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Identification of spectral distributions in light-dosimetry data: Methodology and application to an intervention field study

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Modern life in predominantly indoor environments has led to a profound alteration in the amount, spectral distribution and pattern of light humans are exposed to daily. Given the role of light in health and well-being, and to understand how modern living can be better aligned with human biology, light-dosimetry plays an important role in characterising personal light exposure across individuals. To consider the spectral distribution in light-dosimetry and evaluate the variability and effects of individual ‘spectral diets’, a sufficient spectral resolution is required. In this paper, we present selected analyses of spectrally resolved light-dosimetry data that were collected during a dynamic lighting intervention study in Iceland. Unsupervised clustering was performed to process the collected data, and clusters were classified using various reference spectra. The results not only show that different spectral types can be sufficiently well discriminated, but they can also be used to verify the experimental conditions effectively experienced by participants and to start evaluating the effect of other factors (e.g. daylength, or impact of time outside experimental conditions). Taken together, our findings highlight the benefits and potential uses of spectrally resolved light-dosimetry, which will hopefully contribute to, first, better understand and, ultimately, improve our contemporary relationship with light.

1. Introduction

Light enables visual perception of the world and plays a fundamental role in regulating biological rhythms as well as acute physiological and behavioural functions, such as sleep, alertness, cognitive performance and mood.¹ In daily environments, light is nearly always present, yet our exposure to

light (i.e. personal light exposure) can vary substantially depending on the lighting conditions in the environment and our behaviour in it, as well as on weather conditions, season and geographical location. While these factors influence *how much* light we are exposed to at a given point in time, the light sources and reflecting materials in our immediate environment also determine the *spectral distribution* of light arriving at the eye. As we are constantly exposed to different quantities and spectral distributions of light, personal light exposure can be thought of as a ‘spectral diet’.²

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In modern societies, humans spend most of their time in indoor environments,³ illuminated by a combination of electric light sources and daylight. This shift to indoor-dominated lifestyles profoundly altered the amount, spectral distribution and temporal pattern of light that humans are daily exposed to,⁴ compared to the natural conditions under which humans have evolved.⁵ Given the importance of light not only for vision but also for general health and well-being,⁶ these altered exposure patterns may have short- and long-term negative health consequences, such as impaired sleep, alertness and cognitive performance, as well as depression, obesity, cardiovascular diseases and cancer.^{4,7,8} To better understand how these detrimental health effects can be mitigated and how modern living can be better aligned with human biology, it is important to measure the spectral diets of individuals or groups of people in a personalised fashion (light-dosimetry) in real-life settings. The collected data may help to identify potential for lighting interventions and validate lighting design decisions, as well as to investigate functional relationships between light and physiological and/or behavioural responses.^{9,10}

Light-dosimetry is performed with wearable light sensors, also called dosimeters, that are able to measure relevant quantities of light continuously. In order to quantify the spectral distribution of light, a sufficient spectral resolution is required, meaning that a sensor is able to sample electromagnetic radiation at several separate wavelength bands (spectral channels) across the visible light spectrum. Many dosimeters used in previous research are limited to measurements of illuminance or spectral irradiance across three channels.¹¹ While data from three channels (usually red, green and blue) has been used by some studies to examine major changes in the spectral distribution of light¹⁰ – for instance, over the course of day and seasons¹² – in most cases, a

higher spectral resolution is required to estimate or recover the true spectral power distribution (SPD).¹³ Such spectrally resolved light-dosimetry data enable insights into the different *types of light spectra* people are exposed to on a daily basis and what light sources they most frequently encounter (e.g. daylight, LEDs, fluorescent light). In addition, spectral irradiance data with a higher spectral resolution allow to easily calculate various weighted quantities of light directly from the spectral distribution itself (e.g. illuminance, α -opic quantities, correlated colour temperature (CCT)) without the need for dedicated sensors for each quantity (e.g. illuminance sensor, melanopic irradiance sensor). Thereby, current as well as new lighting standards can be met, even if they undergo revisions and updates. As noted in a recent review,¹¹ most previous light-dosimetry studies were not able to meet the new standard CIE S 026/E:2018¹⁴ defining relevant quantities for the research of physiological and behavioural effects of light (i.e. α -opic quantities) due to outdated dosimeters failing to measure α -opic quantities accurately.

To date, only a few published studies have collected light-dosimetry data at a higher spectral resolution, and little information exists about the insights these kinds of data can offer and how to analyse them. Previous light-dosimetry studies that have measured spectrally resolved data limited their analyses to calculating α -opic quantities,¹⁵ or examined spectral typologies during specific periods of the day using heuristic methods¹⁶ or a clustering approach.¹⁷ As spectrally resolved light-dosimetry is gaining more attention, new analysis approaches for these kinds of data may help researchers to make the most of the collected data and accelerate future light-dosimetry research.

Therefore, in this paper, we present analyses using a clustering and classification approach applied to spectrally resolved light-dosimetry

data collected over several days as part of an intervention study investigating the effects of a dynamic lighting system on high school students in Reykjavik, Iceland. This paper aims to provide an example of how these kinds of data can be analysed, what insights they can offer into the spectral diets of individuals and how they could be used to verify lighting interventions.

2. Methods

In the following section, the study will be briefly described regarding the light-dosimetry methodology that was applied. Note that the study itself comprised several other outcome measures that are not described in this paper. A full description of the study design, measures and protocol will be part of forthcoming publications.

2.1 Study design

Personal light exposure data were collected as part of a repeated-measures between-subjects field study conducted by the University of Reykjavik in collaboration with external consultants during the school year September 2021 to May 2022 in a high school in Reykjavik, Iceland (64.15°N). The study included two experimental lighting conditions simultaneously implemented in several separate classrooms: classrooms with a dynamic bright light setting and classrooms with a static dim lighting setting. The spectrally resolved personal light exposure data reported here were collected in two of the classrooms (bright and dim) during a one-week 'baseline' period (dim light setting in all classrooms) in October and subsequently for three one-week 'intervention' periods across the school year with the experimental conditions implemented (bright vs. dim). Eligible participants were the high school students of the classes in which the experimental lighting conditions were installed.

The study had ethical approval, and informed consent was obtained before participation.

2.2 Lighting conditions

The experimental lighting conditions were implemented using tuneable LED fixtures that replaced the previous luminaires in the classrooms. The fixtures were square-shaped recessed ceiling-mounted luminaires distributed in an evenly spaced grid across the room. In the bright light condition, the CCT and dimming level of the luminaires were dynamically adjusted during the school day, with a CCT of 4000 K around midday and 3000 K otherwise (see Figure 1(a)), whereas in the dim light condition, the CCT was fixed at 3000 K. The relative SPD for the two CCT setpoints in the typical viewing direction towards the teacher (measured at night at eye level) is depicted in Figure 1(b). A detailed overview of the lighting characteristics in the classrooms is provided in Table 1.

The two classrooms in which the spectrally resolved light-dosimetry data were collected were located on the third floor of the school building, adjacent to each other, and identical in layout (square), floor area (~62 m²) and window area. The classrooms were north-west facing with no view obstruction and similar daylight conditions. Except for the grey floor, most surfaces (walls, ceiling, desks) in the classrooms were white. An image of one of the two classrooms is depicted in Figure 1(c).

2.3 Light-dosimetry

2.3.1 Setup

During the four measurement periods, spectrally resolved light-dosimetry data were collected for participating students in two northwest-facing adjacent classrooms (bright and dim light) using the *Spectrace*¹⁸ dosimeter prototype. This dosimeter contains an AS7265x (AMS, Premstätten,

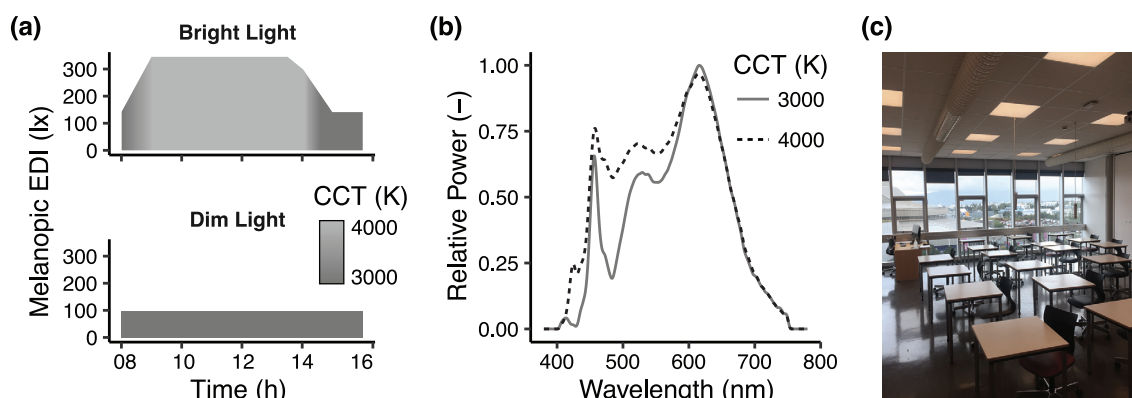


Figure 1 (a) Lighting schedule in the bright and dim light conditions, with melanopic equivalent daylight illuminance (EDI) at eye level (1.2 m) at night; (b) Relative SPD for the two CCT setpoints in a typical viewing direction towards the teacher, measured at eye height at night; (c) Image of the classroom with the dim light condition

Table 1 Lighting settings per study condition

Study condition	CCT (K)	Horizontal illuminance (lx) ^{a,b}	Vertical melanopic EDI (lx) ^{a,c}	Melanopic DER
Dim light ^d	3000	353	99	0.62
Bright light	3000–4000	500–1000	140–344	0.78

CCT: correlated colour temperature; EDI: equivalent daylight (D65) illuminance; DER: daylight (D65) efficacy ratio.

^aMean across several measurement locations in the classrooms.

^bMeasured at 0.75 m height.

^cMeasured at 1.2 m height in typical viewing direction towards the teacher.

^dEquivalent conditions during the baseline period.

Austria) spectral sensor, which collects spectral irradiance across 18 channels, with 14 channels in the visible range (410 nm to 760 nm) and four channels in the near-infrared range, with a spectral bandwidth of 22 nm full width at half maximum per channel. Note that the four near-infrared channels were not calibrated and not considered in the analyses. In addition to the spectral sensor, the dosimeter contains an illuminance, UV and activity (acceleration) sensor. The study employed two versions of the device, sampling with 30 s and 60 s epochs, respectively. The dosimeter was continuously worn during school days at chest level while awake, attached to the outer

layer of clothing and charged during sleep overnight.

2.3.2 Calibration

Each *Spectrace* dosimeter was individually calibrated against a broadband reference light spectrum after the study was conducted to post-process the collected data into meaningful quantities (i.e. spectral irradiance). The calibration setup consisted of an integrating sphere illuminated by a spectrally tuneable LED reference light source (Spectra Tune Lab, Ledmotive Technologies, Barcelona, Spain) and a reference spectroradiometer (Specbos 1201,

JETI Technische Instrumente, Jena, Germany). For each of the dosimeter's 14 channels in the visible range, a calibration factor was obtained by dividing the spectral irradiance of the reference spectrum at the wavelength corresponding to the channel peak by the raw channel output. The calibration factors were applied to the raw dosimeter data collected during the study to obtain calibrated spectral irradiance data. The calibrated data were then interpolated to 380 nm to 780 nm with a 5-nm resolution using piecewise cubic Hermite spline interpolation (*pchip* function, *signal* R package, v.0.7) to obtain approximate spectral irradiance distributions, from which spectrally integrated quantities such as melanopic EDI and CCT were calculated directly.

2.3.3 Data cleaning

Firstly, data with desynchronised timestamps due to battery loss were removed. Then, data sampled with 30 s epochs were averaged to 1 min epochs. Data collected during periods when participants were asleep were removed, with sleep derived from a separate wrist-worn actigraphy device combined with sleep logs. The remaining data were scanned for periods when the dosimeter was not worn or covered by clothing. For the detection of non-wear periods, the data from the dosimeter's activity sensor were normalised, and then scanned for continuous periods of low activity (<0.1) with a minimum length of 30 min and allowing for short interruptions up to 2 min. For the detection of periods where the dosimeter was covered, the data from the dosimeter's illuminance sensor were scanned for continuous periods of low illuminance (<1 lx) with a minimum duration of 5 min and allowing for short interruptions up to 1 min. Data when the device was not worn or covered were subsequently removed for all further analyses. In addition, for the clustering analysis, data where values from the dosimeter's illuminance sensor

were lower than 10 lx were removed to avoid spectral artefacts at low light levels.

2.4 Data analysis

In the following, the methods for clustering and classifying spectrally resolved light-dosimetry data are described. The methods are included as functions in an R package developed for the *Spectrace* dosimeter prototype, which is available on GitHub (github.com/steffenhartmeyer/spectrace), and an example R script with example data using these functions is openly available on Zenodo (<https://doi.org/10.5281/zenodo.10656733>).

2.4.1 Clustering of SPDs

One of the main goals of light exposure data collection was to characterise the spectral diets, that is, identify what general types of light spectra (e.g. daylight, LED light, fluorescent light) participants were exposed to over time. To this end, the resulting SPDs were analysed by unsupervised clustering to identify clusters of similar light spectra. A schematic overview of the clustering procedure is shown in Figure 2(a). Before clustering, the absolute SPDs (i.e. spectral irradiance distributions) were normalised such that the integral equals one to prepare for subsequent principal component analysis (PCA). Note that normalisation to the integral was chosen as it resulted in better separation of principal components than normalisation to the maximum. For clustering, the entire dataset was segregated into data during school hours (08.15 h to 15.50 h) versus outside school hours. Then, for each subset, PCA was performed (*pcomp* function, *stats* R package, v.4.2.2), from which only the principal components were retained that either individually explained more than 1% or cumulatively explained up to 95% of the variance. Finally, k-means clustering was performed (*kmeans*

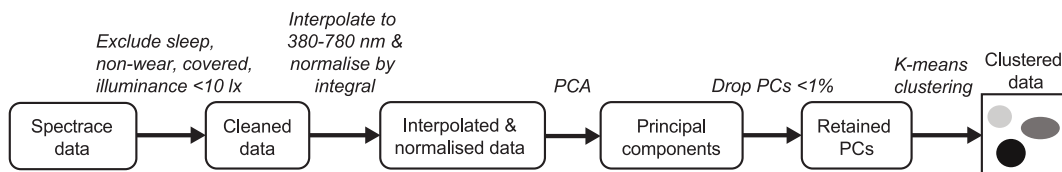
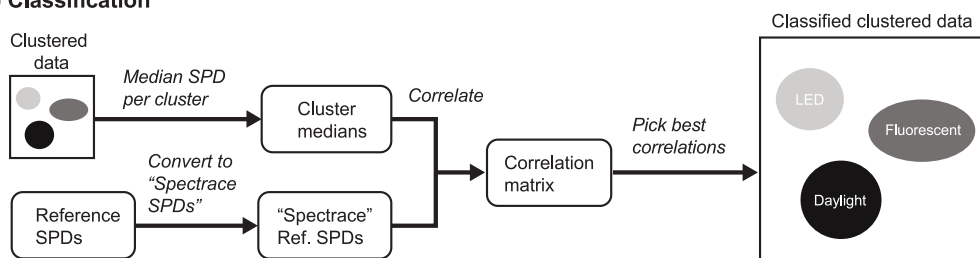
(a) Clustering**(b) Classification**

Figure 2 Schematic overview of the clustering and classification approach

function, *stats* R package, v.4.2.2) on these retained principal components, with 25 random starting partitions and a maximum of 100 iterations. The number of cluster centres (k) was selected by visually examining the clustering results for different k .

2.4.2 Classification of clusters

After clustering the data, the overall type of SPDs in each cluster was classified, schematically shown in Figure 2(b). To this end, the median SPD of each cluster was calculated and correlated with 568 measured reference light source SPDs (Figure 3) available from the literature, consisting of randomised subsets of labelled datasets with electric light source SPDs^{19,20} and outdoor SPDs at different solar elevations,²¹ as well as the intervention luminaire SPDs depicted in Figure 1(a). To correlate the cluster medians with the reference SPDs, the reference SPDs were first converted to ‘Spectrace SPDs’ by matrix multiplication with the 14-channel response curves of the dosimeter’s spectral

sensor. The spectral type of each cluster was then determined by the reference SPD with the highest Pearson correlation coefficient to the cluster median.

2.4.3 Statistical analyses

The distribution of clusters across conditions was compared using general linear mixed models (*glmer* function, *lme4* R package, v1.1-33) with a Poisson distribution, with counts of SPDs per cluster as the dependent variable, and cluster, condition and measurement period as fixed factors, and day nested within subject as a random factor. Significance testing of pairwise comparisons was performed using the *emmeans* function (*emmeans* R package, v1.8.6).

3. Results

3.1 Final dataset

Due to significant dropouts in participants across the four measurement periods and

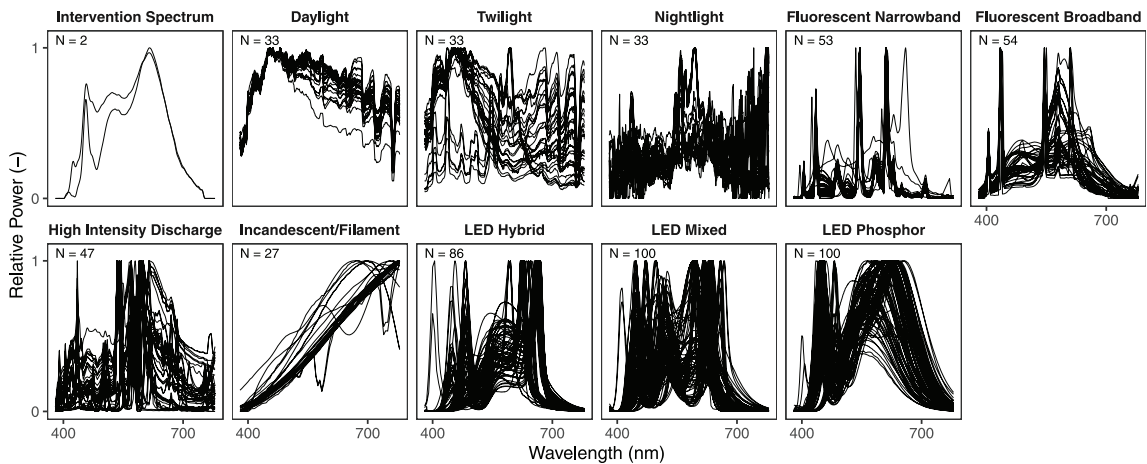


Figure 3 Reference SPDs used for classification, including the intervention SPDs (for 3000 K and 4000 K CCT setpoint) and SPDs from the literature (N = number of SPDs per spectral type)

compliance issues, we only analysed the data collected on school days during the baseline period (04 to 08 October) and the first intervention period (22 to 26 November). From the 25 participants who agreed to wear the *Spectrace* dosimeter during the baseline period, one was excluded due to insufficient valid data (defined as at least one complete day with less than 25% invalid data). Three participants subsequently dropped out for the first intervention period and from the remaining participants, four were excluded due to insufficient valid data. Thus, in total, valid data were available from 24 students (11 bright light, 13 dim light) in the baseline period and 17 students (10 bright light, 7 dim light) in the first intervention period. After the removal of invalid data (45% non-wear, 6% covered, 43% illuminance < 10 lx), the total dataset consisted of 67 116 observations (42 906 during school hours, 24 210 outside school hours). Note that the amount of valid data per day varied across participants; therefore, all analyses were carried out on the combined data from all days per measurement period.

3.2 Analysis of the spectral diet

Overall, participants were exposed to a wide variety of different SPDs throughout their school days, visualised separately for school hours versus outside school hours per measurement period and condition in Figure 4. Strikingly – and reassuringly – comparing the median SPD (indicating the central tendency of all spectra) between the two experimental groups (bright vs. dim light) shows that the median SPDs were only noticeably different between groups for school hours during the intervention period but not for school hours during the baseline period, as well as outside school hours. These results are also reflected in Pearson's correlation coefficient and the Spectral Angle Mapper metric, shown in Table 2. Moreover, the median SPDs for school hours during the intervention period reflect the respective intervention luminaire settings in each experimental group depicted in Figure 1(a).

3.2.1 Clustering of data during school hours

For clustering during school hours, seven principal components were retained, explaining a

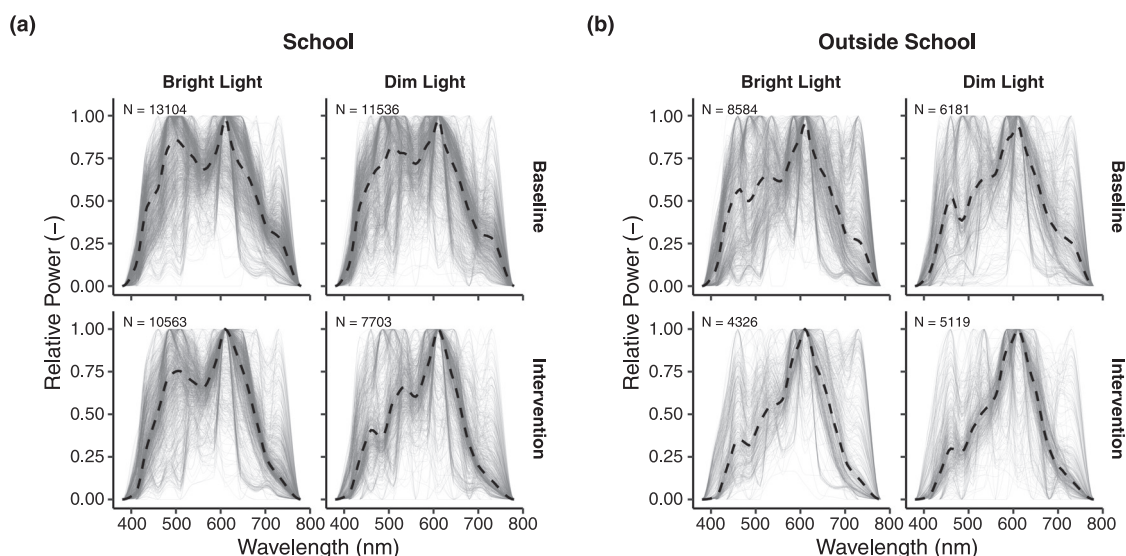


Figure 4 Measured SPDs during and outside school hours per condition and measurement period. Dashed lines indicate the median SPD. For readability purposes, only a random subset of 10% of SPDs per group is shown (N = number of the full set of SPDs per group)

Table 2. Similarity of median SPDs for different periods between experimental groups

Study period	Pearson's r	Spectral Angle Mapper
Baseline		
School hours	0.99	0.93
Outside school hours	0.99	0.91
Intervention		
School hours	0.96	0.84
Outside school hours	0.99	0.92

Spectral Angle Mapper is a similarity metric defined as the angle between two SPDs treated as N -dimensional vectors, with N being the number of bands. A value of 1 indicates a perfect match.

total variance of 97%. Clustering with seven clusters ($k=7$) was performed since higher numbers resulted in an increasingly uneven distribution of SPDs across clusters. The seven clusters were identified as SPDs related to: the

intervention setting at 3000 K (Cluster 1), the intervention setting at 4000 K (Cluster 2), daylight with higher CCTs (Cluster 3) and lower CCTs (Cluster 4), narrowband fluorescent with higher CCTs (Cluster 5) and lower CCTs (Cluster 6), and outdoor illumination at night (Cluster 7), displayed in Figure 5(a) separately for the baseline and intervention period. For all clusters, the median calculated when grouping by measurement period (group median) was similar to the cluster median, indicating that the central tendency of SPDs per cluster was similar between both periods.

The distribution of clusters was mostly similar between groups during the baseline period, with the majority of measured SPDs related to daylight in both groups (Figure 5(b)), although with significantly more SPDs related to the 4000 K intervention setting in the bright light group than the dim light group (29% vs. 23%, $p < 0.01$). In

contrast, during the intervention period, the majority of SPDs were instead related to the 3000 K and 4000 K settings, with significant differences between experimental conditions. Specifically, in the bright light condition, significantly more SPDs related to the 4000 K setting were measured compared to the 3000 K setting (50% vs. 14%, $p < 0.001$) and vice versa for the dim light condition (13% vs. 46%, $p < 0.001$). Moreover, in the bright light condition, significantly more SPDs related to daylight (Cluster 4) were measured compared to the dim light condition (15% vs. 12%, $p < 0.01$).

Differences in the distribution of clusters during the intervention period were even more apparent over time (Figure 5(c)): in the dim light condition during the morning and afternoon, the majority of measured SPDs were related to the 3000 K setting, while around midday, the proportion of SPDs related to daylight increased. In the bright light condition, the school day started with a brief period of SPDs related to the 3000 K setting, followed by SPDs related to the 4000 K setting until the early afternoon followed by a transition back to SPDs related to the 3000 K setting. For both conditions, the spectral dynamics matched the intended dynamic lighting settings during the intervention period depicted in Figure 1(b). Note that Cluster 7 was classified as SPDs related to outdoor illumination at night; however, given the occurrence of these SPDs before sunset, the SPDs might be related to high-intensity discharge lamps often encountered in sports facilities, and/or to mixtures of daylight and electric light.

Interestingly, two clusters with SPDs related to daylight were identified: Cluster 3 consisted of SPDs with more power in the shorter wavelengths, and Cluster 4 consisted of SPDs with a more broadband shape. Given the broadband shape and the higher proportion of SPDs in Cluster 4 compared to Cluster 3 during school

hours in both periods, the SPDs in Cluster 4 could be a mixture of daylight and light from electric light sources (i.e. indoors), while the SPDs in Cluster 3 might be 'pure' daylight (indoors or outdoors). Moreover, during the baseline period, a higher proportion of SPDs in Cluster 3 was observed on days with less cloud cover and higher global irradiation (i.e. more daylight) compared to overcast days. A similar trend was observed for the proportion of SPDs in Cluster 4, albeit less pronounced. This finding supports the assumption that SPDs in Cluster 3 are related to 'pure' daylight since it is likely that on sunny days, the electric lighting may have been turned off or that daylight overrode the contribution of electric lighting, as well as that the students spent more time outside during school breaks.

3.2.2 Clustering of data outside school hours

For clustering outside school hours, eight principal components were retained, explaining a total variance of 98%. Clustering with five clusters ($k=5$) was performed. The five clusters were identified as SPDs related to: daylight (Cluster 1), narrowband fluorescent (Cluster 2), phosphor-coated LED with high CCTs (Cluster 3) and low CCTs (Cluster 4), and outdoor illumination at night (Cluster 5), displayed in Figure 6(a) separately for the baseline and intervention periods. Note that daylight (Cluster 1) was very infrequently recorded during the intervention period since school ended just before sunset. Therefore, the group median was noticeably different to the cluster median, indicating that this cluster also contained spectra other than daylight. Interestingly, during both the baseline and intervention period, the most frequently recorded spectral type corresponded to warm white phosphor LEDs (median CCTs of 2712 K and 2729 K) with low median melanopic DERs (0.51 and 0.52). In contrast, participants were exposed

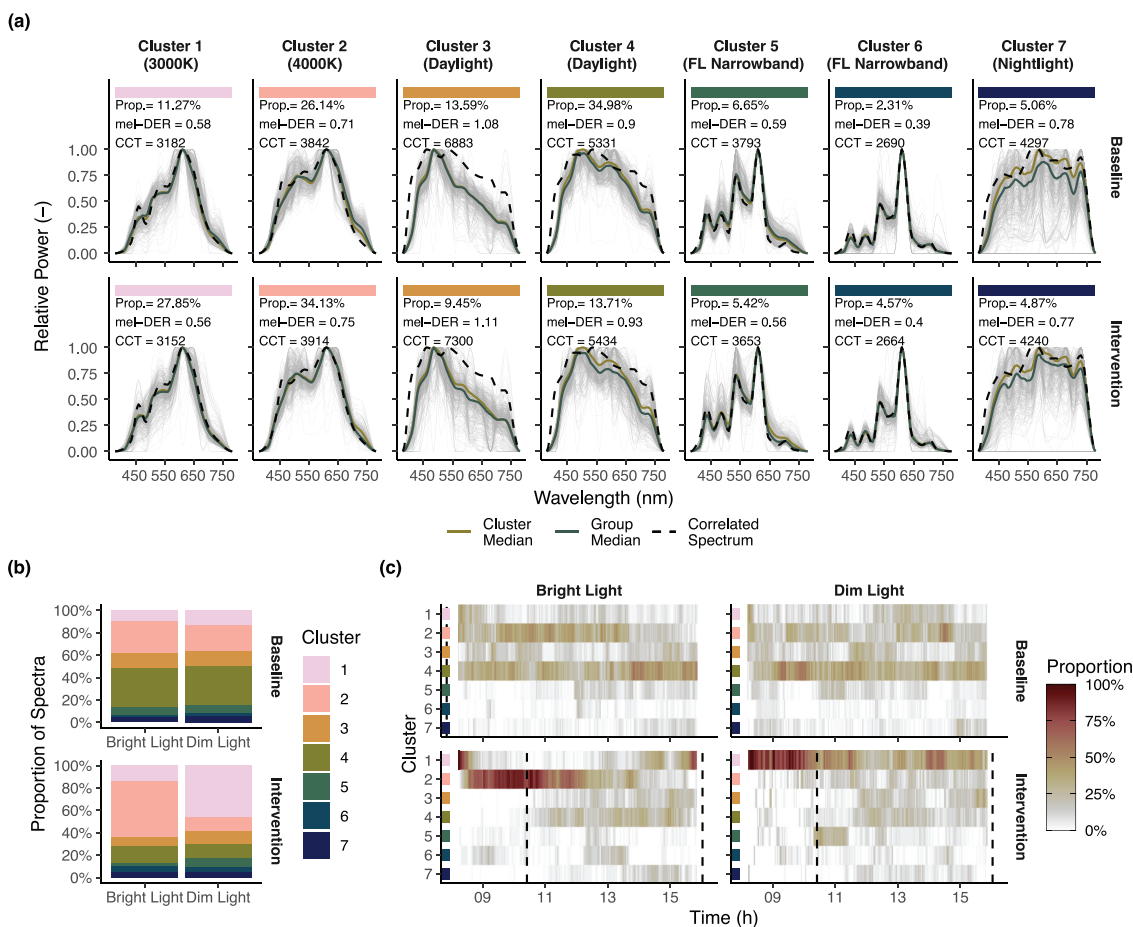


Figure 5 Results of k-means clustering of SPDs during school hours: (a) Clusters with respective cluster median and correlated reference SPD, as well as the median of cluster subset per measurement period (group median). Only a random subset of 500 SPDs per plot is shown. The proportion of SPDs, median melanopic DER and median CCT are indicated. (b) Proportion of cluster SPDs per group (condition $\times$ measurement period). (c) Proportion of cluster SPDs per group over time. Dashed lines indicate the average sunrise and sunset

to very little light from fluorescent light sources (4% to 7% of SPDs).

The distribution of clusters (Figure 6(b)) was relatively similar between experimental groups for both periods, apart from a significantly higher occurrence of SPDs related to outdoor illumination at night in the bright light group compared to the dim light group in both the baseline (30%

vs. 18%, $p=0.001$) and the intervention period (25% vs. 10%, $p < 0.001$). Significant differences were also observed between both measurement periods, notably a higher proportion of daylight in the baseline period compared to the intervention period (20% vs. 4%, $p < 0.001$). This difference is also reflected in the distribution of clusters over time (Figure 6(c)), with the

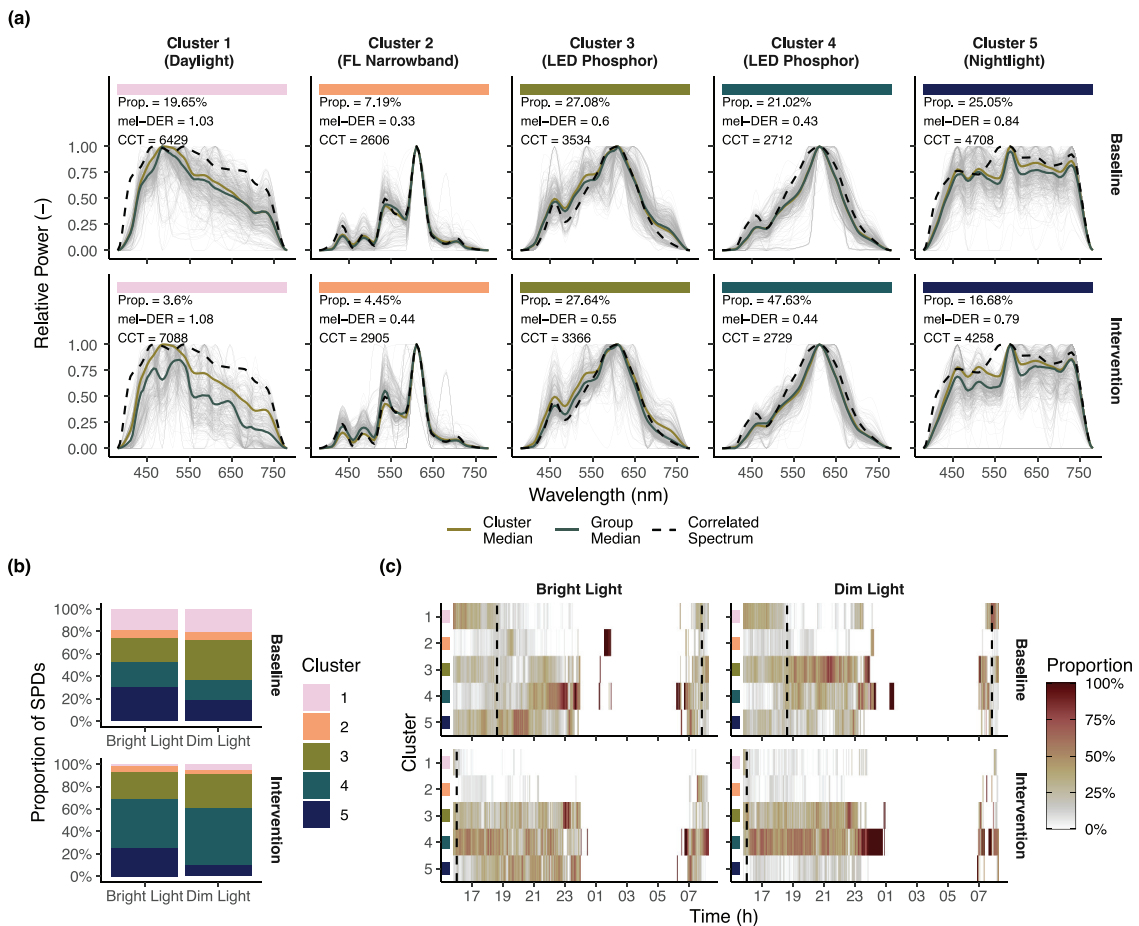


Figure 6 Results of k-means clustering of SPDs outside school hours: (a) clusters with respective cluster median and correlated reference SPD, as well as the median of cluster subset per measurement period (group median). Only a random subset of 500 SPDs per plot is shown. The proportion of SPDs, median melanopic DER and median CCT are indicated. (b) Proportion of SPDs per cluster per group (condition × measurement period). (c) Proportion of SPDs per cluster per group over time. Dashed lines indicate the average sunrise and sunset

presence of daylight clearly linked to sunrise and sunset. Furthermore, a trend for an increased presence of warm white LEDs (Cluster 4) in the later evening can be observed.

3.2.3 Melanopic EDI and CCT

To relate the spectral diet to quantities of light, we calculated the median melanopic EDI and

median CCT in 10 min bins across all school days and participants (Figure 7), revealing, for instance, that during the intervention period, levels of median melanopic EDI were generally lower than during the baseline period. Furthermore, in the baseline period during daytime, the median CCT was mostly higher than 4000 K, and melanopic EDI increased after

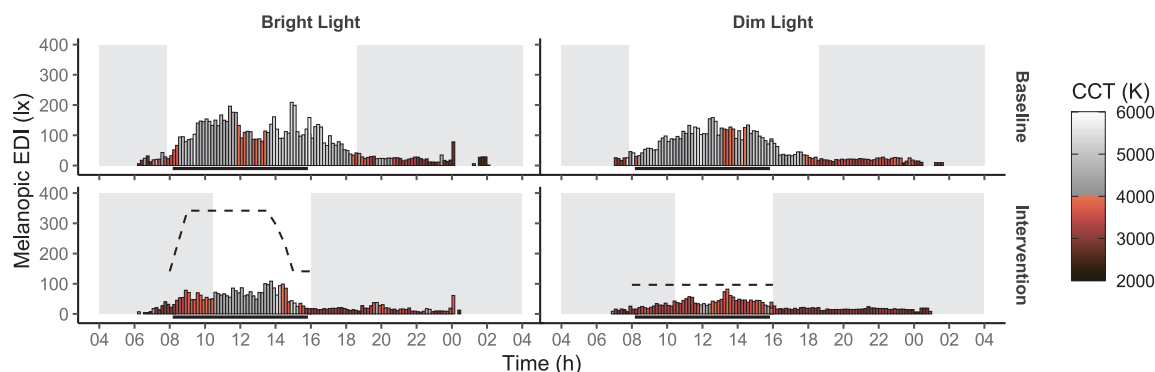


Figure 7 Median melanopic EDI and median CCT in 10 min bins across all school days. The shaded regions indicate night, the solid line school hours and the dashed lines the melanopic EDI settings of the intervention

sunrise and decreased towards sunset, following daylight in line with the clustering results. Moreover, during the intervention period, median CCTs surpassed 4000 K after sunrise and were higher during daytime in the bright light group than in the dim light group, which aligns with a significantly higher proportion of daylight in the bright light group. During night-time, median melanopic EDI levels and CCTs were generally low in both periods (~3000 K, ~35 lx). Interestingly, neither in the bright nor the dim light condition did the median melanopic EDI levels reach the target levels of the intervention (cf. Table 1).

4. Discussion

In this work, we used a relatively simple clustering and classification method to examine spectrally resolved light-dosimetry data collected during an intervention study with two experimental conditions of different CCT settings and SPDs, to exemplify what insights these kinds of data can offer. Importantly, the results show that with this analysis method, spectral types could be sufficiently discriminated, highlighted by the reassuring finding that a distinct difference in

SPDs could be observed in the intervention period during school hours, with two dominant spectral types corresponding to the SPDs of the experimental light settings.

4.1 Insights gained with spectrally resolved light-dosimetry

As described above, the results confirm that the experimental light settings were set up as intended. However, the results also show that the types of spectral distributions that were recorded depended on other factors, particularly, the presence of daylight. During both measurement periods, the proportion of SPDs related to daylight increased after sunrise, contributing to the indoor light exposure during daytime. The results show that during the intervention period, participants in the bright light group were exposed to slightly more daylight than those in the dim light group, indicating that daylight might have been a confounding factor when comparing the effects of the LED lighting settings between conditions. Since both classrooms were identical in terms of size, window area and orientation, differences in daylight exposure between classrooms could have been due to the use of blinds or curtains,

which were not controlled. Moreover, differences in daylight exposure may have been caused by different individual behaviours (e.g. spending time outdoors between classes) and class schedules.

In addition to variations in daylight exposure between classrooms, daylight availability differed between the baseline and intervention periods, due to differences in daylength (photoperiod), solar elevation and weather conditions. Given the high latitude of Reykjavik, the average daylength during the baseline period was nearly double the daylength during the intervention period (10.8 h vs. 5.6 h) and together with the higher solar elevation angle resulted in 10 times higher global solar irradiation levels during school hours in the baseline compared to the intervention period. Moreover, the intervention period was characterised by predominantly overcast sky conditions, whereas the baseline period contained three sunny days. These differences in daylight availability are clearly visible in the data, with a much higher proportion of SPDs related to daylight recorded during the baseline period compared to the intervention period. Consequently, the late sunrise and early sunset during the intervention period made the experimental conditions clearly visible in the morning and afternoon. However, in the presence of daylight, indoor lighting conditions were much harder to discern, especially during the baseline period, where it was difficult to determine whether the lighting conditions were similar between experimental groups as intended.

Beyond the potential confounding influence of daylight, it should be noted that the spectral distributions participants were exposed to could have been influenced by the spectral reflectance properties of the surfaces (e.g. colour) in the classrooms. During this study, care was taken to select two nearly identical classrooms with mainly white surfaces, thus differences due to

reflectance are unlikely. Moreover, the reference spectra characterising the SPDs for the two CCT setpoints were measured in the classrooms in the typical viewing direction of a student, thereby including any spectral alterations due to the surrounding materials. However, even if two classrooms with very different reflectance properties were compared and only the luminaire spectra were available as a reference, spectrally resolved light-dosimetry could help identify such differences in a study.

While it was beyond the scope of this paper to perform a full validation of the intervention, we would like to note the striking difference between the target melanopic EDI levels measured with a reference spectrometer at eye level and the median melanopic EDI levels recorded with the dosimeter during the intervention period. Since the measured SPDs matched the experimental settings, especially before sunrise, the hypothesis that the lights were often turned off or were set at the wrong CCT can be rejected. An explanation might be, on the one hand, that the dosimeter measurements underestimated eye level exposure due to its placement at the chest as opposed to the eye and, hence, potential shading of the sensor by the head. On the other hand, it could just as well be argued that the reference measurements slightly overestimated eye-level exposure if we consider that students are frequently looking down at their desks rather than straight ahead. Together, the actual eye level exposure may have been somewhere between the two measurements. However, it should be noted that the variation in measured melanopic EDI levels across participants and school days was very high, making it difficult to draw conclusions.

Besides verifying the experimental conditions, the data allowed insights into the spectral diets outside the 'controlled' conditions. Here, the results show that the lighting environment of participants outside school hours was predominantly

characterised by warm white LED light sources with a low melanopic DER and little fluorescent light, corresponding to current recommendations for ‘healthy’ lighting practices.²² Nevertheless, the data also shows substantial variation, indicating that this trend does not hold for all participants.

Given the novelty of employing spectrally resolved light-dosimetry to identify spectral distributions, comparable studies are scarce. To our knowledge, only one previous study¹⁶ examined spectral distributions in spectrally resolved light-dosimetry data, using heuristic approaches to classify daylight, LED, fluorescent and incandescent spectra to characterise evening lighting conditions in Australian homes. The study found a high prevalence of both fluorescent and LED lighting spanning a wide range of melanopic DERs, with higher melanopic DER being associated with higher average melanopic EDI before bed-time, which in turn was associated with a negative impact on sleep.¹⁶ Given the rapid transition to energy efficient lighting such as LEDs, both this previous study and our study underscore the importance of epidemiological research using spectrally resolved light-dosimetry in the broader population, allowing insights into the quantity of light and types of spectral distributions people are exposed to. These insights may in turn provide guidance for interventions, public health policies and education, and the lighting industry, aiming towards healthy lighting practices.

4.2 Limitations

A major limitation of this study was the low number of participants wearing the *Spectrace* dosimeter and the large number of invalid data that had to be excluded due to participants not wearing or covering the sensor. Consequently, the number of participants from whom valid light-dosimetry data was available was not

balanced between conditions and measurement periods, and some data points only reflect measurements from a few participants, thus biasing the results.

While it is remarkable that differentiation of spectral types could be achieved with 14-channel spectral irradiance measurements, the interpolated SPDs only represent an approximation of the ‘real’ light spectra participants were exposed to. Due to the limited spectral resolution, not all spectra could be successfully distinguished. Moreover, to appropriately compare the clustered SPDs to the reference SPDs, the reference SPDs were converted to ‘*Spectrace* SPDs’ based on the 14-channel response curves. This conversion may have introduced a bias, dependent on how accurately the response curves characterise the underlying mechanisms of the spectral sensor. Furthermore, due to the calibration of the dosimeter with only one light source spectrum, a calibration bias might have been introduced, given that the accuracy of recovering a given spectrum depends on the reference spectrum that was used for calibration.¹⁷ Since current standards for characterisation and calibration of photometry devices (e.g. ISO/CIE 19476:2014²³) are not directly applicable to light logging dosimeters with multiple spectral channels, updated recommendations for calibration and performance characterisation of dosimeters are urgently needed.¹¹

For clustering the data, we used PCA, a commonly used method for dimensionality reduction that is both robust and computationally efficient. However, PCA in Euclidian space does not consider that SPDs are distribution functions; therefore, other dimensionality reduction techniques, such as PCA on transport maps or autoencoder networks, may yield better separation of the data. Moreover, most unsupervised clustering methods, such as k-means (which was used here), rely on a stopping criterion to indicate a theoretic optimum number of clusters. Typically, heuristic

methods such as the within-cluster sum of squared distances ('elbow' method), silhouette score or gap statistic are used as stopping criteria. However, for the present analyses, we based the selection of the number of clusters on a visual inspection of the clustered SPDs to limit the number of clusters for meaningful comparisons.

Classification of the general spectral type of a cluster was performed by calculating the median, which treats SPDs as vectors of discrete values rather than distributions. The mathematically appropriate way to represent the central tendency of distributions is the Fréchet mean; however, here, we found that the known intervention SPDs were better matched by the median. Furthermore, the similarity between SPDs was assessed using Pearson correlation for its computational efficiency, but other distance functions such as Spectral Angle Mapper or Kullback–Leibler divergence could also be used and might perform better.²⁴ Finally, clusters might contain SPDs of different spectral types. By only comparing the reference data to the median, it is not possible to identify the range of different types in a cluster.

Another limitation of the classification approach is that the identification of spectral types is restricted to the types of spectral distributions included in the reference data. In other words, the classification can only be as good as the reference data is representative of the spectral distributions encountered during a study. Especially spectral distributions that are the result of mixed light sources (e.g. LED and daylight) or alteration due to spectral reflectance properties of surrounding surfaces (e.g. coloured surfaces) are very difficult to classify. Nevertheless, even if the reference data are not fully representative, the general type of the dominant light source (e.g. daylight, LED, fluorescent) should still be able to be classified correctly in many typical real-world scenarios.

As discussed in the previous section, potential limitations may arise from the selected

dosimeter-wearing position, influencing the conclusions that can be drawn about ocular light exposure (see Hartmeyer *et al.*¹¹ for a comprehensive review of the topic). Here, the dosimeters were worn at chest level, resulting in potential discrepancies with actual light exposure at eye level in terms of both the quantity as well as the spectral distribution of light. Especially in indoor environments, the spatial distribution of light in the field of view may substantially differ between chest and eye level placement of the dosimeter.²⁵ For example, ceiling luminaires might be in the field of view of a chest-worn dosimeter but not actually in the field of view of the participant when the gaze is directed downward towards a desk. Depending on the spectral reflectance properties of the desk surface, the spectral distribution recorded at chest level might be different from the spectral distribution at eye level. However, instances where chest-level measurements over- and underestimate light at eye level may 'average out' over time and still provide a relatively good approximation of ocular light exposure.²⁵

4.3 A new era for (spectrally resolved) light-dosimetry

In the last few years, the topic of light-dosimetry has gained more and more attention. With a growing understanding of the relation between light exposure and human health and well-being, the need for measuring and characterising personal light exposure patterns in the broader population is higher than ever.⁶ Especially, the importance of measuring relevant quantities of light (e.g. α -opic quantities) has been recognised, and new (spectrally resolved) dosimeters are currently being developed by several research groups to address this need. Simultaneously, efforts are underway to formalise guidelines for light-dosimetry, such as standards on how to characterise and calibrate

dosimeters (CIE JTC20, MeLiDos EURAMET project), approaches to assess how to quantify personal light exposure data,¹⁰ and recommendations on what metadata to include with light-dosimetry datasets. With all these efforts underway, new opportunities arise to rethink how we look at our relationship with light. Approaches such as the one described here may only scratch the surface of what we could be able to do with spectrally resolved data. Better classification algorithms could allow more detailed insights into the types of spectra people are exposed to in their everyday lives, allowing researchers and lighting designers to better understand the environments experienced by their subjects. Development of novel sensor technologies or spectral reconstruction algorithms could enable more accurate measurement of SPDs, which in turn might enable to assess the spectral sensitivity of visual and non-visual functions in real life. The possibilities are there; a new era for (spectrally resolved) light-dosimetry is underway.

5. Conclusion

This study is among the first to collect personal light exposure data at a relatively high spectral resolution. While spectrally resolved light-dosimetry is still in its infancy, the interest in such data is high, and various projects are underway to develop spectrally resolved dosimeters for use in light-dosimetry studies. Here, we present first insights into the spectral diet of participants in an intervention field study, demonstrating that it is feasible to measure and identify the types of light spectra people are individually exposed to over time (i.e. their 'spectral diet'). With these analyses, we verified the experimental conditions of the study and identified the dominant types of light sources participants were exposed to outside of the experimental conditions. Our findings highlight the impact of daylight on individual spectral diets and lighting

intervention protocols. While it is remarkable that these findings were achieved with a simple analysis approach, further development of the clustering and classification method may improve the insights that can be gained. Taken together, we show that spectrally resolved light-dosimetry can offer multiple benefits and allow novel insights into spectral diets, which can contribute to an advancement of our understanding and, consequently, improvement of our modern life with light.

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