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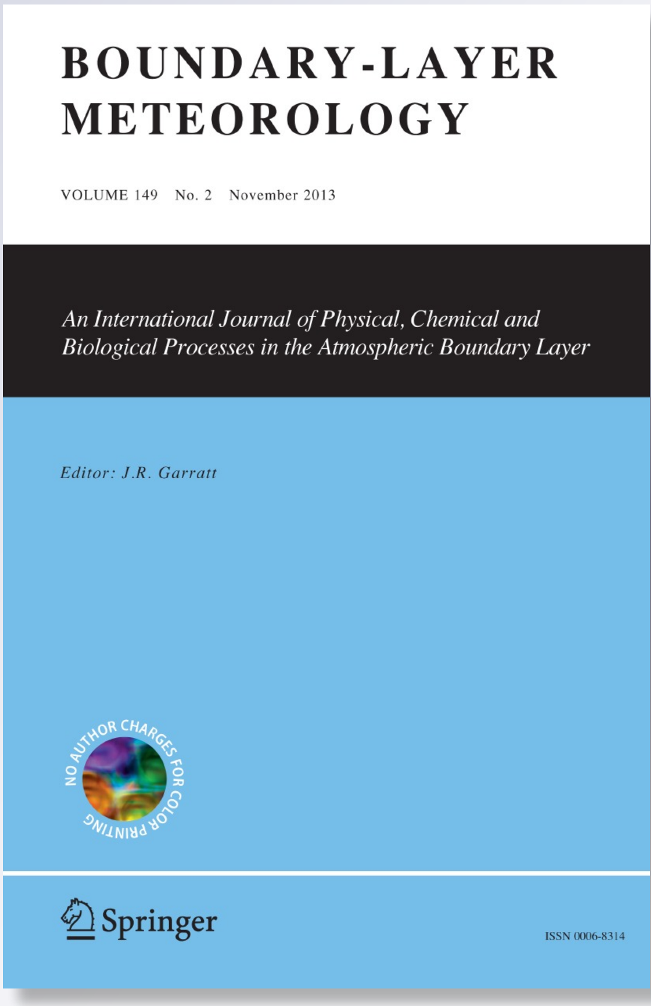

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ARTICLE

The Effects of Non-stationarity on the Clustering Properties of the Boundary-layer Vertical Wind Velocity

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Abstract Non-stationarity is a common feature in geophysical flows, though it still remains an open question on how the non-stationarity of flow affects its statistical structure. Using the telegraph approximation (TA) method, we quantified how non-stationarity in the measured atmospheric turbulent vertical velocity time series affects its clustering properties—one of the two main components of intermittency in turbulence. We compare different TA results between stationary and non-stationary atmospheric turbulent vertical velocity records, and find that the non-stationary data possess different cluster and intermittency exponents from stationary data. The inter-pulse period of the non-stationary records takes a near power-law distribution while the inter-pulse period of the stationary records exhibits a stretched exponential distribution. These results suggest that non-stationarity of the underlying processes can affect the statistical structure of turbulence, especially the clustering properties.

Keywords Clustering property · Intermittency · Inter-pulse period · Non-stationarity · Telegraph approximation

1 Introduction

From a statistical point of view, a time series representing a stochastic process is considered stationary when its probabilistic structure is independent of the time origin (Bendat and Piersol 2000). It is well known that most time-series analysis, linear or non-linear, requires the data under investigation to be stationary. The presence of non-stationarity may yield spurious interpretation of the underlying dynamics, such as the false detection of a large correlation dimension or low entropies (Yu and Lu 1998).

Many of the data in natural complex geophysical systems are non-stationary when viewed as a whole (Bendat and Piersol 2000). Cullen and Steffen collected data for 25 days during

Q. Li · Z. Fu (✉)
Laboratory for Climate and Ocean-Atmosphere Studies, Department of Atmospheric and Oceanic Sciences, School of Physics, Peking University, Beijing 100871, China
e-mail: fuzt@pku.edu.cn

two summers to describe processes responsible for the non-stationarity of turbulent sensible heat fluxes at Summit, Greenland. A stationarity test shows that about 40% of the data are classified as non-stationary (Cullen et al. 2007). Mahrt et al. (2012) examined the relationship of turbulence to the non-stationary wind shear and thermal stratification, and found that the turbulence is simultaneously generated by different non-stationary mechanisms.

The non-stationarity of measurement sequences usually takes an intermittent behaviour. Intermittency implies that small-scale quantities, such as energy dissipation, are distributed unevenly in space and perhaps also in time (Sreenivasan and Bershadskii 2006). There are two main aspects of intermittency: one related to the amplitude of small-scale fluctuations and the other to the local frequency of oscillations. To explore a narrower scope, we use the telegraph approximation (TA for short, see Bershadskii et al. 2004) to eliminate amplitude effects, and study only the tendency of small-scale fluctuations to cluster. Bershadskii et al. (2004) exploited the TA method for the study of temperature time traces obtained in turbulent thermal convection at high Rayleigh number, and concluded that amplitude intermittency might mitigate clusterization effects. Sreenivasan and Bershadskii (2006) found a unique relation between the spectral scaling of the signal and its TA, and also showed there are two classes of signals: the white noise type and the Markovian–Lorentzian type, which was verified in our work related to these two kinds of time series. Cava and Katul (2009) studied the intermittent structure of turbulence within the canopy sub-layer, and explored the clustering properties of canopy sub-layer turbulence and their independence on atmospheric stability, and found amplitude variations play only a minor role in scalar intermittency.

However, little emphasis has been placed on the effects of non-stationarity (Li et al. 2001; Wang et al. 2005; Sreenivasan and Bershadskii 2006; Cava and Katul 2009), especially on the clustering characteristics in boundary-layer turbulence, which is the subject of our study. Different features are found for stationary and non-stationary time series investigated herein.

We outline the paper as follows: firstly we generate the telegraph approximation of the stationary and non-stationary records as mentioned below to separate the clustering tendency from amplitude effects. Secondly, we show that the spectral scaling of TA gives important information about the spectral scaling of the full signal. Thirdly, the cluster exponent and intermittency exponent are calculated to show the effects of non-stationarity on the scaling statistics. Then different inter-pulse period distributions are obtained for the two types of time series, with the white noise type and the Markovian–Lorentzian type for reference.

2 Data and Methods

2.1 Data

The data used herein were obtained from a field experiment performed by the State Key Laboratory of Atmospheric Boundary-Layer Physics and Atmospheric Chemistry (LAPC), from 9 to 22 June, 1998. The underlying surface comprises paddy fields and the observation height is 4 m. The instrument used in the experiment is a SAT-211/3k 3-D ultrasonic anemometer, whose sampling frequency is 10 Hz and where each 40,000 points of sampling are taken as one record. More details of the statistical characteristics of the experimental data have been derived elsewhere (Chen and Hu 2003; Wang et al. 2005; Li et al. 2013). We select some representative series from the datasets after the diagnosis of non-stationarity by means of the space–time index (STI) method. The STI is a graphical method, and can effectively detect dynamical non-stationarity in a time series. Further descriptions of the STI method are presented in Yu and Lu (1998, 1999) and are not repeated here. We have investigated

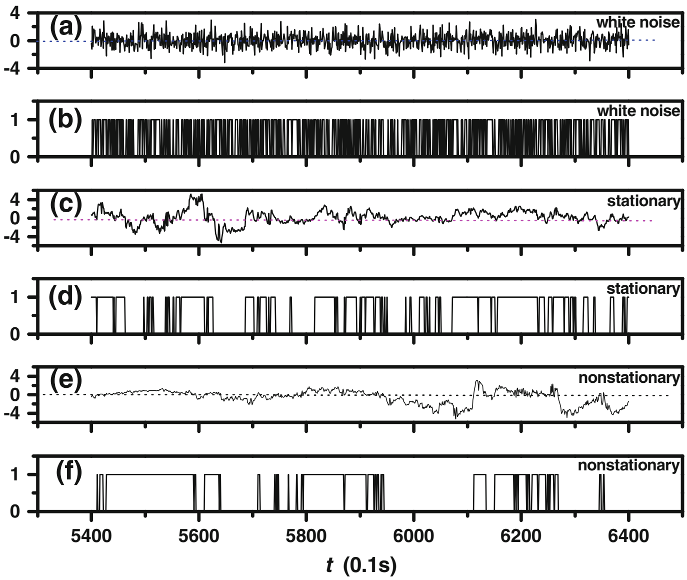

Fig. 1 The normalized segments of **a** white noise, **c** stationary vertical velocity time series, **e** non-stationary vertical velocity time series and the TA results for white noise (**b**), stationary series (**d**) and non-stationary series (**f**). Since the TA only takes values of 1 or zero, no amplitude variations are considered

24 vertical velocity time series, 12 of which are the most non-stationary among the dataset, while the other 12 are the most stationary. We show the ensemble-averaged results of 12 samples for each classification group.

2.2 Methods

2.2.1 Telegraph Approximation

In the classical methods of time-series analysis (Kantz and Schreiber 2004), it is difficult to separate the clustering effect from the traditional intermittency effects arising from amplitude variability. To separate these two effects, we ignore the variation of the amplitude and replace the fluctuation time series of the type shown in Fig. 1a, c, e by their telegraph approximation (TA), shown in Fig. 1b, d, f. This approximation is generated from the measured velocity by setting the fluctuation magnitude to 1 or zero depending on whether or not the magnitude exceeds the mean value (marked as zero and shown by the dashed line in Fig. 1a, c, e). A reverse definition, below the mean value and zero above the mean value, does not alter the results. Formally, for the normalized vertical velocity fluctuation $w'(t)$ (with zero mean), the $TA(t)$ is constructed as

$$TA(t) = \frac{1}{2}\left(\frac{w'(t)}{|w'(t)|} + 1\right), \qquad (1)$$

where $w'(t) = w(t) - \overline{w}$, and the overbar indicates the time average.

By definition, *TA* can admit either 1 or 0. The telegraph approximation can be generated by setting different “thresholds” from the mean, where it turns out that most properties examined here are reasonably independent of the threshold (Bershadskii et al. 2004).

2.2.2 Energy Spectrum Analysis

First of all, it may be useful to summarize how the classical statistics for the TA compare with those of the boundary-layer turbulence signal (Bershadskii et al. 2004). We will calculate the spectral density $S(f)$ of the TA and the full signal, and then the comparisons are made separately for stationary and non-stationary cases between the original record and its TA.

2.2.3 Cluster Exponent and Intermittency Exponent

The clustering information can be extracted from the TA. Let us count the number of 'zero'-crossing points of the TA (the same as the 'zero'-crossing points of the original signal) in a time interval t and consider their average density n_t. We denote the fluctuation of the running density as

$$\delta n_t = n_t - \langle n_t \rangle \tag{2}$$

and where brackets mean the average over long times (Sreenivasan and Bershadskii 2006). We are interested in the variation of the standard deviation of the running density fluctuations $\langle \delta n_t^2 \rangle^{1/2}$ with t. For reference, we show the result for the white noise signal in Fig. 4, which presumably has no clustering. The straight line denotes the scaling relation

$$\langle \delta n_t^2 \rangle^{1/2} \sim t^{-\alpha}, \tag{3}$$

with $\alpha = 0.5$ for white noise. This result for white noise can be derived analytically (Leadbetter and Cryer 1965; Barnett and Kedem 1991). We wish to explore the cluster exponent α for the stationary and non-stationary time series, and whether these two kinds of time series possess the same clustering properties can be quantitatively shown according to α.

This intermittency measure was first proposed by Obukhov (1962) and subsequently used by Kuznetsov et al. (1992), and Sreenivasan and Antonia (1997) among others. Recently Sreenivasan and Bershadskii (2006), Cava and Katul (2009), Poggi and Katul (2009), Lee (2011), and Cava et al. (2012) have used this quantity described below to study turbulent flow. Because the variance (or kinetic energy) dissipation rate is proportional to the squared spatial gradients, which can be converted to temporal gradients via Taylor's frozen turbulence hypothesis, the quantities

$$\chi(t) = \left| \frac{\mathrm{d}w'(t)}{\mathrm{d}t} \right|^2, \tag{4}$$

and,

$$\chi_\tau = \frac{1}{\tau} \int_t^{t+\tau} \chi(t)\mathrm{d}t \tag{5}$$

can be simultaneously used to determine the so-called intermittency exponent μ_q, from the scaling of the moments

$$\frac{\overline{(\chi_\tau(t))^q}}{(\overline{(\chi_\tau(t))})^q} \sim \tau^{-\mu_q}. \tag{6}$$

In this paper, μ_2 computed from w' and $TA(w')$ is referred to as μ'_w and μ_{TA}, respectively for notational simplicity. For white noise, we obtain $\mu_2 = 0$ above a certain scale. For $TA(w')$ the dissipation rate is a composite of pulses (i.e. δ functions) located at the edges of the boxes of the telegraph signal (Bershadskii et al. 2004), a non-zero value of μ_{TA} indicating a clusterized distribution of pulses. On the other hand, $\mu_{w'}$ contains information on both amplitude variability and clustering of the signal. Therefore $\mu_{TA} > \mu_{w'}$ indicates that amplitude variations mitigate intermittency; $\mu_{TA} < \mu_{w'}$ indicates that amplitude variations amplify intermittency; $\mu_{TA} \sim \mu_{w'}$ indicates that much of the observed intermittency may be due to clusterization and not amplitude variations (Cava and Katul 2009). Whether the stationary and non-stationary time series show similar relations is explored below.

2.2.4 Inter-pulse Period Distribution

We term the duration between two successive pulses in TA results as the inter-pulse period r. Whether the non-stationarity affects the inter-pulse period distributions or whether the inter-pulse period distribution shows similar features for the white noise, stationary time series and non-stationary time series, is explored. Considering that the inter-pulse periods ignore the amplitude influence and focus just on the frequency changes, it will be of benefit to investigate the information over frequency of multi-scale structures. This distribution does not have any information about the ordering of events in space (or time) unlike the cluster exponent mentioned above (Sreenivasan and Bershadskii 2006).

3 Results

3.1 The Probability Density Function and Energy Spectrum Analysis

We normalize the original data by their standard deviation σ. Figure 2 shows the probability density function (PDF) of white noise, stationary vertical velocity time series and their non-stationary counterparts. Compared with white noise, the PDFs of the stationary and non-stationary traces are both characterized by fat tails and a peak around the mean value. Such PDFs are called intermittent and differ considerably from the Gaussian distribution that is commonly considered to be suitable for continuous random processes (Boettcher et al. 2003). Note that the probability of measured large vertical velocity ($w = 4\sigma$) located in the tails of the PDFs as shown in Fig. 2, is more than 10 times higher than that of the Gaussian distribution, however no marked differences can be found for the stationary and non-stationary time series. So the PDF of measured series cannot be used to distinguish the non-stationary measurement from the stationary one, and it of course cannot be used to quantify the effect of non-stationarity on their statistics.

Figure 3 shows the results of energy spectrum analysis for the original vertical velocity time series and their TA. The main difference is that the TA has a larger spectral content above a certain frequency. This is not difficult to understand from a visual inspection of Fig. 1. Of particular interest is the power-law behaviour of the spectral densities of the TA,

$$E(f) = f^{-\beta}. \tag{7}$$

The TA series show the same exponent $\beta = 4/3$ for both the stationary time series and the non-stationary time series, different from the Kolmogorov exponent $\beta = 5/3$ in the inertial range (Frisch and Orszag 1990). The fit obtained for the time series is indicative of a slower spectral energy decay (there is more memory) in the telegraph signal. Still the spectral analysis cannot be used to quantify the difference between the stationary time series and the non-stationary time series. A reasonable shift of the TA threshold does not change the spectral exponent β (Bershadskii et al. 2004).

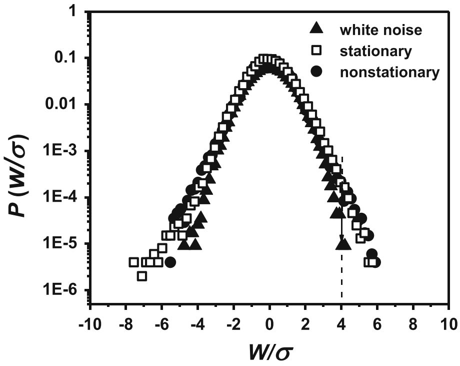

Fig. 2 The PDFs of white noise, stationary vertical velocity time series, and non-stationary vertical velocity time series. The original data are normalized by the standard deviation σ

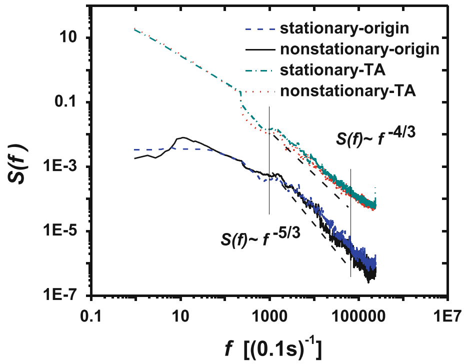

Fig. 3 The comparative results of energy spectrum analysis for the vertical velocity series and their TA. The TA series show the exponent $\beta = 4/3$ for both the stationary time series and the non-stationary time series, different from the Kolmogorov exponent $\beta = 5/3$ in the inertial range

Our results are consistent with those found at the inertial scales by Sreenivasan and Bershadskii (2006) who observed a unique relationship between the spectral exponent, n, of the full signal and that of its TA, m. The relation is $m = (n + 1)/2$ based on numerical results. However, Cava and Katul (2009) studied the stratification effects and found, for the deeper layers of the canopy, both TA and the original spectra deviated from their $f^{-4/3}$ and $f^{-5/3}$ scaling, with the spectra of w decaying faster than −5/3 and the spectra of $TA(w)$ decaying slower than −4/3.

From the results shown above, the PDF and energy spectrum analysis cannot differentiate the effects of the non-stationarity of the underlying processes on their statistics, so we need other quantities to quantify the difference resulting from the non-stationarity of the underlying processes.

3.2 Cluster Exponent and Intermittency Exponent

The first difference can be found in the clustering exponents, and we calculate the clustering exponent results for the white noise, stationary and non-stationary boundary-layer vertical velocity traces, see Fig. 4, where the different results are shifted vertically for clarity. Different scaling behaviours are discovered. The non-stationary series show a clustering exponent as 0.24, while the stationary series has a value 0.39 that is much closer to that of white noise, 0.5. According to Sreenivasan and Bershadskii (2006), the cluster exponent α for small scales decreases with increasing Reynolds number, which implies an increasing tendency to cluster. It can readily be seen from visual inspection that the non-stationary time series has larger clustering effect than the stationary series, see Fig 1. In the wind-tunnel experiment for

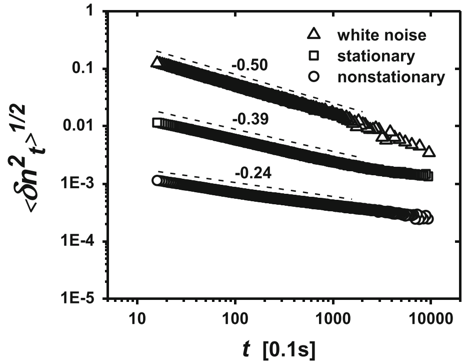

Fig. 4 The clustering exponents for the white noise, stationary and non-stationary vertical velocity time series. The results are shifted vertically for clarity

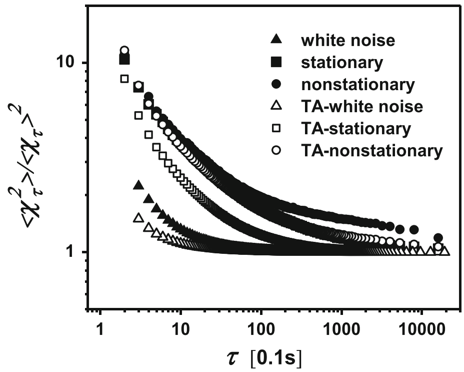

Fig. 5 The comparison intermittency exponent results for the white noise, the stationary and non-stationary vertical velocity time series, as well as their TA series

different Reynolds numbers, Sreenivasan and Bershadskii (2006) focused on the transition from dissipative and inertial ranges to the integral scale, and found two values of the cluster exponent. Our results from the cluster exponents for stationary time series are consistent with those of Sreenivasan and Bershadskii (2006). The effects of non-stationarity were not explored in their wind-tunnel experiment (Sreenivasan and Bershadskii 2006), and the scale regimes we delineate here are more likely to be affected by any non-stationarity that occurs in the real atmosphere. Cava and Katul (2009) pointed out that clustering was much more connected to space than to time in the canopy sub-layer and that atmospheric stability had minor effects only on clustering above the canopy. The similar conclusion can be found in our results, where the atmospheric stability had minor effects on clustering for both stationary and non-stationary cases (figures not shown).

Secondly the difference statistics between the stationary and the non-stationary cases can be found in the intermittency exponents, see Fig. 5, where we show the results of intermittency exponents for the white noise, the stationary and non-stationary boundary-layer vertical velocity traces. In the log–log plots, the intermittency exponent $\mu_{w'}$ is represented by the slope of the curves. For white noise, μ deviated from the theoretical value of zero at small scales and is mainly due to the statistical error. Considered the statistical errors, $\mu_{w'}$ is not a constant for the stationary and non-stationary time series at different time scales. We can see clearly from Fig. 5 that, as time scales increase, the intermittency exponent of the non-stationary time series decreases slower than the stationary time series, especially at large scales. That is to say, the non-stationary time series is more intermittent than the stationary series at large scales. When we compare the results of the TA series and their original

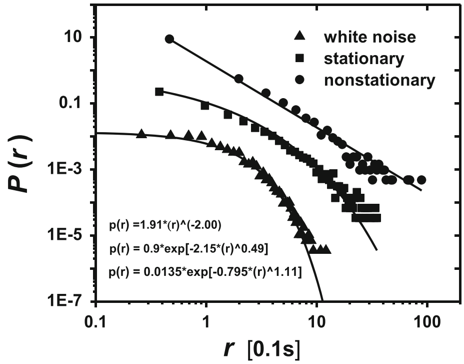

Fig. 6 The probability density functions of the inter-pulse periods r for the white noise, the stationary and non-stationary vertical velocity time series. The results are shifted vertically for clarity. The formulae of the fitting lines are listed on the *bottom left corner*: white noise, stationary time series, and non-stationary traces from *bottom to top*

traces at small scales for both stationary and non-stationary traces, we obtain $\mu_{TA} > \mu_{w'}$, which indicates that amplitude variations mitigate intermittency, according to Cava and Katul (2009). At large scales the intermittency exponents tend to be the same value respectively for the two types of series, as the effects of amplitude decrease. The intermittency exponents of the TA series collapse to zero more quickly than those of the original data. At large scales, all the intermittency exponents tend to be zero, since there is little memory at large scales and the time series act like white noise.

3.3 Inter-Pulse Period Distribution

Thirdly the difference statistics between the stationary and the non-stationary cases can be found in the inter-pulse period distributions. The probability density function of the inter-pulse periods r for the vertical velocity is shown in Fig. 6. In order to make a comparison, the results of white noise, stationary and non-stationary time series are shown in one frame, and are shifted vertically for clarity. The log–log scale has been used to emphasize the power-law structure for the non-stationary series and the stretched exponential distribution of the white noise and stationary series (Eichner et al. 2007). The fitting of the data can be seen clearly in Fig. 6. As mentioned above, since there is no amplitude variation involved, the marked difference must be related to clustering entirely (Bershadskii et al. 2004).

In Fig. 6, we can clearly see that the PDFs of the inter-pulse period for the non-stationary vertical velocity time series are different from those of the stationary series. Sreenivasan and Bershadskii (2006), who focused on the transition from the inertial to viscous dissipation ranges, a major departure here, have suggested that there are two classes of signals, the white-noise type and the Markovian–Lorentzian type, which have two different behaviours for the PDFs of the inter-pulse distance of the TA signals. The Markovian–Lorentzian type signal exhibits power-law PDF behaviour for the inter-pulse period and has a spectrum $E(f) = \frac{2\sigma}{1+(f/f_0)^2}$. Unlike Sreenivasan and Bershadskii (2006), we focus on the effects of non-stationarity on the statistics of the atmospheric turbulence. Here, our results suggest that non-stationarity can affect the distribution of the inter-pulse periods for vertical velocity time series. The stationary vertical velocity time series is closer to the white-noise type whose inter-pulse periods possess the stretched exponential distribution, while the non-stationary series corresponds to the Markovian–Lorentzian type that has the near power-law structure, as shown in Fig. 6. Cava and Katul (2009) investigated the distribution of the inter-pulse period for longitudinal velocity, vertical velocity, temperature and for all atmospheric stability conditions at all levels within the canopy. They found a ‘double regime’ characterized by a

Table 1 The comparative results of cluster exponents and inter-pulse period PDFs for vertical velocity w, longitudinal velocity u and temperature T

Variables	Cluster exponent: α		PDF of inter-pulse period r: $p(r)$	
	Stationary	Non-stationary	Stationary	Non-stationary
w	0.39	0.24	$e^{-2.15*r^{0.49}}$	$r^{-2.0}$
u	0.29	0.10	$r^{-1.69}$	$r^{-4.0}$
T	0.34	0.18	$r^{-1.75}$	$r^{-2.0}$

power law for shorter inter-pulse periods and a log-normal distribution for the large inter-pulse periods, and the regime is more evident in the velocity components and in unstable conditions. They have suggested the power-law description is optimum for small inter-pulse periods; for large inter-pulse periods, a quasi-exponential cut-off preventing the extrapolation of the power law beyond the integral time scale emerges (Cava et al. 2012). Compared with their works, our analysis shows that the near-power PDF of inter-pulse periods is found in the non-stationary vertical velocity series, and the log-normal distribution indicates the stationary vertical velocity time series in Fig. 6.

4 Discussion and Conclusion

For longitudinal velocity u and temperature T, stationary and non-stationary time series are selected for investigation, and the comparative results are shown in Table 1. Since non-stationarity occurs more severely and frequently in u and T than in vertical velocity w, and the stationary time series selected in the u and T datasets are not as close to being stationary as in w, the effects of non-stationarity are not as evident as in the vertical velocity time series.

It seems that non-stationarity affects statistics connected to small-scale features, appearing more in the intermittency exponents and inter-pulse PDFs, and there is some interaction between large scales and small scales. There are more large-scale structures in the non-stationary than in the stationary records, which may result from the stable stratification, gravity waves or shear (Mahrt 2011). We select representative non-stationary time series in stable atmospheric conditions to show that the large-scale structures affect directly small-scale features in Fig. 7. Using the ensemble empirical mode decomposition (EEMD) method (detailed descriptions of the EEMD method are presented in Huang et al. (1998) and are not repeated here), we extract large-scale structures from the original non-stationary time series as shown in Fig. 7a, and its TA segments shown in Fig. 7b and derive small-scale fluctuations (with large-scale structures removed) as shown in Fig. 7c, shows segments of the TA results of the small-scale fluctuations. The intermittency exponents and distributions of the inter-pulse periods are obtained for the small-scale fluctuations, compared with the original non-stationary time series in Fig. 7e, f. Comparing Fig. 7b with Fig. 7c, we can see that the large-scale structures in the non-stationary time series affect the TA results. For the small-scale fluctuations, the intermittency exponent becomes smaller and the PDF of the inter-pulse periods changes from a near power law to a lognormal distribution, especially at large scales, see Fig. 7e, f. Given that non-stationarity can affect statistical properties connected to small-scale intermittency. Mahrt (2011) has pointed out that turbulence in the very stable regime might be generated primarily by wave-like motions and small sub-meso motions

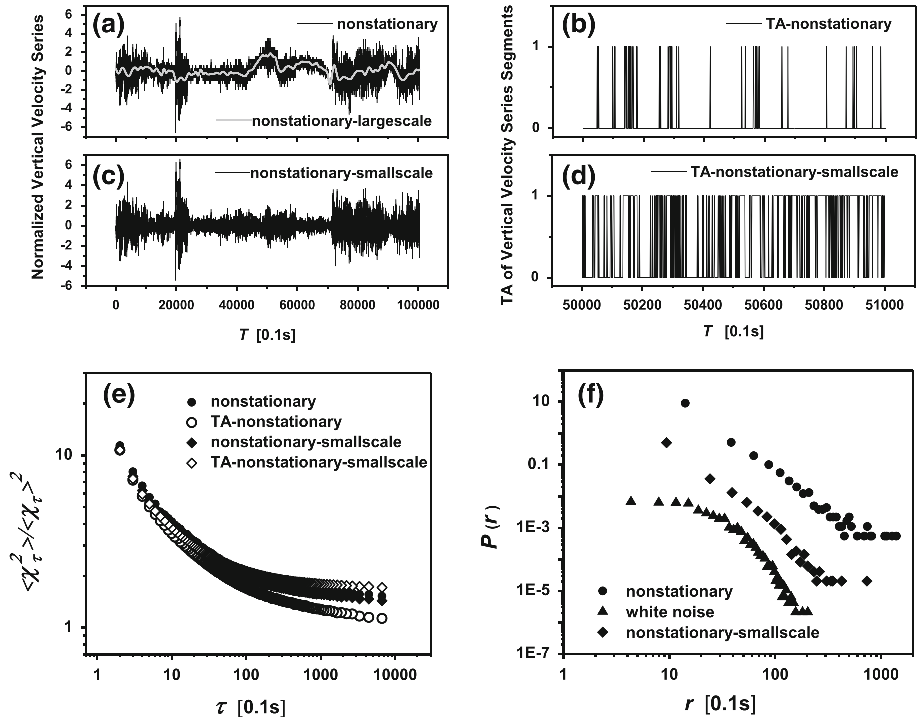

Fig. 7 Extracting large-scale fluctuations from the original non-stationary vertical velocity time series (**a**), we obtain small-scale fluctuations (**c**); **b**, **d** are segments of the TA results of (**a**) and (**c**). The intermittency exponents for the original time series and their small-scale fluctuations are shown in (**e**); **f** shows the distributions of the inter-pulse periods

on time scales of minutes or tens of minutes (Conangla et al. 2008) such that equilibrium between the turbulence and non-turbulent flows is not established. These un-established equilibrium motions cause the interaction between very large scales and small scales, and lead to non-stationarity in the scale regimes analyzed here.

The effects of non-stationarity on the statistics of boundary-layer turbulence, especially on the clustering, have been explored by using the vertical velocity time series obtained in the boundary layer. The telegraphic approximation was used to remove any amplitude variability in turbulent excursions, thereby permitting us to readily identify clustering effects known to be one of the two key aspects responsible for the intermittency. For some stochastic processes known to possess long-memory (e.g. fractal Brown motion), there are explicit linkages between the spectral exponents and zero-crossing properties (Cava and Katul 2009). Hence, PDFs, spectra, clustering-exponent, intermittency-exponent and inter-pulse period distributions are computed for the stationary and non-stationary time series, and clear differences have been shown.

As for the PDFs and the spectral analysis of the stationary and non-stationary vertical velocity time series, they both show intermittency characteristics in PDFs and the shifting of spectral exponent from −5/3 to −4/3, which indicates little difference. That is to say, traditional statistical methods cannot effectively show the non-stationarity influences on turbulence statistics, so we make use of TA to explore a narrower scope, and study the effects of non-stationarity on the clustering properties in turbulence.

As to the clustering and intermittency exponents, the non-stationary time series show significant differences from the stationary series, the latter is more like white noise. The results seem to provide indicators for distinguishing the non-stationary time series from stationary. When comparing intermittency for the original traces and their TA series, we found that amplitude variations mitigate intermittency effect.

With regards to the inter-pulse period distribution of the vertical velocity traces, the stationary time series with stretched exponential distribution is more close to the white-noise type, while the non-stationary series corresponds to the Markovian–Lorentzian type with a near power-law inter-pulse period distribution.

The findings of different TA features, such as clustering and intermittency exponents for non-stationary and stationary records, can be explained by the different distribution of multi-scale structures, just as the inter-pulse period distribution, see Fig. 6. This marked difference also can be viewed directly from the TA series in Fig. 1; the clustering in the non-stationary records is more obvious, since more large-scale structures can be found in the non-stationary records, which may have resulted from the stable stratification, gravity waves or shear. So there are more large-scale structures in the non-stationary records and they cannot be found in the stationary record, see Fig. 6. Large-scale structures do affect statistics connected to small-scale intermittency, and there is some interaction between very large scales and small scales, see Fig. 7.

In fact, here we have only considered one aspect of intermittency and did not consider the amplitude variation, which can also take on a different behavior when non-stationarity is involved.

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