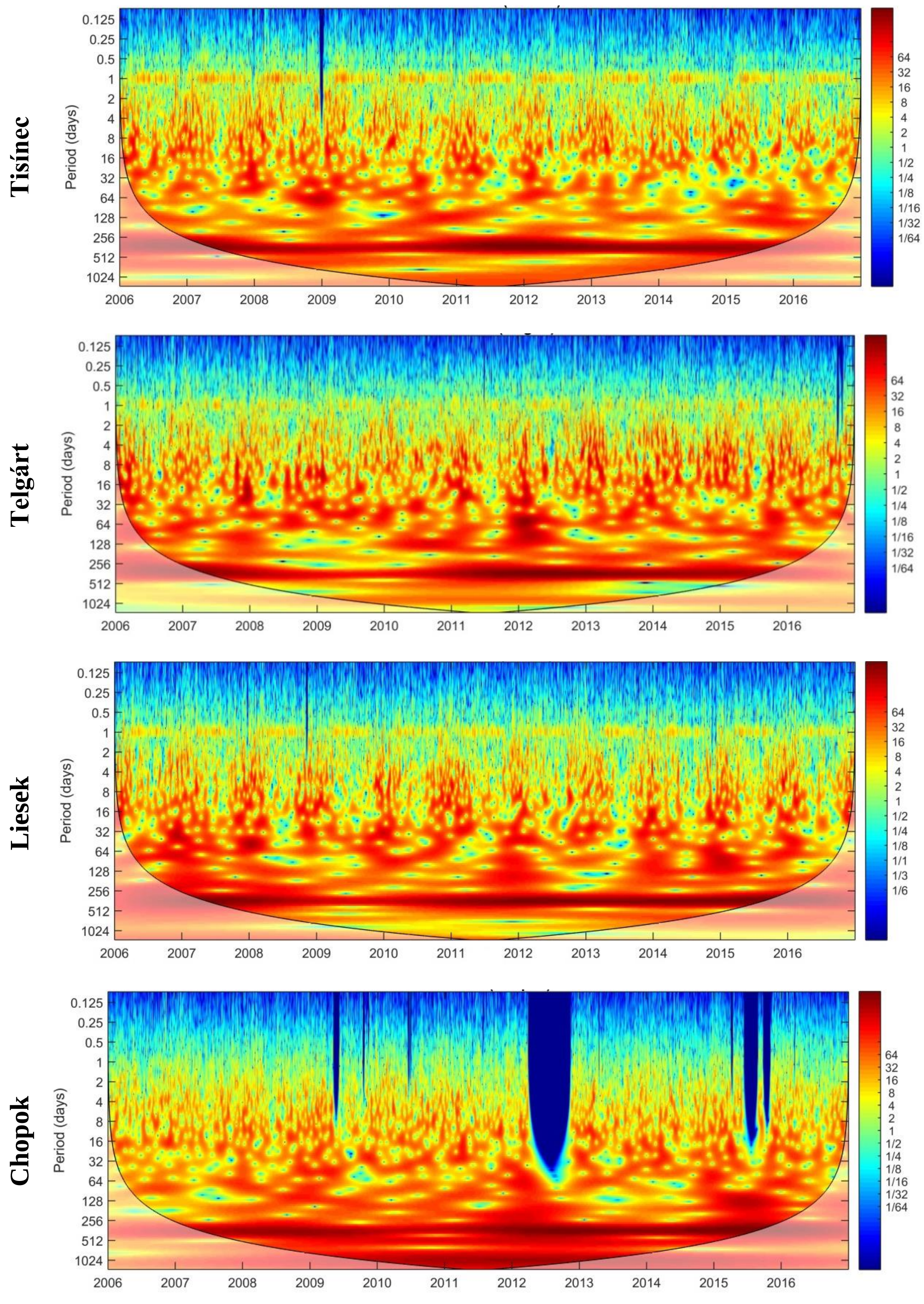
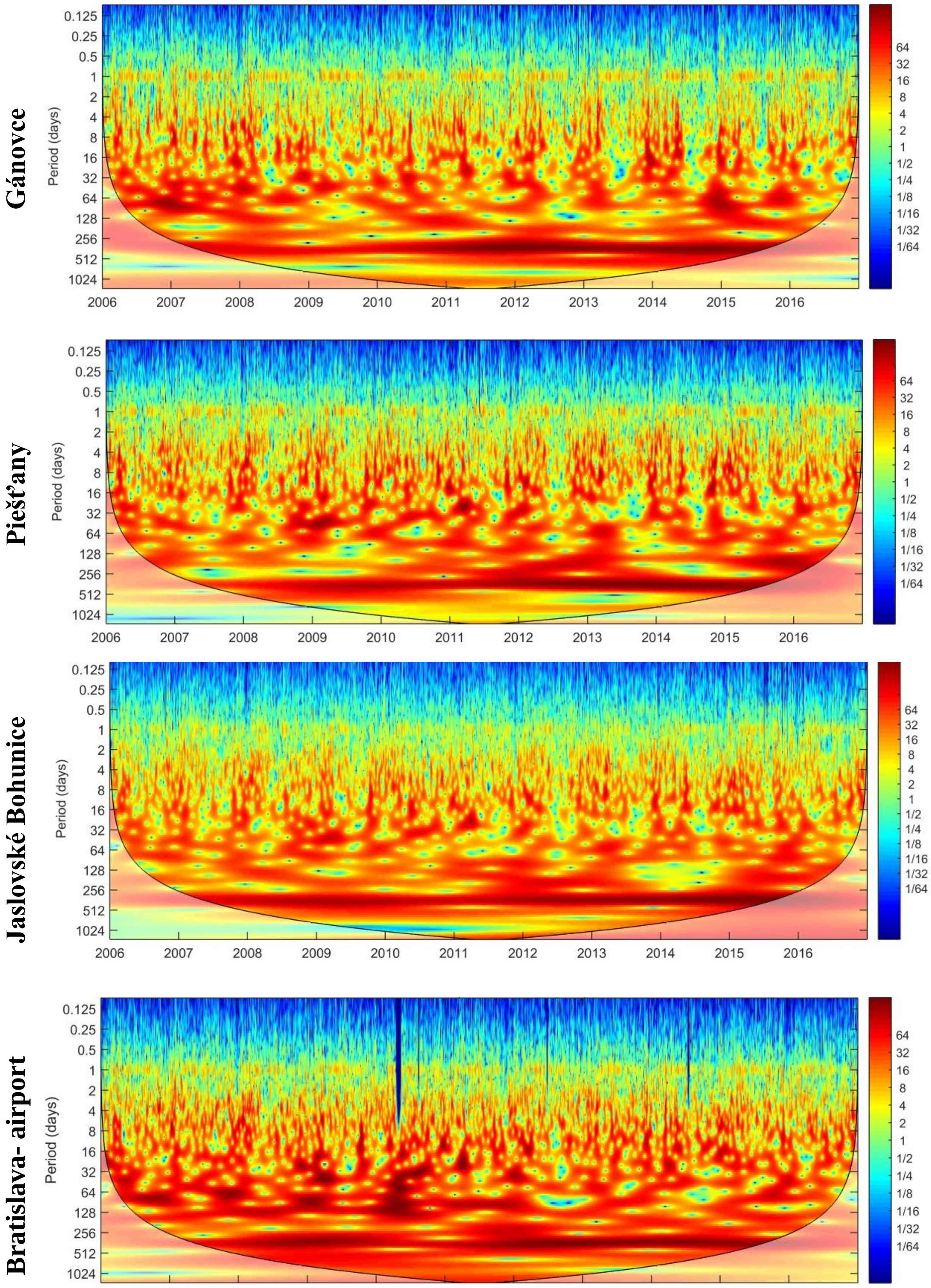


Figure 1 Fourier power spectrum of wind speed data. A noticeable scaling break is apparent in the spectra around 3,5 days (see Table 1).

Wavelet spectrogram make easier to visualised how various frequency contents in the analysed signal of wind speed change in time.

In Figure 2 the *x*-axis represents a position along the signal (time), the *y*-axis represents scale, and the colour at each point represents the magnitude of the coefficient. There is a visible diurnal cycle in all stations except Chopok (2005 m a.s.l). However, the diurnal signal seems to be discontinuous, i.e. it diminished from November to February and becomes more evident from March to October.




Gánovce
Piešťany
Jaslovské Bohunice
Bratislava- airport
Period (days)
0.125
0.25
0.5
1
2
4
8
16
32
64
128
256
512
1024
2006
2007
2008
2009
2010
2011
2012
2013
2014
2015
2016
64
32
16
8
4
2
1
1/2
1/4
1/8
1/16
1/32
1/64

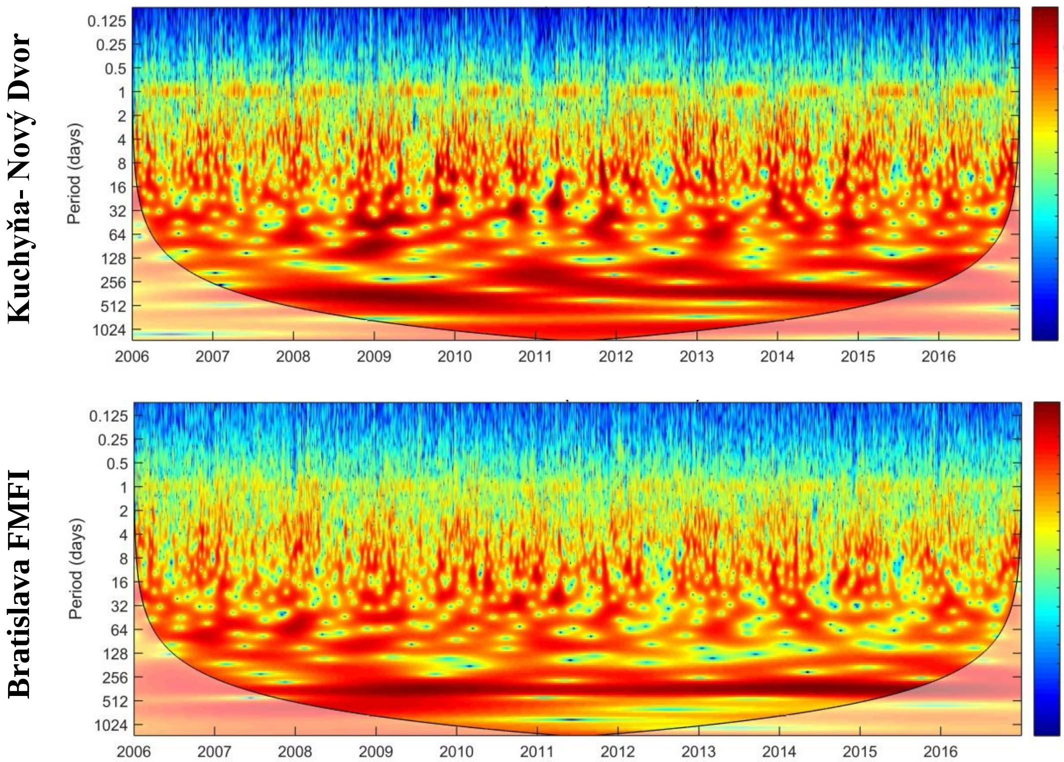


Figure 2 Wavelets power spectra of wind power for certain sites .The *x*-axis represents a position along the signal (time), the *y*-axis represents scale, and the colour at each point represents the magnitude of the coefficient.

Discussion

Two distinct scaling regimes were identified in the analysed time series of wind speed. The spectral slopes and the breakpoints in scaling were quantified by the Fast Fourier Transform and visualized by the CWT. The analyses revealed that wind data at the analysed sites fluctuate persistently with long term correlations. Within mesoscales, the average spectral slope of wind speed was β_1 = 0,886. The spectral slopes indicate that the time series can be described as pink noise. We found the average breakpoint period at 3,5 days. The average spectral slope above breakpoint period was β_2 = 0,142 We assume this period as the boundary period between mesoscale and synoptic scale. Station Kuchyňa – Nový Dvor was excluded from calculation of averages, because of very high deviation from other values. There were no evidence of statistic relationship of elevation and slope of spectra. For more precise results it is necessary to analyse long term data for better statistic and to observe events at smaller scale, microscale regime according to Vinichenko (1970), require data with higher frequency than hourly data.

CWT shows that the wind speed exhibit intermittent diurnal cycles preferably from spring to autumn, which can be explained by more a pronounced convective heating of the ground. Spectral gaps between the diurnal cycles and the synoptic scales are also visible in the wavelet spectrograms. In some wavelet spectra appears dark patches between caused by gap in the times series that was interpolated (for example in Figure 2 Chopok) it might be, because of sites elevation 2005 m a.s.l. and because of mountainous environment around the site.

Conclusions

This is first known analyse of wind speed data by FFT and CWT for ten sites in Slovakia. In speed records were identified two scaling regimes (mesoscale and synoptic) described by distinct spectral slope changing at the crossover periods. Was found that the crossover period occurs earlier in the case of wind speed on average at 3,5 days.

Results shows that wind speed fluctuates persistently with long term correlations, as indicated by the average spectral slope of β_1 = 0.886 for wind speed within mesoscales. And spectral slope for synoptic scale longer than the crossover periods, the power spectra of the analysed records show properties of white noise with spectral slope β_2 = 0,142. By Continuous Wavelet Transform were created wavelet spectrum where were observed intermittent diurnal cycles chiefly from spring to autumn, which can be explained by more a pronounced convective heating of the ground. A spectral gap between the diurnal cycles and the synoptic scales is clearly visible in the wavelet spectrograms.

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Vietor pod mikroskopom

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Rozšírený abstrakt

Je veľmi náročné bližšie sledovať vietor ako taký, vieme ho opísať priemernou rýchlosťou alebo nárazmi vetra, minimom, maximom, avšak niekedy ani toto nestačí na skúmanie správania sa vetra. V takýchto prípadoch vieme použiť veľmi silný nástroj, matematiku. V tomto príspevku sa budeme venovať skúmaniu správania sa škálovania pre hodinový priemer rýchlosti vetra v 10 miestach na Slovensku počas jednej dekády (2006-2016), ktoré sme získali vďaka SHMÚ. Na spracovanie údajov o rýchlosti vetra boli použité dve metódy Fast Fourier Transform (FFT) a Continous Wavelet Transform (CWT). Analýza prebiehala v programe MATLABe.

FFT poskytuje informácie o frekvencii a o energii obsiahnutej pri jednotlivých frekvenciách. Z FFT vieme určiť výkonové spektrum, vďaka ktorému vieme vypočítať následnú auto koreláciu údajov, tzn. nakoľko za sebou idúce údaje sú na sebe závislé. Ak použijeme log-log škálu pre výkonové spektrum, tak trend spektra, jeho sklon, vieme vyjadriť smernicou β. Ak je proces samo-podobný, tak štatistické vlastnosti časového radu sa pri

zmene škály zachovávajú. Vieme že platí nasledovné, ak $\beta = 2$, tak signál je podobný Brownovmu pohybu, ak $\beta = 0$, vtedy je signál podobný bielemu šumu, čiže náhodnému signálu. Pri bližšej analýze bola pozorovaná zmena trendu spektra v škálovaní, čo naznačuje rôzne škálovacie režimy, to znamená že od určitého bodu sa signál správa inakšie. Identifikáciou bodu zlomu, časový bod zmeny trendu, vieme rozdeliť spektrum na dve časti. Pomocou určitého algoritmu a Monte Carlo metódou boli vypočítané trendy spektra, teda smernica β_1 pre jeden režim a β_2 pre ďalší.

Výsledky ukazujú, že rýchlosť vetra pretrváva s dlhodobými koreláciami, čo naznačuje priemerný spektrálny sklon $\beta_1 = 0.886$ pre jeden z režimov. Ako už bolo povedané boli identifikované dva škálovacie režimy, ktoré zodpovedajú dvom meteorologickým režimom pre rýchlosť vetra, mezoškála a synoptická škála, ktorým zodpovedajú dané sklony spektra so zmenou v bode zlomu. Pre bod zlomu zodpovedá časová doba v priemere 3,5 dňa. V synoptickej škále, to je spektrum v časovom rade nad bodom zlomu, výkonové spektrum vykazuje vlastnosti bieleho šumu, priemerná smernica $\beta_2 = 0,142$ je bližšie k nule. To znamená časový rad od bodu zlomu je v čase takmer nezávislý.

CWT umožňuje časovo-frekvenčný popis signálu. CWT je schopná odhaliť rôzne vlastnosti signálu, ktoré iné analýzy signálu neposkytujú. Používa sa aj pri analýze časového radu, ktorý obsahuje nestacionárny výkon pre rôzne frekvencie. Pomocou CWT vytvoríme maticu koeficientov pre určité frekvencie, ktoré sa nachádzajú v danom čase. Veľkosť týchto koeficientov je na waveletovom spektrograme zobrazené pomocou farby. Takéto spektrum nám poskytuje široký pohľad na zmenu a lokalizáciu frekvencií v čase.

Analýza waveletového spektra naznačuje, že údaje o rýchlosti vetra vykazujú denný cyklus tieto denné cykly sa vyskytujú najmä od jari do jesene, čo možno vysvetliť výraznejším konvektívnym prúdením. Spektrálna medzera medzi dennými cyklami a synoptickou škálou je taktiež jasne viditeľná vo wavletovom spektrograme.