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ORIGINAL ARTICLE

Novel approach to analysing large data sets of personal sun exposure measurements

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Personal sun exposure measurements provide important information to guide the development of sun awareness and disease prevention campaigns. We assess the scaling properties of personal ultraviolet radiation (pUVR) sun exposure measurements using the wavelet transform (WT) spectral analysis to process long-range, high-frequency personal recordings collected by electronic UVR dosimeters designed to measure erythemal UVR exposure. We analysed the sun exposure recordings of school children, farmers, marathon runners and outdoor workers in South Africa, and construction workers and work site supervisors in New Zealand. We found scaling behaviour in all the analysed pUVR data sets. We found that the observed scaling changes from uncorrelated to long-range correlated with increasing duration of sun exposure. Peaks in the WT spectra that we found suggest the existence of characteristic times in sun exposure behaviour that were to some extent universal across our data set. Our study also showed that WT measures enable group classification, as well as distinction between individual UVR exposures, otherwise unattainable by conventional statistical methods.

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INTRODUCTION

In recent decades, the harmful human health effects associated with excess sun exposure have been increasing.[1] The main causes are changes in (1) ambient solar ultraviolet radiation (UVR) levels reaching the Earth's surface and (2) in factors related to human behaviour when spending time outdoors.[1–3] Although some sun exposure is beneficial for vitamin D production, excess short-term sun exposure is associated with DNA damage.[4]

The most prominent adverse health effect, skin cancer, has seen increased rates in several countries around the world.[1] UVR exposure is the only known modifiable risk factor for skin cancer.[5] Artificial UVR exposure sources, such as electric welding arcs and sunbeds, have proven an association between exposure and skin carcinogenesis, whereas excess sunburning from solar UVR exposure, particularly during childhood, has been linked to melanoma skin cancer.[6] To be optimally effective in reducing incidence of excess UVR exposure, especially during childhood, and thus reducing subsequent risk of skin cancer, sufficient UVR exposure information is required to tailor design of intervention programmes so that they are cost effective, appropriately targeted and ethically acceptable.

Since the 1970s, some studies have measured sun exposure during selected activities such as gardening or walking.[7–11] Others have focussed on measuring personal solar UVR exposure to generate baseline exposures in different population groups and behavioural settings.[12,13] There have also been a few longitudinal studies concerning child sun exposure.[14–16] Whereas some studies have directly measured personal UVR exposure,[17,18] others have focused on assessing sun-protective practices and indirectly estimating personal UVR exposure.[19,20] These data are used for planning and development of skin cancer prevention and sun awareness campaigns. The ultimate goal is for individuals to take heed of campaign messages, alter their sun exposure behaviour and thereby reduce their skin cancer risk.

In personal dosimetry, measurements are performed by a dosimeter attached to each individual participating in the particular study. A dosimeter indicates UVR effect on a specific biological system when a measurable property changes in a reproducible manner upon exposure to UVR.[21] A dosimeter is calibrated in physical units against a meteorological-grade instrument that measures UVR; for example, a spectroradiometer whose calibration can ideally be traced to the US National Institute of Standards and Technology (NIST).[22] Calibration is performed by cross-referencing the systems under a source that is spectrally similar to that to which the dosimeters will be exposed.[21] A dosimeter's suitability depends on its specific response spectrum. Ideally, a dosimeter should be precise, accurate, reliable and independent of temperature and humidity; it should have a reproducible biological response; and be inexpensive.[11] To date, dosimeters used to measure personal UVR exposure have had a response that closely mimicked the erythemal action spectrum (EAS) (sunburning response) as defined by the International Commission on Illumination.[18,23,24] Other dosimeters are tailored for different action spectra, such as a biological spore dosimeter that is used to estimate DNA-damaging UVR exposure EAS.[25]

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Three dosimeter types have been used to measure personal UVR exposure (pUVR): chemical (such as polysulphone film), biological and digital electronic. However, the focus here is on digital electronic dosimeters that are increasingly used today. The advantages of digital electronic dosimeters include online data logging and download capabilities, repeated use within a certain battery life and small dimensions and weight to permit ease of personal use.[21] Furthermore, their internal loggers can be set to measure and record pUVR levels at various intervals. When recording intervals are set for frequent data measurement, and when individuals wear the UVR dosimeter for a prolonged period of time (several days, weeks or months), measurements result in a large data set that requires intense processing, analysis and interpretation.[13,26]

Despite the large number of data points collected, the studies of pUVR exposure are typically limited to conventional statistical measures: determining mean and/or median total daily or hourly UVR exposures for all participants or by specified participant subgroups of interest (see, e.g., Liley et al.[27]). Heuristic search algorithms, statistical data processing and supervised and unsupervised machine learning were applied to a study of pUVR exposure measurements among 517 participants (8 to 10 weeks of dosimeter use).[27] Attempts were made to remove false, unreliable measurements and interpolate data across areas with missing data using prediction techniques. Despite these efforts, data were finally combined into three periods per day to match participant's clothing logs recorded in diaries. Given the highly variable nature of personal solar UVR exposure and the often unpredictability of daily human behaviour, the use of more sophisticated analytical techniques is necessary to optimally interpret such large data sets to draw as much value and information as possible from the data. In this paper, we apply one such method, the wavelet transform (WT) spectral analysis, to uncover dynamical and behavioural features of pUVR data in order to introduce new measures that will be able to discriminate between individual or group exposure in a general data set. WT spectral analysis is an advanced statistical technique for processing long-range, high-frequency personal recordings; WT spectral analysis, like conventional Fourier analysis, estimates the spectral characteristics of a time series as a function of time.[28] In this way, it represents an extension to conventional methods of data analysis.

WT analysis is a widely used method to quantify correlations in non-linear and sometimes non-stationary natural or human-made time series, such as the heart rate[29] or neuronal activity,[30] stock market[31] or global climate variability.[32,33] For a time series of natural or human-made records, WT analysis provides a systematic way of obtaining information that is not readily available in the raw data.[34] It aids the understanding of phenomena characterized by fluctuations over many timescales. If the WT spectral functions of the relevant data set are of the power-law type, the correlations in the fluctuations at different timescales are described by the scale-invariant or scaling exponent β, the power exponent of the power-law function. This quantitative measure provides a description of the underlying dynamical processes in the system. The system dynamics at a given timescale is reflected by a particular shape of the scaling function, values of scaling exponent at different timescales and positions of crossovers in scaling. Scaling functions, therefore, offer additional information on the existence of trends or characteristic times in investigated data sets. Finally, a large WT power value at a given scale and at a particular point in time implies that the oscillation at the frequency related to that scale exists over the time period centred around this time location.[34] The existence of peaks within the calculated WT power spectra then informs on the existence of cycles in the data.

This study addresses the question of whether WT spectral analysis can be utilized to compare pUVR time series from different population groups or from different activities, and to examine differences or similarities across groups and/or activities. We also made an attempt to address the question of whether the complexity of pUVR records is specifically limited to the statistical behaviour of each individual time series, or whether parts of a pUVR series complexity can be attributed to the effects related to the influence of atmospheric environmental factors.

MATERIALS AND METHODS

Data

Data were collected using digital electronic UVR dosimeter badges worn by volunteers of different occupations and in different activities and environments. Volunteers included South African school children, teachers, sailors, cyclists, marathon runners, farm workers and gardeners, and New Zealand construction workers. The UVR dosimeter badges were developed at the University of Canterbury, New Zealand, to measure personal exposure to solar erythemal UVR (290–400 nm) and have been described in detail elsewhere.[22,26] Briefly, the main component of the dosimeter badge is a miniature, aluminium gallium nitride (AlGaN) photodetector with an engineered spectral response that closely matches the CIE erythemal action spectrum. The detector response is electronically converted into a time-stamped digital count (on a scale from 1 to 1024) that is directly proportional to the incident erythemally weighted UVR irradiance. The detector is encased in a weatherproof polytetrafluoroethylene (PTFE) enclosure that also acts as a diffuser to ensure that the angular response of the instrument is reasonably close to the cosine response of human skin.[35] The badge is powered by a small lithium coin cell battery (CR 1632, 3 V). It has a diameter of 35 mm, thickness of 10 mm, weighs ~ 19 g and can either be worn on a wrist strap, pinned to clothing or in the case of construction industry workers attached to a hard hat. The badges were set to record data every 1 min in day/night mode (programmed to record from 0700 to 2100 h) for records taken in South Africa, or every 8 s for records from New Zealand. Each badge had sufficient on-board memory and battery capacity to store numerous days of data that were then retrieved via a USB-serial data cable.

UVR dosimeter badge data in counts were used in the WT analysis, described below. In some cases, the counts were converted to erythemally weighted UVR irradiance in units of ultraviolet index (UVI), using proportionality constants established via cross calibration against "Robertson–Berger type" meteorological grade instruments.[22] The UVI is a non-dimensional quantity defined by the formula:

$$\mathrm{UVI} = \mathrm{k_{er}} \times \int_{250\mathrm{nm}}^{400\mathrm{nm}} E_\lambda \times S_{er}(\lambda) d\lambda, \tag{1}$$

where E_λ is the solar spectral irradiance expressed in W/m^2/nm at wavelength λ and $d\lambda$ is the wavelength interval used in the summation. *Ser(λ)* is the CIE reference erythemal action spectrum and k_{er} is a constant equal to 40 W/ m^2. Consequently, 1 UVI is equivalent to 0.025 W/m^2 of erythemally weighted UVR irradiance. Individual UVI data points can then be integrated over any required time period to determine the received UV dose in units of standard erythemal dose (SED) where 1 SED = 100 J/m^2.

WT Analysis

The WT method was originally introduced to study complex natural signals. The technique was devised to achieve good signal localization in both time and frequency that a classical Fourier transform approach lacks.[36,37] Namely, in WT the window of examination length is adjusted to the frequency analysed; slow events are examined with a long window, whereas a shorter window is used for fast events. In this way, an adequate time resolution for high frequencies and a good frequency resolution for low frequencies are achieved in a single transformation.[38]

The continuous WT of a discrete sequence *U(k)* is defined as the convolution of *U(k)* with wavelet functions $\psi_{a,b}(\mathrm{k})$ in the following way:

$$W_p(a,b) = \sum_{k=0}^{N-1} U(k)\psi^*_{a,b}(k), \tag{2}$$

with a and b being the scale and translation-in-time (coordinate) parameters, N the total length of the data series (in this study, pUVR) and the asterisk stands for complex conjugate. To examine the existence of scaling, trends and cycles in the pUVR data, the wavelet scalegrams (the mean wavelet power spectra) $E_W(a)$, defined by:

$$E_W(a) = \int W_p^2(a,b) db \tag{3}$$

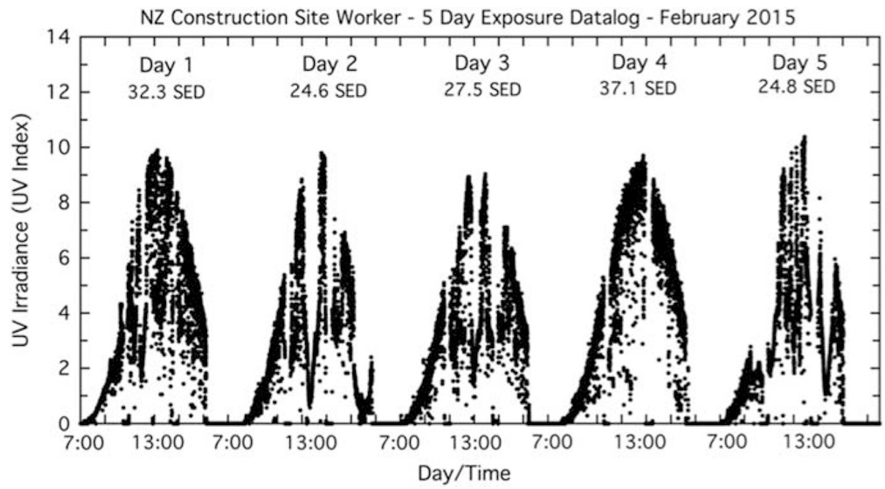

Figure 1. Examples of five daily pUVR records of a construction worker, taken in New Zealand. The UVR dosimeter badge was attached to the participant's safety hard hat. Graph depicts recorded 8 s UV irradiance measures, together with the total integrated SED measure for the respective days (note that 1 UV index unit is equivalent to 0.025 W/m^2 of erythemally weighted UV irradiance). Because of the high density of data points (i.e., 450 per hour), not all data points will be individually resolved and some will appear to be stacked vertically.

are used. The scalegram $E_W(a)$ can be related[39] to the corresponding Fourier power spectrum $E_F(\omega)$ via the formula:

$$E_W(a) = \int E_F(\omega)\left|\hat{\psi}(a\omega)\right|^2 d\omega, \tag{4}$$

where the caret symbol designates Fourier transforms. Equation (4) implies that if two spectra, $E_W(a)$ and $E_F(\omega)$, exhibit power-law behaviour, then they have the same power-law exponent β.

In a wavelet-based analysis, the scale invariance of the time series is reflected by the scaling of the WT power spectrum $E_W(a)$ with timescale a in a form $E_W(a) \sim a^{-\beta}$. The exponent β is related to the decay of the corresponding autocorrelation function.[40] For β between 0 and 1, autocorrelation function decays by a power-law. In this case, the mean correlation time diverges, and the system is regarded as long-term correlated. For $\beta = 0$, the data are linearly uncorrelated on long timescales and look like "white noise" in the spectrum. The meaning of the wavelet scalegram is the same as in the case of a classical spectrum—it gives the contribution to the signal energy at the specific scale (time) parameter a. This property enables examination and identification of the peaks in wavelet spectra in the same way the classical Fourier approach does.

In this paper, we chose to apply the standard set of Morlet wavelet functions as $\psi_{a,b}(\mathrm{k})$. The Morlet wavelet[41] has proven to have the optimal joint time–frequency localization, and can therefore be used to detect locations and spatial distribution of singularities in the time series.[42]

Ethics Statement

All procedures performed in studies involving human participants were in accordance with the ethical standards of the institutional and/or national research committees of South Africa and New Zealand, and with the 1964 Helsinki declaration and its later amendments or comparable ethical standards. South African study has a research ethics clearance granted by the Council for Scientific and Industrial Research (CSIR) Research Ethics Committee (Certificate number: 64/2013, 15 February 2015).

RESULTS

We applied WT spectral analysis to the pUVR time series $U(k)$, derived from the daily exposure records of school children, farmers, outdoor workers and a marathon runner from South Africa, and construction workers and a construction site supervisor from New Zealand in order to learn the relevant statistical properties of these series. Time series $U(k)$ consist of the UVR dosimeter badges counts recorded at time interval k. The recording time step was $\Delta k = 60$ s for the South African data, and $\Delta k = 8$ s for the New Zealand data. An example of daily pUVR records of a construction worker is given in Figure 1, together with the calculated SED values for the particular days.

We found scaling behaviour in all our pUVR data. Their WT spectra are power-law functions of time, and we calculated the corresponding scaling exponents β as slopes of WT functions from a log (WT power spectra)–log (times) graphs. Our results show significant differences in the behaviour of WT power spectra depending on the duration of an individual's solar exposure, distinguishing both between the participants (individuals) investigated and the activities they performed while the pUVR data were recorded. Using this approach, we obtained the scaling exponents β with values close to 0 for the uncorrelated cases, that is, for individuals with erratic activities with regard to their UVR exposure, in some of the farmer's recordings and all of our school children records. In the case of long-range correlated pUVR data, for individuals spending longer periods in the sun because of the nature of their job (e.g., farmers, outdoor workers) or sports activity (i.e., the marathon runner), the calculated slope was $\beta > 0$.

Figure 2 shows wavelet power spectra, together with the corresponding pUVR records, for the two representative cases of difference in scaling behaviour that we found across our data set: the uncorrelated case of a schoolchild and the correlated behaviour of a marathon runner. WT spectra are given in a log–log form, where the logarithm of $E_W(t)$ is given as a function of the logarithm of the timescale t; real timescale t was extracted from wavelet scale a following the algorithm given in Torrence and Compo.[43] The slopes of WT functions, used for calculating scaling exponents β, are represented by straight lines; we only took into consideration the values of the WT spectra between the minimum timescale of $a = 1$ and the statistically meaningful maximum timescale[44] of $a = N/5$.

Peaks (local maxima) in the WT power spectra that may point to the existence of characteristic times in sun exposure behaviour were found in all investigated pUVR records. The peaks are already visible in Figure 2, but are given in Figure 3 for emphasis. The characteristic peaks that give periods of characteristic cycles can be recognized on different timescales: 10–15 min, half an hour and 1 and 2 h in all of the pUVR data. Additional peaks, at longer periods of 3–4 h, in long-range correlated cases of individuals with longer sun exposure were also found (see example in Figure 3).

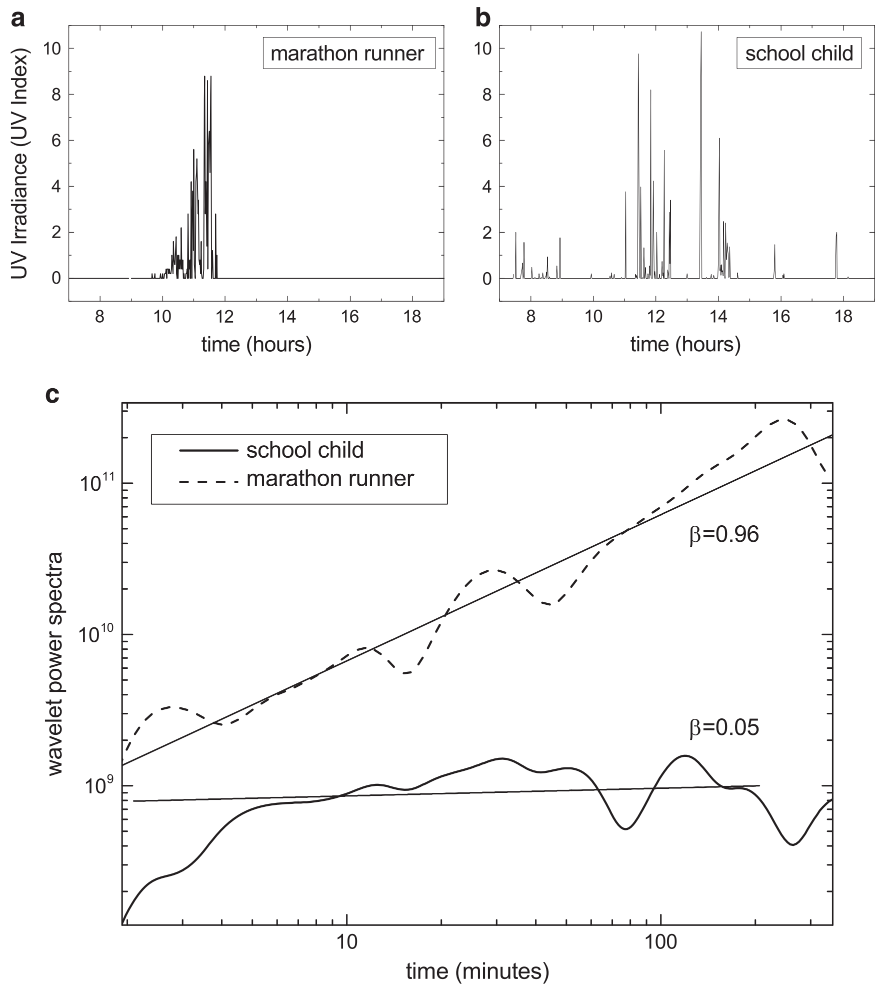

Figure 2. Examples of scaling in pUVR records: comparison of daily pUVR records of a school child (a) and a marathon runner (b) during their usual daily activities with log–log plots of their wavelet spectra (c). The UVR dosimeter badges were attached to the school child's wrist and marathon runner's upper arm. In (c) the straight lines represent linear fits to the wavelet spectra, from which the slopes, that is, exponents β were calculated. One can discern the uncorrelated exposure behaviour of a school child (with $\beta \approx 0$) and the highly correlated behaviour of a marathon runner (with $\beta \approx 1$).

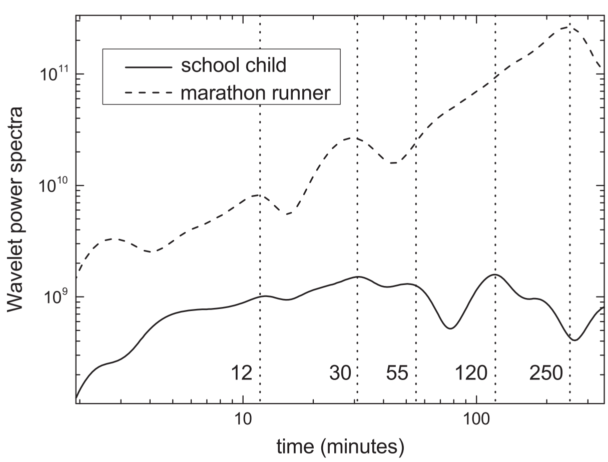

Figure 3. Illustration of the existence of characteristic times, or cycles, in the pUVR time series of a school child and a marathon runner for the daily records depicted in Figure 2. The vertical lines indicate peaks in the WT spectra for these two cases that indicate characteristic cycles of a duration of 10–15 min, half an hour and 1 and 2 h in the school child's daily pUVR records, and a peak on longer time interval of ~3 h in the marathon runner's sun exposure record.

The above findings demonstrate that WT analysis can provide two new measures of pUVR exposure: the duration of exposure, quantified by the slope of WT power spectra, and the characteristic times of exposure, manifested by the peaks in WT scalegrams. We extended our analysis to explore its potential in investigating a specific group's exposure patterns. To accomplish this, we grouped individuals of similar population subgroups—in our data set, groups of outdoor workers and of farmers—to see whether the analysis gives the same types of results as for any individual group member. Within the group, we compared randomly selected individual daily data, recorded on different days, under different outside conditions, even from different locations in different countries: the results of our analysis are given in Figure 4. Because of a small number of individuals, we are presenting only the basic statistical group measures—the mean, SD and position of 95% confidence intervals are given for each group. The results for the group of farmers' records, consisting of six individuals, recorded in South Africa, point to a diverse pUVR behavioural patterns (Figure 4). Farmers' data span different types of behaviour: from random behaviour (with $\beta \approx 0$, that is $\beta_{F,min} = 0.29$) to long-range correlated behaviour (with $0 < \beta \leq 1$ and $\beta_{F,max} = 1.14$). The group mean WT slope is $\beta_{F,mean} = 0.64 \pm 0.31$; as the farmers' data do not cluster, some individual WT scaling exponents in the group scatter outside of the SD error

Figure 4. Results of the group behaviour WT analysis for pUVR records in groups of farmers and outdoor workers. Statistical group measures—mean values (filled squares), SD (error bars) and positions of 95% confidence intervals (boxes)—are given for each group, together with the calculated WT exponents β (data, hollow squares and hollow circles) for each group member. The Figure shows obtained dissimilarity in behaviour in group of farmers and similarity in behaviour (clustering of data points) in group of outdoor workers.

interval. To be able to discern group properties in the farmer population, this group probably needs to be further differentiated (by place or time of recording and/or nature of work and/or other parameters). In contrast, the findings obtained for the group of outdoor workers point to the similarity of pUVR WT results. Namely, WT power spectra for all members of the group (five outdoor workers from our data set recorded in South Africa and in New Zealand) show long-range correlated behaviour, with slopes $\beta \approx 1$ (and range $\beta_{\mathrm{OW,min}} = 0.89$ to $\beta_{\mathrm{OW,max}} = 1.35$) and the mean WT slope $\beta_{\mathrm{OW,min}} = 1.06 \pm 0.18$ Only one individual slope value from this sample does not fall into the SD error interval. It is important to notice that the group of outdoor workers shows a similarity in behaviour even though the individual records were taken under different conditions and during different types of outdoor work.

The last step in our analysis was a test for further distinction of pUVR data in cases of seemingly similar daily erythemal UVR exposure by way of considering scaling measures for individuals with continual daily exposure, associated with high daily exposure doses. We found that even if pUVR data correspond to very similar daily exposure indexes, their long-range correlated behaviour may still be different. Figure 5 shows the WT scalegrams, together with the corresponding pUVR records, for the representative cases of daily pUVR exposures of one construction worker and a construction site supervisor recorded on the same day. The difference in slopes of the WT spectra for both cases is visible from Figure 5. The construction worker's data (of a total daily exposure of 11.8 SED for the particular day) have the scaling exponent $\beta \approx 0.8$. This is different from the supervisor's scaling (with a total daily exposure of 9.8 SED units for the same day) that is of the so-called 1/f type (that is, with $\beta = 1$). Figure 5 shows how the difference in individualal behavioural patterns in these two cases stems from different behaviour on smaller timescales. Namely, on scales ranging from several seconds to 15 min, the slopes of the two WT spectra are markedly different, and contribute to the overall difference in corresponding WT exponents β. This is how, for the construction worker, the peaks on longer timescales are somewhat balanced by a random behaviour on smaller timescales that reduces the value of β, whereas in the case of a construction supervisor the predominant behaviour is on longer timescales. The explained difference in sun exposure behaviour is also visible in the pUVR records given in Figures 5a and b, where a continuous, but frequently changing exposure pattern of a construction worker, and a long-term intermittent exposure of a construction site supervisor are evident. Thus, the WT analysis helped us reveal differences in personal behavioural patterns related to the solar UVR exposure that were not visible from the conventional pUVR measures (daily exposure indexes) and that are related to the difference in the manner individuals spend their time outdoors.

DISCUSSION

In this paper, we use the wavelet-based spectral analysis to investigate and quantify dynamical behaviour of personal solar UVR exposure records from different groups and to understand better patterns of personal solar UVR exposure. The advantage of this method stems from its construction that overcomes problems of non-linearity or even non-stationarity of natural data series: WT deduces the typical behaviour, or long-term characteristics of the analysed records, rather than monitor for linear coincidences of data values at each time step. In this paper, WT allowed us to objectively identify two new measures of pUVR behaviour: the duration of exposure, quantified by the slopes of WT power spectra, and the characteristic times of exposure, related to the times of appearance of peaks in WT scalegrams. These measures allowed us to search for similarities within specific group's exposure patterns and to differentiate between sun exposure behaviours with similar cumulative properties. This is the first study (to our knowledge) that has shown that pUVR data can be objectively differentiated or collated for different population groups.

Our findings show that a scale-invariant behaviour exists in the analysed pUVR data sets. With an increase in the duration of an individual's solar exposure, the behaviour changes from uncorrelated, for individuals with erratic activities with regard to their UVR exposure, to long-range correlated, for individuals spending longer periods in the sun. The presence of scaling in climate records have been confirmed in a large number of studies; as data records extend over longer periods of time, increasing evidence of long-term trends in the climate systems are observed.[33,45,46] These trends show evidence of persistence in records behaviour, that is, long periods of one kind of behaviour alternate with long periods of usually opposite kind of behaviour.[47] In the pUVR case, the existence of strong long-range correlations would suggest that an individual spends long uninterrupted periods outdoors, followed by long periods spent indoors. This individual would be exposed to higher daily UVR doses[48] than an individual with uncorrelated or slightly correlated pUVR series.

We also found multiple peaks in wavelet spectra in all our pUVR time series, pointing to the existence of characteristic times in personal sun exposure behaviour. Moreover, we found that these spectral peaks occur at roughly the same times (or time intervals) in all our data sets, pointing to a certain level of similarity in sun exposure behaviour across activities or population groups. Characteristic peaks at ~15 min, half an hour and 1 and 2 h were present in all of the pUVR data. In the recordings of longer sun exposure, additional peaks at longer periods were detected. The question of whether some of these WT peaks appear as a result of the influence of daily sun or other atmospheric cycles, rather than an individual's voluntary behaviour, was not raised in our analysis. Further investigation of this issue is required in order to be able to use WT analysis to better characterize different personal behavioural patterns related to solar UVR exposure.

We further examined the potential of WT analysis to add to our understanding of a specific group's exposure patterns—in the case of our data set, groups of outdoor workers and of farmers. Our results show similarity in group behaviour of outdoor workers' records that points to general long exposure to solar UVR (group

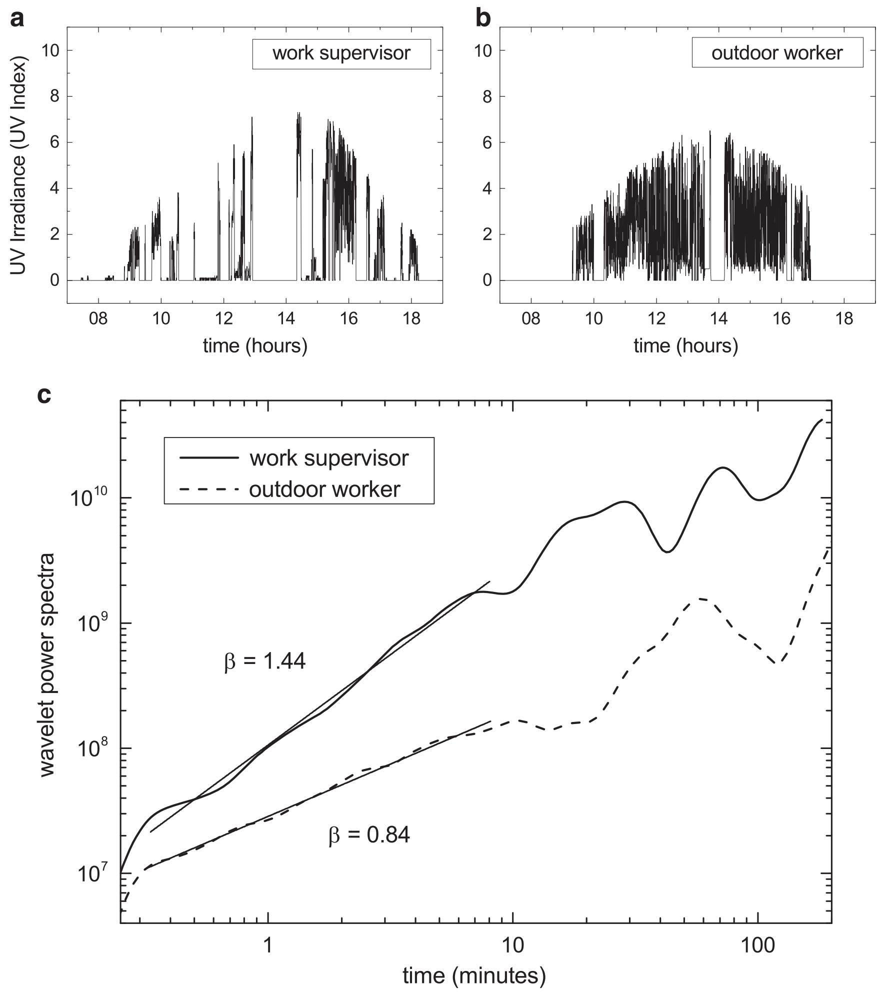

Figure 5. Comparison of daily pUVR records of a construction worker (a) and a construction site supervisor (b), recorded during the same day at similar outdoor conditions, with their wavelet power spectra (c). The UVR dosimeter badges were attached to the participant's safety hard hat. In (c) the straight lines represent linear fits to the wavelet spectra in the small timescale region (ranging from several seconds to 15 min), from which the slopes, that is, exponents β were calculated. One can discern that the slopes of WT spectra differ in these two cases, in the region of small timescales, even if their SED measures are very similar for that particular day. This result indicates different behavioural patterns of sun exposure—long intermittent exposure of a construction site supervisor and a frequently changing exposure of a construction site worker.

mean indicates a long-range correlated, the so-called 1/f exposure behaviour, characterized by scaling exponent $\beta \approx 1$). As the group of outdoor workers in our data set showed similarity in behaviour even though individual records were taken under different conditions and for different types of outdoor work, there may be potential for future use of WT to build up meaningful population UVR exposure patterns that could further be used in epidemiology. This conclusion needs to be to be corroborated on larger population groups in order to provide better statistics. The approach could also be tested on other groups that show similarity in exposure behaviour, such as golfers or gardeners,[24] especially for the importance of the knowledge of their group behaviour from a public health point of view.[49]

Finally, to examine whether the observed scaling and temporal patterns in the observed pUVR behaviour could be used to distinguish pUVR data of individuals with seemingly similar daily erythemal UVR exposures, we performed an analysis on a subset of individual records taken on the same day under very similar outdoor conditions. The recordings in this subset consisted of continuous personal daily exposures that were associated with high daily exposure indices and would be considered indistinguishable by conventional statistical methods. Our method indeed differentiated the two types of behaviour. In the first type, there was a highly persistent UVR exposure, characterized by the slope $\beta = 1$ in the WT spectrum, and a presence of a long characteristic period of $\sim$3–4 h. The second type involved less intense long-term exposure, with a WT slope $0 < \beta < 1$, and an evident contribution of outdoor behaviour at timescales of < 3 h. We argued that the differences in the WT slopes in these two cases are probably because of the less pronounced effects of fast (occurring at a small timescale) changes in the overall sun exposure behaviour in pUVR data with $\beta = 1$.[38,50] In the case of ambient UVR data, it has already been shown that the exponent of the power-law relationship between the fluctuations of the solar spectral irradiance *versus* UVR wavelength at the ground is consistently close to unity (i.e., that the time series correlations are of the 1/f type) throughout the day.[51] This could mean that after several hours of persistent daily exposure the 1/f property of the solar UV flux may become a major influencing factor in the 1/f behaviour of pUVR records. The question of the critical time interval of uninterrupted solar exposure sufficient for the "1/f effect" to occur, the critical exposure duration, remains open for further research; this information could help improve prediction models that rely on the use of ground irradiance data to estimate individual UVR exposure.[52,53]

In summary, the scaling analysis based on the wavelet transformations proved to be a powerful tool in investigation of personal solar UVR recordings. The analysis offered identification of characteristic patterns and characteristic intervals in sun exposure that enables group classification, as well as distinction between individual UVR exposures, otherwise unattainable by conventional statistical methods. The nature of these data may be useful in determining patterns in sun exposure that are known to increase risk of skin cancers as, for example, intermittent sun exposure is generally associated with basal cell carcinoma and melanoma, whereas chronic sun exposure is associated with squamous cell carcinoma.[54]

CONFLICT OF INTEREST

The authors declare no conflict of interest.

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