Diffusive and subdiffusive dynamics of indoor microclimate: A time series modeling

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The indoor microclimate is an issue in modern society, where people spend about 90% of their time indoors. Temperature and relative humidity are commonly used for its evaluation. In this context, the two parameters are usually considered as behaving in the same manner, just inversely correlated. This opinion comes from observation of the deterministic components of temperature and humidity time series. We focus on the dynamics and the dependency structure of the time series of these parameters, without deterministic components. Here we apply the mean square displacement, the autoregressive integrated moving average (ARIMA), and the methodology for studying anomalous diffusion. The analyzed data originated from five monitoring locations inside a modern office building, covering a period of nearly one week. It was found that the temperature data exhibited a transition between diffusive and subdiffusive behavior, when the building occupancy pattern changed from the weekday to the weekend pattern. At the same time the relative humidity consistently showed diffusive character. Also the structures of the dependencies of the temperature and humidity data sets were different, as shown by the different structures of the ARIMA models which were found appropriate. In the space domain, the dynamics and dependency structure of the particular parameter were preserved. This work proposes an approach to describe the very complex conditions of indoor air and it contributes to the improvement of the representative character of microclimate monitoring.

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I. INTRODUCTION

In industrialized countries people spent about 90% of their time indoors. Despite efforts to create an appropriate indoor microclimate, complaints about discomfort and health problems have increased during recent years. This in particular refers to air-conditioned spaces. Nowadays, more and more office workers are employed in such conditions. They often experience sick building symptoms and building-related illnesses, which result in low performance and absenteeism. On the other hand, a suitable indoor environment leads to improved productivity in the workplace. Therefore, estimation of indoor air quality and thermal comfort inside enclosed spaces is of paramount importance [1].

Indoor air is a complex system. It is affected by numerous factors, e.g., the outdoor environment (e.g., meteorological conditions), the structure and construction of the building, the internal spatial arrangement, heating, ventilation, and air-conditioning (HVAC) systems, and patterns of occupant activity [2]. It is difficult to quantify the influence and relative importance of so many factors of various kinds. Therefore evaluation of the indoor environment on the basis of their total effect is justified. The joint influence of these factors is reflected in the physical, chemical, and microbiological state of indoor air. Information about the state of the indoor air is contained in the environmental parameters [3,4].

The mentioned factors are not only numerous and versatile. They additionally exhibit spatial and temporal variability in their own dynamics. As a result of their mutual interactions the state of indoor air may rarely be considered as steady. Actually, it is transient most of the time. Because of these circumstances, valuable knowledge of the environmental parameters should be based on series of measurements performed in the time domain in properly selected locations [5,6].

A wide range of information may be obtained as a result of such data examination. For example, in [7] the autocorrelation and variability of indoor air quality measurements was analyzed as a means of improving the representativeness of such measurements. A similar goal was addressed in [8] but using cross correlation of time series of different pollutants. The same tool was applied in [9] for characterizing the time scales of airborne contaminant transport from outdoors to indoors. Improved simulation of diurnal time series of pollutants in residences was achieved by applying a nonstationary Poisson process for modeling the occurrence of emission events and including it in indoor air quality (IAQ) models [10]. A more general study on including stochastic factors in deterministic models of IAQ was given in [11]. Finally, a time series model of indoor temperature data was developed with the aim of controlling plant growth conditions in greenhouses [12].

In our work we focus attention on two basic parameters of indoor microclimate: temperature and humidity. These parameters are commonly used to evaluate the air quality and thermal comfort conditions as well as building energy consumption. Typically, the central tendency exhibited by their short-term time series is utilized for that purpose. This is sufficient in the framework of the most commonly applied air conditioning strategy, which has been based on the

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concept of maintaining environmental parameters at a constant level. Currently, more advanced strategies are used, developed mainly in the context of energy saving requirements [13,14].

The main objectives of this work were to investigate the dynamics and internal dependencies of microclimate parameters and to model their variability. The dynamics of these parameters considerably affects the perception of microclimate conditions by the occupants.

In our approach we do not plan to use the results of time series analysis as inputs for an automatic system for IAQ control. In practice it is impossible, because this equipment requires input data in real time. Instead, we would like to address the problem of IAQ evaluation. Based on our working experience this problem remains unsolved in a satisfactory manner. This fact inspired us to find methods and tools (analytical and computational) which can be used for diagnostic tasks. At this stage of our work, we do not intend to propose guidelines for HVAC system design and control. We would like to exploit a different source of information for the purpose of identifying different factors which affect indoor air quality. In this sense we propose a generic approach.

To reach the goal of this study, the work incorporates the analysis of multiple time series of temperature and relative humidity using stochastic methods. We investigate the dynamics of the data using the mean squared displacement (MSD). Moreover we model the time series that exhibit diffusive behavior using autoregressive integrated moving average (ARIMA) systems. For data sets with no observable MSD linear in time, we propose to use methodology presented in [15–17] where anomalous diffusion systems were examined. We show that our approach is a proper way to evaluate the very complex conditions of indoor air and to improve the representativeness of microclimate studies.

The rest of the paper is organized as follows: In Sec. II we give a complete description of the examined data sets. Section III contains the diffusion and anomalous diffusion methodology that is used here in the stochastic analysis of the examined time series. In Sec. IV we present and discuss the main results obtained for the analyzed humidity and temperature. The last section contains our conclusions.

II. DATA

We analyzed time series of temperature and humidity measurements in a typical modern office building. Its individual floors host spacious, open plan offices for several dozen workers each. The building is equipped with a HVAC system which provides a central air supply at a controlled temperature and flow rate for heating or cooling various zones in the building. The occupancy pattern was determined by the periods of presence of office workers and the associated activity (approx. 7 a.m. to 9 p.m.) as well as by the intervals of their absence (approx. 9 p.m. to 7 a.m.).

The temperature and relative humidity were monitored at five measurement points. Points 1 and 2 were located at two opposite ends of an open space several meters long, while points 3, 4, and 5 were distributed in separate offices. The elevation of all sampling points was approx. 1.8 m above the floor level. The microclimate parameters were continuously measured for a period of 5 days, in August 2010 from Friday 13th to Tuesday 17th. During this week, the weather was quite warm (18–25 °C during the day and 14–21 °C at night) and very humid (66%–80% relative humidity during the day and 88%–98% at night). Wireless sensors AR435 were used for the measuremnts. They offered measurement accuracy of relative humidity ±3% and temperature ±0.5 °C. The data were recorded at 30 s intervals. In this work we use the abbreviation si to indicate the sensor located at the ith measurement point.

We used stochastic methods to study the temporal and spatial aspects of the indoor microclimate parameters temperature and humidity. In principle the variability which occurred in the time domain was addressed with these methods. The space dimension was considered by comparing the data analysis results for the different locations of monitoring points.

The scope of the temporal analysis of the microclimate conditions was defined by grouping the measurement data into categories. A generic principle of creating subdivisions was applied, which consisted in utilizing the knowledge about the most important factors influencing indoor air quality in the investigated object. For our method of analysis those periods of time are of interest in which different combinations of factors act in a particular manner. This problem has to be addressed on an individual basis. In that sense, the subdivisions in this work are arbitrary.

There are also other possibilities for approaching the problem of time interval selection. In principle, they are data driven. An example of a method that can be useful in decomposition of the examined nonstationary time series is the empirical mode decomposition technique [18]. It is based on a Hilbert spectral analysis applied to intrinsic mode functions that describe a given data set. However, we did not apply this approach at the current stage of our work.

It was proposed to distinguish between the working part of the week and the weekend and additionally between the daytime (7 a.m. to 9 p.m.) and the nighttime (9 p.m. to 7 a.m.). Four categories of data were obtained, called weekday, weeknight, weekend day, and weekend night. The time series of humidity and temperature were investigated within these categories. The data from separate days were collected to form a single time series. The scope of the analysis in the spatial domain was defined by four distinct open plan offices where the measurement data were collected.

The categories were defined by the occupation patterns and HVAC system operation regimes which are encountered during 24-h cycles of building exploitation. These two factors together with the natural day-night rhythm were considered as setting a sort of framework for indoor microclimate formation. The presence of people was certainly associated with an increased, chaotic indoor air mixing. This was due to thermal phenomena taking place at the human-air interface, heat release by the office equipment, computers in particular, as well as random movement of people. They were all counteracted by the HVAC system operation. It is usually aimed at keeping the temperature and humidity within the limits of thermal comfort. With the absence of office workers, the HVAC system was also operating at defined, but different, temperature and humidity values. In these periods its task was to balance the influence of weather conditions mainly. During the night and on the weekends, wide scale, undisturbed, air motion patterns could be established as determined by the spatial structure and operation parameters of the HVAC system.

III. METHODS

In this section we present the main tools used in the analysis of the real data sets described in the previous section. The stochastic analysis is concentrated on many aspects, such as identification of the dynamics of the time series, the structure of the dependence, time series modeling, and advanced methods used in analysis of subdiffusive processes. The main tool that allowed us to recognize the stochastic dynamics of the examined time series is the time-averaged mean squared displacement.

Let $\{X_i,\ i=1,\dots,n\}$ be a stationary sample of length n. The sample MSD was introduced in [19] as

$$M_n(\tau)=\frac{1}{n-\tau}\sum_{k=1}^{n-\tau}(X_{k+\tau}-X_k)^2. \qquad (1)$$

The sample MSD is a time-averaged MSD on a finite sample regarded as a function of the difference τ between observations. It is a random variable, in contrast to the ensemble average, which is deterministic [20].

If the sample comes from an H-self-similar process with stationary increments belonging to the domain of attraction of the Lévy α-stable law, then for large n

$$M_n(\tau)\sim\tau^{2D+1}, \qquad (2)$$

where $D=H-1/\alpha$ and $\sim$ indicates similarity in distribution. More precisely, if $\alpha=2$, then for large n and small τ, $M_n(\tau)\sim\tau^{2D+1}E(X_1^2)$, where $D=H-1/2$. If $\alpha<2$, then for large n/τ, $M_n(\tau)\sim C(n)\tau^{2D+1}U_{\alpha/2}$, where $C(n)=n^{2/\alpha}$, $D=H-1/\alpha$, and $U_{\alpha/2}$ is an $\alpha/2$-stable random variable with the skewness parameter $\beta=1$ [19,21].

As a by-product, the sample MSD can serve as a method of estimating D. The method is well defined for the general α-stable case and the estimator has a very small variance. In order to apply it, first, the sample MSD is calculated for the partial sum process $\{Y_n=\sum_{i=1}^{n}X_i,\ n=1,2,\dots,n\}$:

$$M_n(\tau)=\frac{1}{n-\tau}\sum_{k=1}^{n-\tau}(Y_{k+\tau}-Y_k)^2\,.$$

Next, applying (2), a linear regression line is fitted according to

$$\ln[M_n(\tau)]=\ln(C)+(2D+1)\ln(\tau),\quad \tau=1,2,\dots 10,$$

where C is assumed to be constant.

As a consequence, we see that the memory parameter D controls the type of anomalous diffusion. If $D<0\,(H<1/\alpha)$, and thus in the negative dependence case, the process follows subdiffusive dynamics; if $D>0$ $(H>1/\alpha)$, the character of the process changes to superdiffusive. The subdiffusion pattern arises when the dependence is negative, so possible large positive jumps are quickly compensated by large negative jumps, and on average a random walker representing microclimate factors overcomes shorter distances than in light-tailed Brownian motion.

In order to analyze the dependence in the considered time series the autocorrelation (ACF) and partial autocorrelation (PACF) functions are examined. They are major tools in testing the order of dependence in data sets. The ACF is an empirical equivalent to the theoretical correlation function and for a random sample $\{X_i,\ i=1,\dots,n\}$ is defined as follows [22]:

$$A(h)=\frac{\sum_{i=1}^{n-|h|}(X_i-\bar{X})(X_{i+|h|}-\bar{X})}{\sum_{i=1}^{n}(X_i-\bar{X})^2},\quad h=0,1,2,3,\dots, \qquad (3)$$

where $\bar{X}=\frac{1}{n}\sum_{i=1}^{n}X_i$. The other measure of dependence that indicates a relationship inside the examined time series is the PACF. This function plays an important role in data analyses aimed at identifying the extent of the lag in an autoregressive model. From the theoretical point of view the PACF at lag h of the stationary time series $\{X_t\}$ is defined by

$$P(1)=\mathrm{Corr}(X_t,X_{t+1}).$$

For $h=2,3,4,\dots$,

$$P(h)=\mathrm{Corr}(X_t-L_{X_{t+1},\dots,X_{t+h-1}}(X_t),X_{t+h}-L_{X_{t+1},\dots,X_{t+h-1}}(X_{t+h})),$$

where $L_{X_1,X_2,\dots,X_n}(X_{n+1})$ denotes the best (in terms of minimizing the mean squared error) linear predictor of X_{n+1} based on $X_1,X_2,\dots,X_n$. Therefore it is defined as

$$L_{X_1,X_2,\dots,X_n}(X_{n+1})=a_1X_1+a_2X_2++a_nX_n,$$

where $a_1,a_2,\dots,a_n$ are determined by minimizing

$$E[(X_{n+1}-L_{X_1,X_2,\dots,X_n}(X_{n+1})]^2.$$

The ACF and PACF are useful in identifying orders in an autoregressive moving average–(ARMA-) type time series, namely, the ACF is zero after lag q for a moving average of order q (MA(q)) models, while the PACF can help to identify the value of the order in autoregressive processes (ARs) [23].

In our methodology, the time series that exhibit diffusive behavior we propose to model using ARIMA processes. An ARIMA model is a generalization of an ARMA model. These models are fitted to time series data either to better understand the data or to predict future points in the series (forecasting). They are applied in some cases where data show evidence of nonstationarity, where an initial differencing step (corresponding to the integrated part of the model) can be applied to remove the nonstationarity. The model is generally referred to as an ARIMA(p,d,q) system, where p, d, and q are non-negative integers that refer to the order of the autoregressive, integrated, and moving average parts of the model, respectively [23]. The time series $\{X_t\}$ is ARIMA(p,d,q) if the transformed sequence $Y_t=(1-B)^dX_t$ is ARMA(p,q). Here B denotes the backward shift operator defined as $BX_t=X_{t-1}$. In the above definition $\{Y_t\}$ satisfies the equation

$$Y_t-\sum_{j=1}^{p}b_jY_{t-j}=\xi_t+\sum_{i=1}^{q}a_i\xi_{t-i} \qquad (4)$$

for some parameters b_j, $j=1,2,\dots,p$, and a_i, $i=1,2,\dots,q$. The sequence $\{\xi_t\}$ denotes the innovation series, i.e., the sequence of uncorrelated random variables with the same distribution. The ARIMA time series were introduced by Box and Jenkins in [24]. They have been widely used in many areas of interest including econometrics [25], energy [26], and tourism industry [27].

Because in our case only models with $d = 1$ are considered, the procedure of estimating parameters of ARIMA model is as follows: For the differenced series on the basis of the ACF and PACF, recognize the parameters p and q, and then estimate the parameters of the ARMA(p,q) time series using the least squares method.

Some of the examined data sets exhibit subdiffusive behavior, so in our methodology the advanced techniques adequate to analysis of such processes are used. Because for the analyzed time series with subdiffusive behavior we observe clear constant time periods (also called trapping events), we propose to use the approach presented in [15–17], where data with trap behavior were also examined. The methodology is based on the assumption that the examined time series can be described in the Langevin picture by the following process:

$$X_t = Y(S_\alpha(t)), \tag{5}$$

where $\{Y(t)\}$ is a diffusive external process and $\{S_\alpha(t)\}$ is called an inverse subordinator, i.e., it is defined as follows:

$$S_\alpha(t) = \inf\{\tau > 0 : U_\alpha(\tau) > t\}, \tag{6}$$

where $\{U_\alpha(\tau)\}$ is an increasing Lévy process (called a subordinator). The process $\{X_t\}$ exhibits subdiffusive behavior and the representation (5) reveals that subdiffusion is a combination of two independent mechanisms: the first one is based on the standard diffusion represented by some Itô process $\{Y(t)\}$, and the second one is represented by the inverse subordinator that is related to the waiting time distribution, [28–32]. Moreover it is assumed that the processes $\{Y(t)\}$ and $\{S_\alpha(t)\}$ are independent [33]. The process $\{X_t\}$ is called a time-changed system and has been analyzed in many applications. For example, the system (5) with an external process that is a Brownian motion and α-stable subordinator $\{U_\alpha(\tau)\}$ was examined in [15] for modeling financial time series, while the tempered stable subordinator was considered in [20] in the context of microclimate data.

In our paper to analyze time series with subdiffusive behavior we propose to use the α-stable subordinator while the external time series we model with an ARIMA system. The α-stable subordinator is a Lévy process $\{U_\alpha(\tau)\}$ with the following Laplace transform:

$$E(e^{-zU_\alpha(\tau)}) = e^{-\tau z^\alpha}, \tag{7}$$

where $0 < \alpha < 1$. More details of α-stable subordinators can be found in [34].

In order to fit the model given in (5) to real data, according to the methodology presented in [15], the time series is divided into two vectors. The first one represents lengths of constant time series, while the second vector arises after removing the constant time periods. Because the lengths of trapping events are independent realizations of the subordinator $\{U_\alpha(\tau)\}$, to estimate the α parameter we propose to use the tail behavior of the α-stable distribution, namely, for this distribution the right tail behaves like the power function $x^{-\alpha}$, so this function is fitted to the empirical tail using the least squares method [15,17]. The vector that arises after removing constant time periods represents realizations of the external process; therefore in the first step the orders of ARIMA(p,1,q) series are recognized using the ACF and PACF. Next the parameters are estimated using the least squares method.

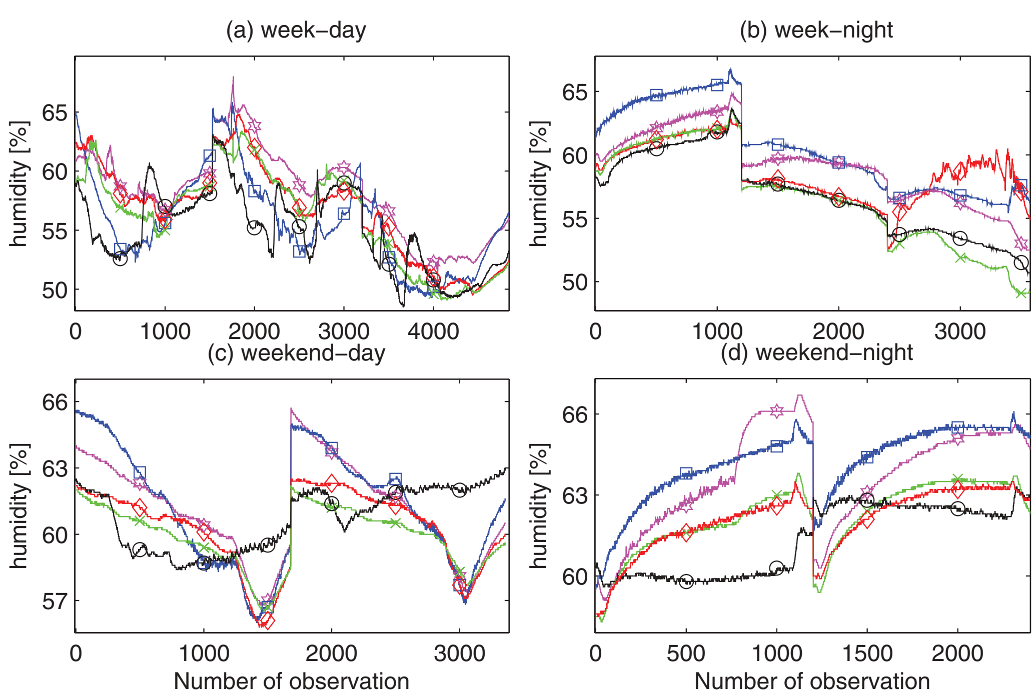

FIG. 1. (Color online) Humidity data recorded by five sensors: sensor 1 (squares), sensor 2 (diamonds), sensor 3 (crosses), sensor 4 (stars), and sensor 5 (circles).

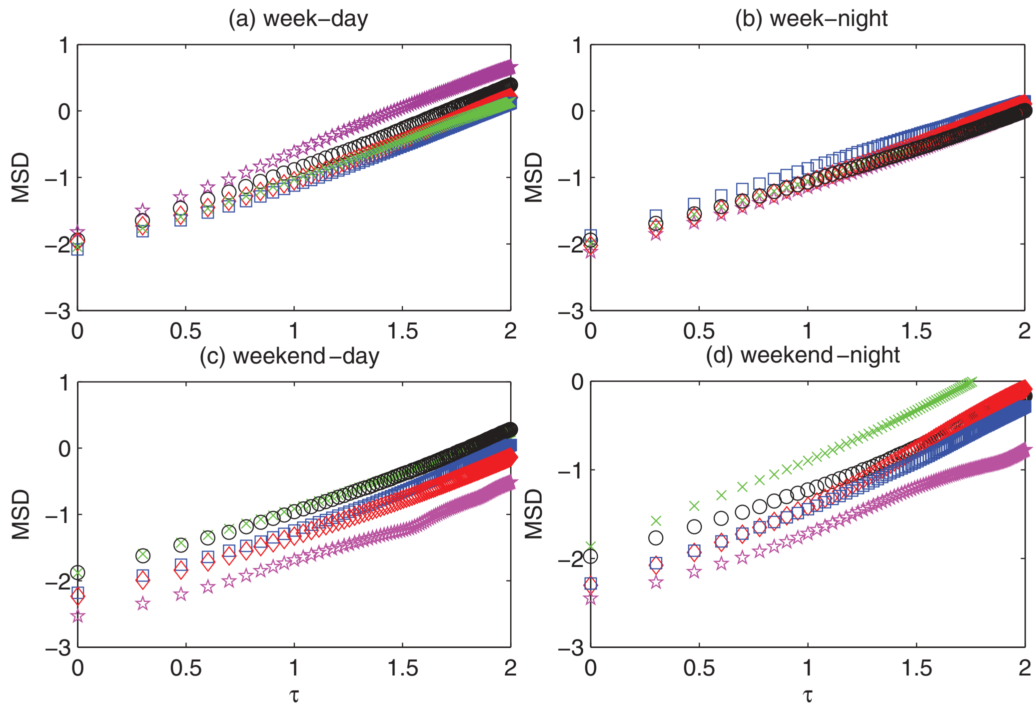

FIG. 2. (Color online) The mean square displacement for humidity recorded by the five sensors in each of four periods (weekday, weeknight, weekend day, weekend night): sensor 1 (squares), sensor 2 (diamonds), sensor 3 (crosses), sensor 4 (stars), and sensor 5 (circles).

IV. RESULTS AND DISCUSSION

A. Humidity

The time series of relative humidity are shown in Fig. 1 as examined, in four data categories: weekday, weeknight, weekend day, and weekend night. The similarities are noticeable among the analyzed vectors in each data category. The relative humidity at five monitoring locations exhibited deterministic patterns, which were alike. Upon comparing data categories, a distinctive character of the humidity time series in the weekday periods was observed. It consisted in a significant short-term variability.

The dynamics of the data was examined using the mean square displacement, as mentioned in Sec. III. We calculated the MSD for the humidity time series from the five sensors, in each data category. The results are presented in Fig. 2.

As we observe in Fig. 2, the MSD indicates the diffusive behavior of the examined humidity time series in each case. We confirmed this by estimating the D parameter; see Table I. The calculated values were close to zero.

TABLE I. The estimated D parameter for humidity recorded by five sensors.

Sensor	Weekday	Weeknight	Weekend day	Weekend night
s1	−0.02	0.01	−0.03	−0.08
s2	−0.04	−0.02	−0.04	−0.05
s3	0.01	−0.03	−0.01	−0.02
s4	0.10	−0.01	−0.07	−0.13
s5	0.03	−0.06	−0.04	−0.12

In order to find the structure of the dependence in the examined time series, we analyzed the autocorrelation function and partial autocorelation function. The ACF for the differenced humidity time series is presented in Fig. 3. The functions behave similarly for all the data. The same regularity was observed in the case of PACFs. On the basis of the ACFs and PACFs we can assume that all examined time series of humidity can be described by the ARIMA(0,1,2) model. This assumption was confirmed by constructing the confidence intervals for the estimated parameters. In Table II the results are presented for the exemplary sensor s1. The zero-order AR component together with the second order of the MA component indicated that the data could be considered as a linear combination of the innovation series $\{\xi_n\}$ given in (4).

It is notable that ARIMA models of the same order were adequate for modeling different measurements of humidity. Hence, a similar structure of dependence was discovered in time series which were collected at different locations and which belonged to different data categories. However, the analysis of model parameters indicated differences among time series. Overlap between confidence intervals of model parameters occurs occasionally across sensors in one data category. It was similar as well as for one sensor in different data categories. Despite the similar structure of dependence, the examined time series required separate modeling.

B. Temperature

The time series of temperature recorded by the five sensors are shown in Fig. 4 in four data categories, as they were analyzed. Evident diurnal cycles of temperature were observed on weekdays. Similar but much less regular variability occurred

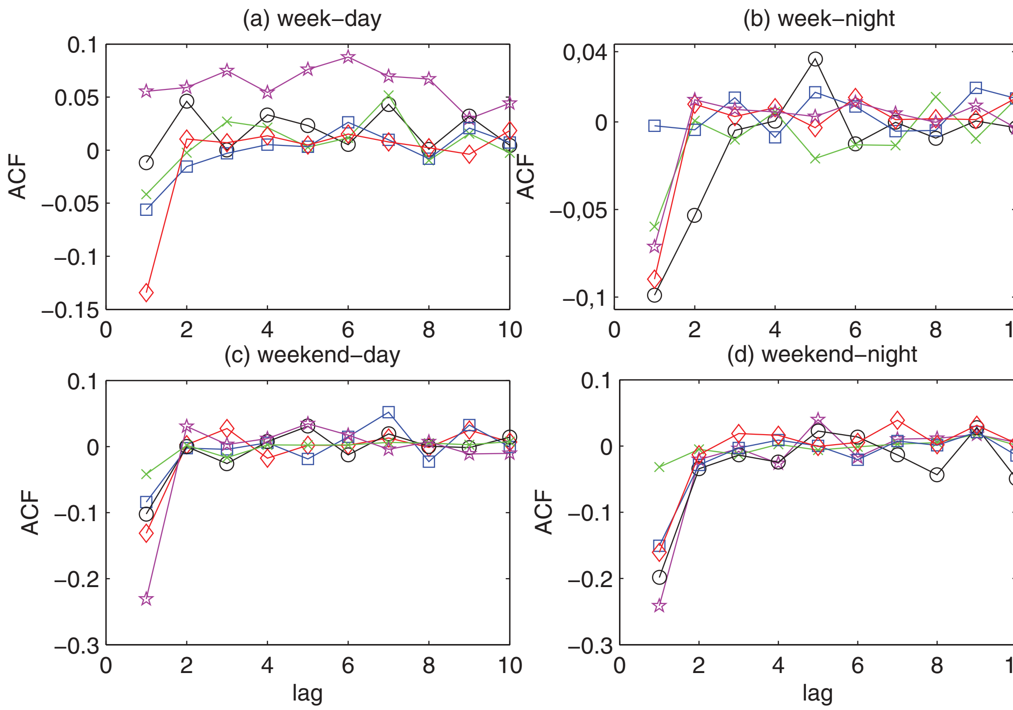

FIG. 3. (Color online) The autocorrelation function for differenced humidity recorded by the five sensors in each of four periods (weekday, weeknight, weekend day, weekend night): sensor 1 (squares), sensor 2 (diamonds), sensor 3 (crosses), sensor 4 (stars), and sensor 5 (circles).

during weekend days. In the nights, the temperature changed extremely slowly and in a very narrow range. We noticed similar behavior of the temperature measured by different sensors, except for the weekend-day data category. As for humidity, the dynamics of the temperature data was analyzed using the mean square displacement (see Fig. 5). The MSD plots indicate different dynamics of the temperature time series during the week and over the weekend. We supported this observation by estimating the D parameter, on the basis of the mean square displacement (see Table III). Low D values were obtained for the weekend data, especially weekend night, as compared to week data, in particular weekday. The behavior of the MSD as well as that of the D parameter both confirm that the temperature time series exhibited a transition between two kinds of dynamics. During working days and nights the temperature showed a diffusive character. The subdiffusive behavior occurred during the weekends.

Waiting times of a considerable lengths, from 15 up to 284, were found in the subdiffusive process. Thus, in our opinion, it is very unlikely that we observed a property of the measurement device and not a physical property.

The week and weekend temperature data were analyzed using different methodology depending on the diffusive and subdiffusive behavior which they exhibited. The structure of dependence in the week data (diffusive) was examined using autocorrelation and partial autocorrelation functions. On the basis of the ACF (see top panel in Fig. 6) (as well as the PACF), we concluded that all the considered time series could be modeled using the ARIMA(1,1,2) approach. Therefore the data had the same dependence structure. Let us point out that the order of the model for temperature is different from that for the humidity time series (see Sec. IV A). They also exhibited diffusive behavior and one model structure was sufficient for modeling them all. In Table IV we demonstrate the estimated parameters from the ARIMA(1,1,2) time series for sensor 1.

We observed only occasional overlap of the confidence intervals of the corresponding parameters in different models. This indicates the need for individual modeling of different time series for the sake of reproducing the actual values of the investigated parameter. A similar result was obtained in Sec. IV A for the humidity time series.

TABLE II. The parameters of the ARIMA(0,1,2) model for humidity recorded by sensor 1. In brackets we present the corresponding confidence intervals for estimated parameters calculated by using Monte Carlo simulations.

s1	Weekday	Weeknight	Weekend day	Weekend night
MA(1)	−0.06 [−0.08, −0.03]	−0.01 [−0.03, 0.03]	−0.08 [−0.11, −0.05]	−0.16 [−0.19, −0.12]
MA(2)	−0.02 [−0.04, 0.01]	−0.01 [−0.04, 0.03]	−0.01 [−0.04, 0.03]	−0.03 [−0.07,0.01]

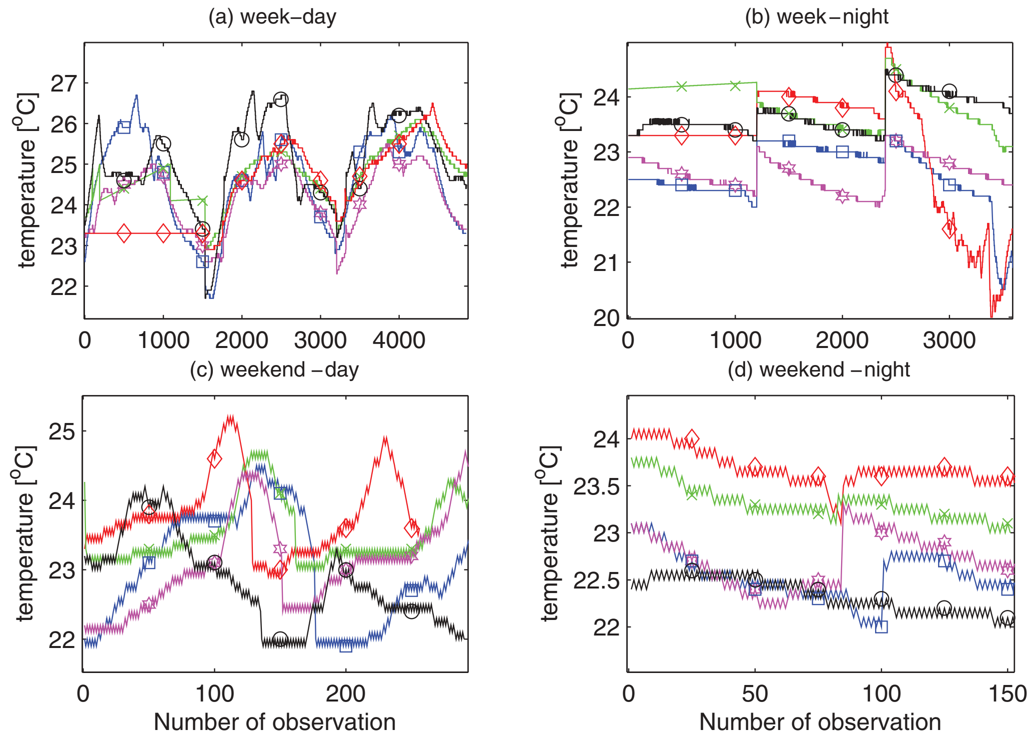

FIG. 4. (Color online) Temperature data recorded by the five sensors: sensor 1 (squares), sensor 2 (diamonds), sensor 3 (crosses), sensor 4 (stars), and sensor 5 (circles).

As shown in Fig. 4 as well as in Fig. 5 the temperature reordered during the weekend exhibited different behavior from that observed during the week. The estimated D parameters clearly indicate the subdiffusive behavior of the weekend temperature time series. The procedure presented in Sec. III was used and the examined time series were divided into two vectors: lengths of constant time periods and time series that remained after removing the constant time periods. On the

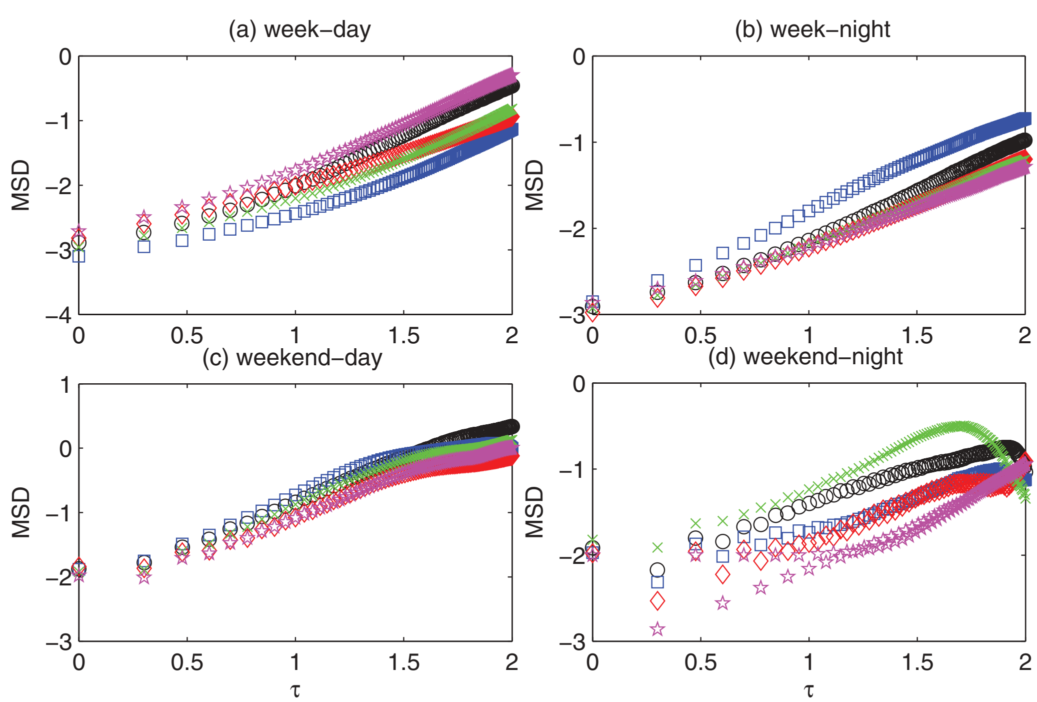

FIG. 5. (Color online) The mean square displacement for temperature recorded by the five sensors in each of four periods (weekday, weeknight, weekend day, weekend night): sensor 1 (squares), sensor 2 (diamonds), sensor 3 (crosses), sensor 4 (stars), and sensor 5 (circles).

TABLE III. The estimated D parameter for temperature recorded by the five sensors.

Sensor	Weekday	Weeknight	Weekend day	Weekend night
s1	−0.16	0.04	−0.14	−0.32
s2	−0.09	−0.11	−0.27	−0.37
s3	−0.11	−0.12	−0.20	−0.20
s4	−0.02	−0.16	−0.22	−0.46
s5	−0.05	−0.11	−0.14	−0.26

TABLE IV. The parameters of the ARIMA(1,1,2) model for temperature recorded by sensor 1 in days and nights during the week. In brackets we present the corresponding confidence intervals for estimated parameters calculated by using Monte Carlo simulations.

s1	Weekday	Weeknight
AR(1)	0.72	−0.8558
	[−0.49, 0.95]	[−0.92, −0.74]
MA(1)	0.39	−0.98
	[−0.83, 0.61]	[−1.05, −0.87]
MA(2)	−0.27	0.17
	[−0.34, 0.15]	[0.14, 0.20]

basis of the constant values, which were realizations of stable distributions, we estimated the index of stability α. The method based on the empirical tail behavior of the examined time series was used. The obtained results are presented in Table V. It was observed that in each considered case very similar values of the stability index were obtained. This indicates that the waiting times, represented by the constant time periods, had the same α-stable distribution for each sensor.

The structure of dependence was examined for the vectors that represented the temperature time series after removing the constant time periods, by analyzing the ACF (as well as the PACF); see the bottom panel of Fig. 6. Based on that, it was assumed that all time series could be modeled using ARIMA(2,1,3) structure. The assumption was valid as shown by the estimates of the model parameters. The obtained results are presented in Table VI, using sensor 1 as an example.

The temperature with subdiffusive behavior (i.e., at weekends) was also analyzed with two-step discretization (i.e., we take into consideration every second data point). The MSDs for data selected in this case are presented in Fig. 7. Moreover, the D parameter was tested for the temperature at weekends with two-step discretization and the results of the test are presented in Table VII. The values of the α parameter for the waiting times in the case of two-step discretization temperature series that exhibit subdiffusive behavior, i.e., at weekend nights, were also checked. The estimated parameters are presented in Table VIII.

For the two-step discretization the temperature after removing constant time periods can be modeled by using the ARIMA(1,1,4) time series. This model is appropriate for each sensor.

The interpretation of results provided by the time series analysis has to take into consideration the properties of diffusion processes which occur indoors and the performance

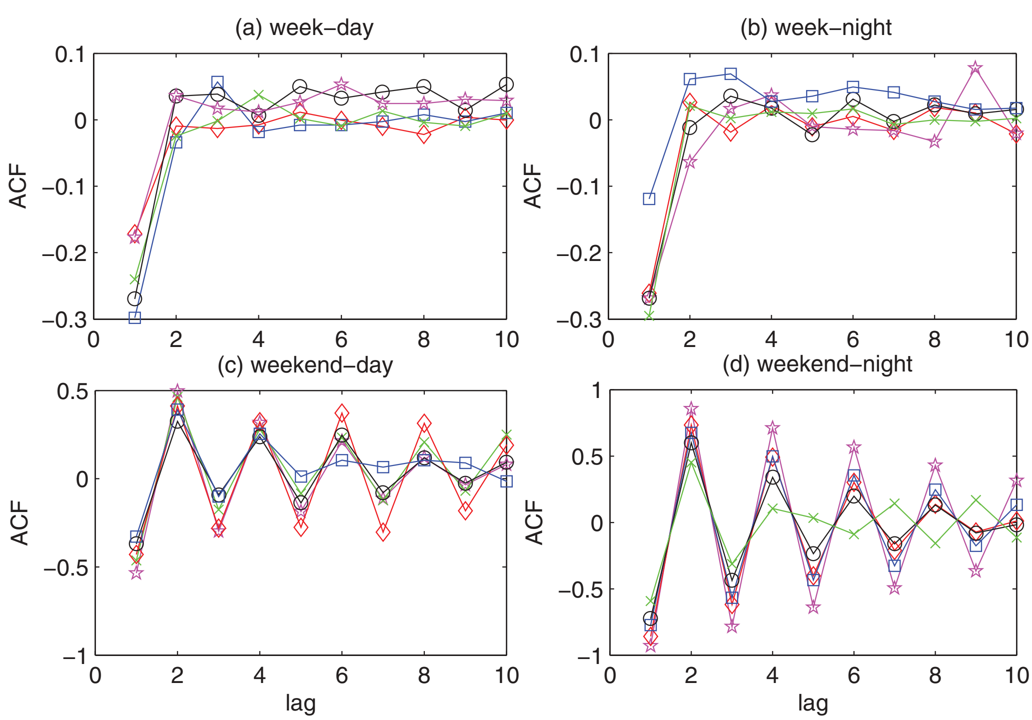

FIG. 6. (Color online) The autocorrelation function for differenced temperature recorded by the five sensors in each of four periods (weekday, weeknight, weekend day, weekend night): sensor 1 (squares), sensor 2 (diamonds), sensor 3 (crosses), sensor 4 (stars), and sensor 5 (circles). Let us mention that for temperature at the weekends (day and night) we consider the data after removing constant time periods.

TABLE V. The index of stability α of the inverse stable subordinator estimated for subdiffusive models (temperature at weekends—day and night) calculated on the basis of constant time periods observed in appropriate time series.

Sensor	Weekend day	Weekend night
s1	0.55	0.54
s2	0.53	0.51
s3	0.59	0.4
s4	0.52	0.62
s5	0.58	0.52

TABLE VI. The parameters of the ARIMA(2,1,3) model for time series that describe the temperature after removing constant time periods recorded by sensor 1 in days and nights during the weekend. In brackets we present the corresponding confidence intervals for estimated parameters calculated by using Monte Carlo simulations.

s1	Weekend day	Weekend night
AR(1)	−0.19	0.54
	[−0.61, 0.25]	[−0.22, 1.73]
AR(2)	−0.65	−0.29
	[−0.84, −0.24]	[−0.89, 0.75]
MA(1)	−0.50	−0.07
	[−0.95, −0.05]	[−0.86, 1.17]
MA(2)	−0.23	−0.03
	[−0.57, 0.27]	[−0.32, 0.33]
MA(3)	0.08	0.06
	[−0.14, 0.29]	[−0.15, 0.25]

characteristics of the measurement devices. The classical diffusion models are based upon processes that are local in space and do not have any memory of the history of the system. The mean square displacement in this case is proportional to the diffusion coefficient and it increases linearly with time. The diffusion equations assume a homogeneous environment surrounding the diffusing particle. In many systems that exist, for example, indoors, transport phenomena cannot be described on this basis. Simple models based on Brownian motion or Fickian diffusion are likely to fail in explaining mobility through the interior. Therefore different approaches are needed.

Diffusion in more complex systems is called anomalous [35,36]. Indoors, this phenomenon can appear as subdiffusion. It is hindered and exhibits a nonlinear relationship with time. The mean square displacement in this process is proportional to a fractional power of time that is less than 1. Subdiffusion inside rooms can result from several causes. It is a frequent phenomenon in crowded media. Fundamentally, subdiffusion arises when slow processes hinder the mobility of molecules in space and time. Inside rooms, molecules of air encounter a wide variety of obstacles. The disordered indoor environment with the heterogeneous, irregular geometry of the space domain generate conditions where diffusion is hindered due to collisions of particles and gas molecules with inert, mobile or immobile obstacles and transient capture of the diffusive molecules by traps (e.g., weak binding) with broadly distributed trapping times. The lifetimes of these cages may be broadly distributed at high obstacle density [37]. In the presence of moderate concentrations of obstacles, diffusion is anomalous over short distances and normal over long distances. For anomalous diffusion, the measured diffusion coefficient depends on the size of the obstacles relative to the size of the observation volume, as well as the observation time. For instance, if the obstacles are smaller than the observation volume, then for short observation times the diffusion generally appears normal as the particles do not interact with the obstacles. At medium observation times the diffusion is anomalous as the particle traces are obstructed by the obstacles. At long times the effect of obstruction is averaged out, and apparently normal diffusion is again observed, but the observed diffusion coefficient is lower than at shorter times. It is expected that the anomalous regime might be crucially dependent on the dynamics (or the lack of dynamics) of the obstacles themselves. Indeed, when the obstacles are allowed to diffuse even at a much slower rate than the tracked molecule, the transient anomalous regime

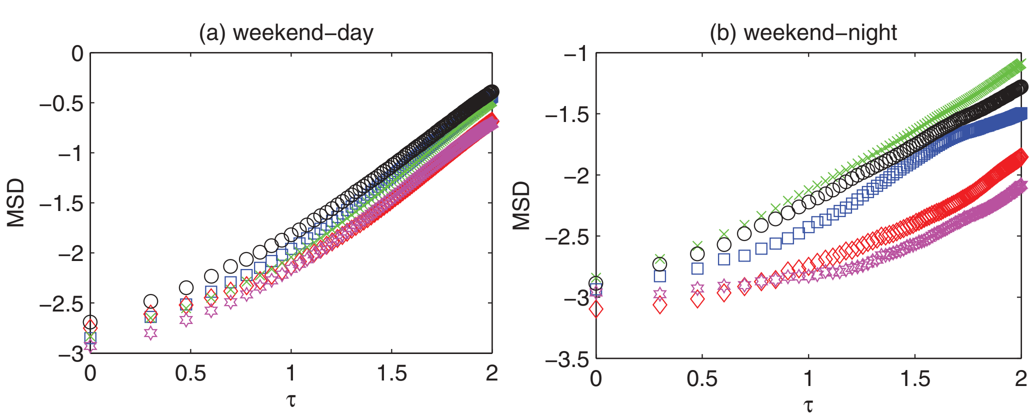

FIG. 7. (Color online) The mean square displacement for temperature series with two-step discretization recorded by the five sensors on weekend days and weekend nights: sensor 1 (squares), sensor 2 (diamonds), sensor 3 (crosses), sensor 4 (stars), and sensor 5 (circles).

TABLE VII. The estimated D parameter for temperature series with two-step discretization recorded by the five sensors on weekend days and weekend nights.

Sensor	Weekend day	Weekend night
s1	−0.05	−0.25
s2	−0.1	−0.31
s3	−0.1	−0.13
s4	−0.1	−0.42
s5	−0.06	−0.16

is predicted to disappear rapidly. Additionally, subdiffusion is caused by complex physical and/or chemical interactions, e.g., the (presence of) binding phenomena. Long temporal and/or spatial correlations might exist due to trapping of particles in coherent structures like vortices, or due to advection by zonal flows. In real conditions, indoor air is a turbulent system. A turbulent flow can be viewed as a nonlinear system out of thermodynamical equilibrium. Thus, in this medium, unsteady regular structures like vortices are generated on many different length scales. Trapping molecules in coherent structures and the presence of zonal flows will lead to "memory" effects and to non-Markovian behavior.

It should be noted that the results of this work required consideration of the performance characteristics of the measurement devices, because recorded data result from direct interaction of air molecules with the sensors. Particular attention must be paid to sensitivity, resolution of measurements, frequency of sampling, and intervals between samples. Appropriate sensitivity and resolution are necessary to detect small temporal changes of temperature and relative humidity. In this study, the analysis of time series was based on discrete signals. They were in the form of sequences of measurement results. The sampling rate during measurements could be adjusted, but we applied a fixed one. The frequency of sampling and the time interval between measurements had to be suitably selected. Turbulent flow, which exists in most room flow situations, involves a mixture of eddies of widely different sizes. In order to accurately capture the behavior of the smallest eddies, fine sampling is required. A high frequency of sampling allows for the detection of cages with a short waiting time. A too long time interval between measurements results in a decrease of subdiffusion events, as observed.

TABLE VIII. The index of stability α of the inverse stable subordinator estimated for the subdiffusive model from the two-step discretization (temperature series, weekend night).

Sensor	Weekend night
s1	0.49
s2	0.42
s3	0.35
s4	0.54
s5	0.4

V. CONCLUSIONS

In this paper stochastic methods were employed for studying the dynamics and structure of dependencies in microclimate data. Temperature and humidity time series were investigated. The examined data represented indoor conditions in a modern office building. They were sampled in five open plan offices over a period of nearly a week.

The first important result of this work was the fact that all temperature time series exhibited a transition between diffusive and subdiffusive behavior. At the same time, all humidity time series consistently showed diffusive character. The two parameters are usually considered as behaving in the same manner, just inversely correlated. The change of dynamics was linked with the switch between the week and the weekend building operation regimes. It is extremely interesting that only one of the two parameters confirmed this. The reason could be a completely different physical nature of the two quantities.

The second conclusion from our analysis was that all humidity time series had the same structure of dependencies. All temperature time series which exhibited the same dynamics also had the same dependency structure. However, the complexity of adequate ARIMA models increased in the following manner: ARIMA(0,1,2) for the humidity data, ARIMA(1,1,2) for the diffusive temperature data, and ARIMA(2,1,3) for the subdiffusive temperature data where the traps were removed. This order corresponds to the increasing complexity of the structure of the dependencies of the investigated microclimate parameters.

The third major observation was that despite the common dynamics and structure of dependencies the distinct time series must be individually modeled, if the actual values of the investigated parameters are needed. We showed that the estimated parameters of corresponding models differed and their confidence intervals seldom overlapped.

The conclusions obtained are important for indoor microclimate investigations. The analysis allows us to hypothesize about the existence of large and small scale factors influencing conditions in indoor air. Large scale factors would show consistent characteristics in space and time (across various locations in the building and over considerable periods of time). They could be considered responsible for the dynamics and for the dependence structure of the microclimate parameters. Based on our work, one should remember that physically different parameters may exhibit distinctive characteristics in that respect. There are also other, local factors. Their levels, even their existence, change in space and in time. The influence of these factors on microclimate parameters would be observed in terms of the individual character of the time series, as we have shown that different sets of parameters are required to represent their variability.

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