INSIGHTS INTO SPECTRALLY RESOLVED LIGHT-DOSIMETRY DATA

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Abstract

Modern life in predominantly indoor environments has led to a profound alteration in the amount, spectral composition, and pattern of light humans are daily exposed to. Given the role of light in health and wellbeing, and with the aim 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 composition 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. To process the collected data, unsupervised clustering was performed and clusters were classified using various reference spectra. The results show that different spectral types can not only be sufficiently well discriminated but 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.

Keywords: Light-Dosimetry, Daylight, Non-Visual, Circadian, Spectral Measurement

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 (Blume *et al.,* 2019). 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 composition, or *spectral quality,* of light arriving at the eye. As we are constantly exposed to different quantities and spectral qualities of light, personal light exposure can be thought of as a "spectral diet" (Webler *et al.,* 2019).

In modern societies humans spend most of their time in indoor environments (Schweizer *et al.*, 2007), illuminated by a combination of electric light sources and daylight. This shift to indoor-dominated lifestyles profoundly altered the amount, spectral composition, and temporal pattern of light that humans are daily exposed to (Lunn *et al.* 2017), compared to the natural conditions under which humans have evolved (Wright *et al.,* 2013). Given the importance of light not only for vision but also for general health and wellbeing (Vetter *et al.,* 2021), 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 (Lunn et al., 2017; Mason *et al.,* 2018; Stevens *et al.* 2014). 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 (Hartmeyer and Andersen, 2023; Spitschan *et al.*, 2022).

Light-dosimetry is performed with wearable light sensors, also called dosimeters, that are able to continuously measure relevant quantities of light. While many dosimeters used in previous research are limited to measurements of illuminance or spectral irradiance across three channels (Hartmeyer *et al.* 2022), for quantifying the spectral composition of light, dosimeters with a higher spectral resolution are required. Such spectrally resolved light-dosimetry allows to get 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, spectrally resolved data allow to easily calculate weighted quantities of light directly from the measured spectrum itself (e.g., illuminance, α-opic quantities, correlated color temperature), without the need for specific sensor channels for each quantity.

To date, only few published studies have collected light-dosimetry data at a higher spectral resolution. Therefore, in this paper we present analyses of spectrally resolved light-dosimetry data collected as part of an intervention study investigating the effects of a dynamic lighting system on high school students in Reykjavik, Iceland. The aim of the present paper is to show 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, 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 schoolyear September 2021 to May 2022 in a high school in Reykjavik, Iceland (64.15° N). The study included two experimental conditions implemented in the school's classrooms: a dynamic bright light setting and a static dim lighting setting using tuneable LED fixtures with different spectral power distributions (SPD) shown in Figure 1a, and different correlated color temperatures (CCT), melanopic equivalent daylight illuminances (mel-EDI), and melanopic equivalent daylight efficacy ratios (mel-DER) described in Table 1. In the bright light setting, the lighting was dynamically adjusted during the school day, as depicted in Figure 1b. Personal light exposure data were collected during a one-week baseline period in October with the dim light setting in all classrooms and subsequently for three one-week intervention periods across the schoolyear 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.

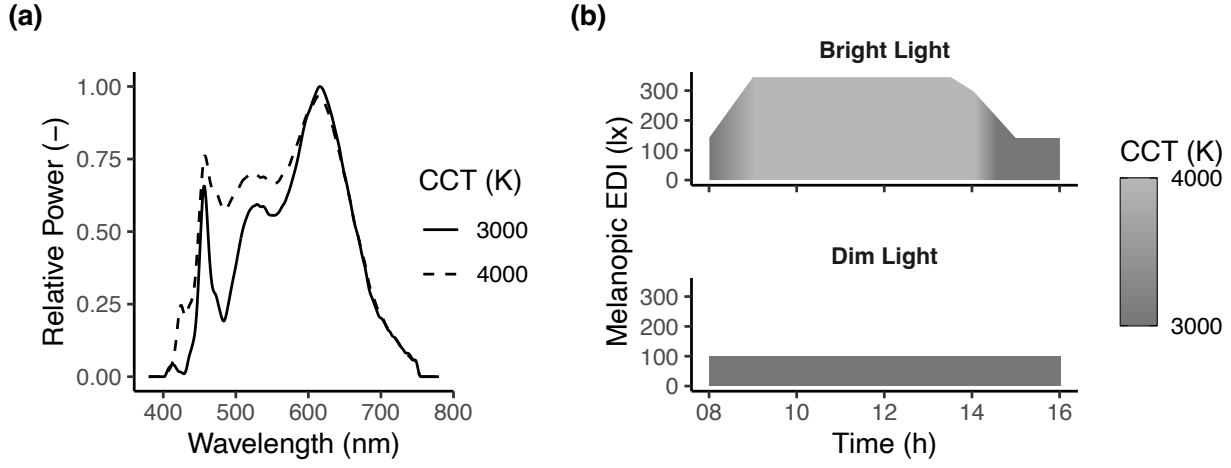

Figure 1 – (a) Spectral power distribution of luminaires for the two CCT settings; (b) Lighting schedule in the bright and dim light conditions, with melanopic EDI at eye-level.

Table 1 – Lighting settings per study condition.

Experimental Condition	CCT (K)	Horizontal Illuminance (lx)[1]	Vertical mel-EDI (lx)[1]	mel-DER
Baseline and Dim Light	3000	353	99	0.62
Bright Light	3000–4000	500–1000	140–344	0.78

[1] Mean across several measurement locations in classroom.
Note. CCT = correlated color temperature, mel-EDI = melanopic equivalent daylight (D65) illuminance, mel-DER = melanopic daylight (D65) efficacy ratio.

2.2 Light-dosimetry

2.2.1 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* (Webler *et al.,* 2021) dosimeter prototype. This dosimeter contains an AS7265x (AMS, Austria) spectral sensor, which collects spectral irradiance across 18 channels, with 14 channels in the visible range (410–760 nm)[1], with a spectral bandwidth of 22 nm full width at half maximum per channel. In addition, the dosimeter contains an illuminance, UV, and activity sensor. Two versions of the device were employed in the study, sampling with 30s and 60s epochs, respectively. The dosimeter was continuously worn at chest-level while awake, attached to the outer layer of clothing, and charged during sleep overnight.

2.2.2 Calibration

Each *Spectrace* dosimeter was individually calibrated against a broadband reference light spectrum after the study was conducted to be able to post-process the collected data into meaningful quantities. 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 380–780 nm with a 5 nm resolution using piecewise cubic Hermite spline interpolation to obtain approximate SPDs.

2.2.3 Data cleaning

First, data with desynchronised timestamps due to battery loss were removed. Then, data sampled with 30s epochs were averaged to 1min 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 30min and allowing for short interruptions up to 2min. 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 5min and allowing for short interruptions up to 1min.

2.3 Data analysis

2.3.1 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 etc.) participants were exposed to over time. To this end, the resulting SPDs were analysed by unsupervised clustering to identify clusters of similar light spectra. Before clustering invalid data were removed, specified as data when the device was not worn or covered, and, in addition, data where values from the dosimeter's illuminance sensor were lower than 10 lx to avoid spectral artifacts at low light levels. Then the SPDs were normalised such that the integral

[1] The sensor contains four near-infrared channels, which were not calibrated and not considered in the analyses.

equals one[2] to prepare for subsequent principal component analysis (PCA). For clustering, the entire dataset was segregated into data during school hours (08:15–15:50) vs. 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 variance. Finally, k-means clustering was performed (*kmeans* function, *stats* R package, v.4.2.2) on these retained principal components, with 25 random starting partitions and maximum 100 iterations. The number of cluster centres (*k*) was selected through visual inspection of the clustering results for different *k*.

2.3.2 Classification of clusters

To classify the overall type of SPD per cluster, the median SPD of each cluster was calculated and correlated with 568 measured reference light source SPDs (Figure 2) available from the literature, consisting of randomised subsets of labelled datasets with electric light source SPDs (Houser *et al.*, 2022; Royer, 2020) and outdoor SPDs at different solar elevations (Spitschan *et al.*, 2016), as well as the intervention luminaire SPDs depicted in Figure 1a. 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.

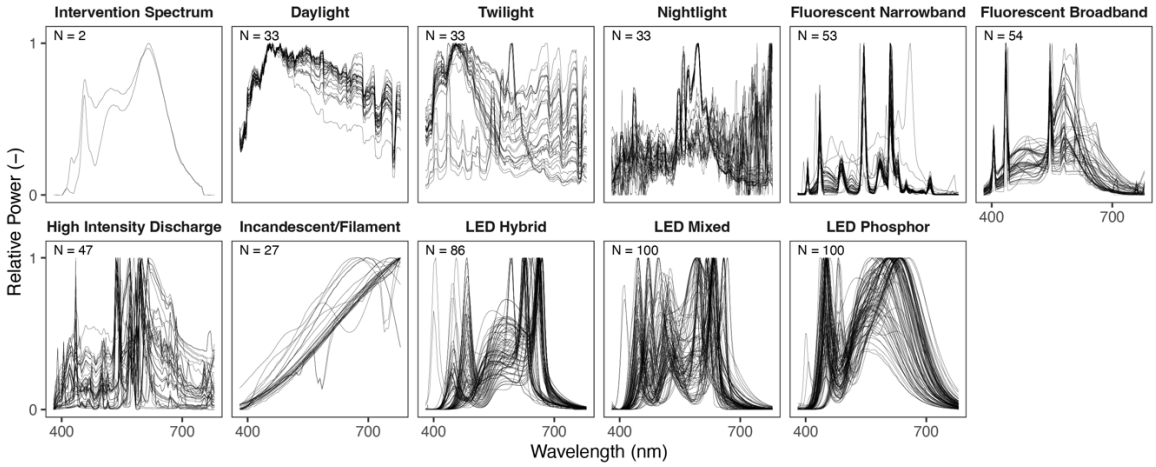

Figure 2 – Reference spectral power distributions (SPDs) used for classification, including the intervention SPDs and SPDs from the literature (*N* = number of SPDs per spectral type).

2.3.3 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 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 compliance issues, we only analysed the data collected on school days during the baseline period (04–08 October) and the first intervention period (22–26 November), for which data from 24 (11 bright light, 13 dim light) and 17 (10 bright light, 7 dim light) students, respectively, were available. After removal of invalid data (45 % non-wear, 6 % covered, 43 % illuminance <10 lx), the total dataset consisted of 67116 observations (42906 during school hours, 24210 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.

[2] Normalisation to the integral led to better separation of principal components than normalisation to the maximum.

3.2 Analysis of the spectral diet

Overall, participants were exposed to a wide variety of SPDs throughout their school days, visualised separately for school hours vs. outside school hours per measurement period and condition in Figure 3. 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 SPDs were very similar during school hours in the baseline period (SAM[3] = 0.93) and outside school hours in both periods (SAM = 0.91 and 0.92). In contrast, in the intervention period during school hours, the median SPDs were noticeably different between the two conditions (SAM = 0.84), with median SPDs similar to the respective intervention luminaire settings depicted in Figure 1a.

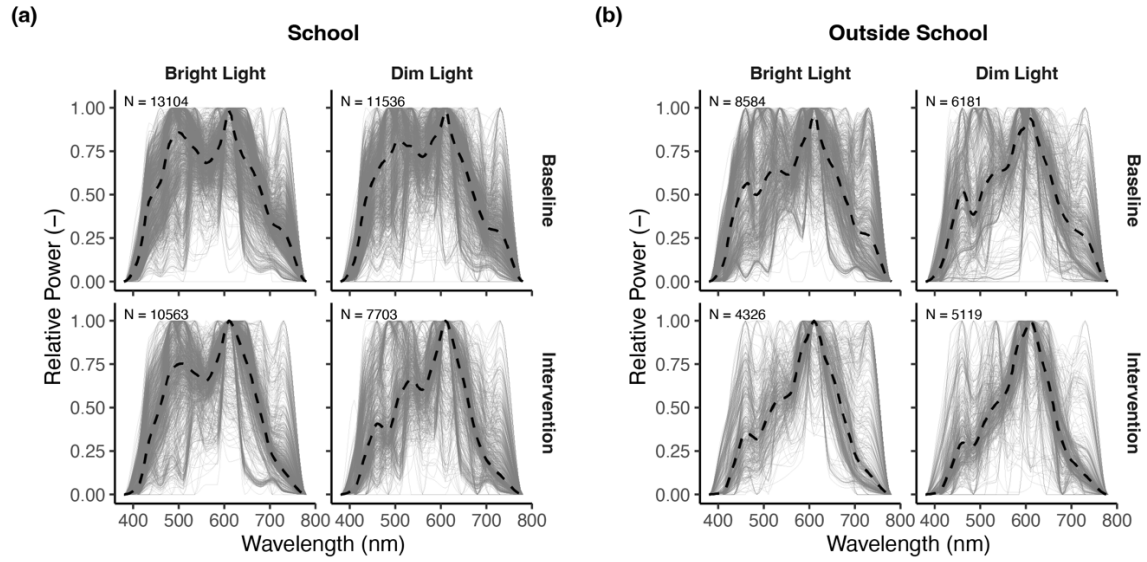

Figure 3 – Measured spectral power distributions (SPDs) during school hours and outside school hours per condition and measurement period. Dashed lines indicate the median SPD. For readability purposes, only a random subset of 10% of SPDs per group is shown.

3.2.1 Clustering of data during school hours

For clustering during school hours, seven principal components were retained, explaining a 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 4a 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 4b), 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 < .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 < .001) and vice versa for the dim light condition (13 % vs. 46 %, p < .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 < .01).

[3] SAM = Spectral Angle Mapper. 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.

Differences in the distribution of clusters during the intervention period were even more apparent over time (Figure 4c): 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 1b. 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.

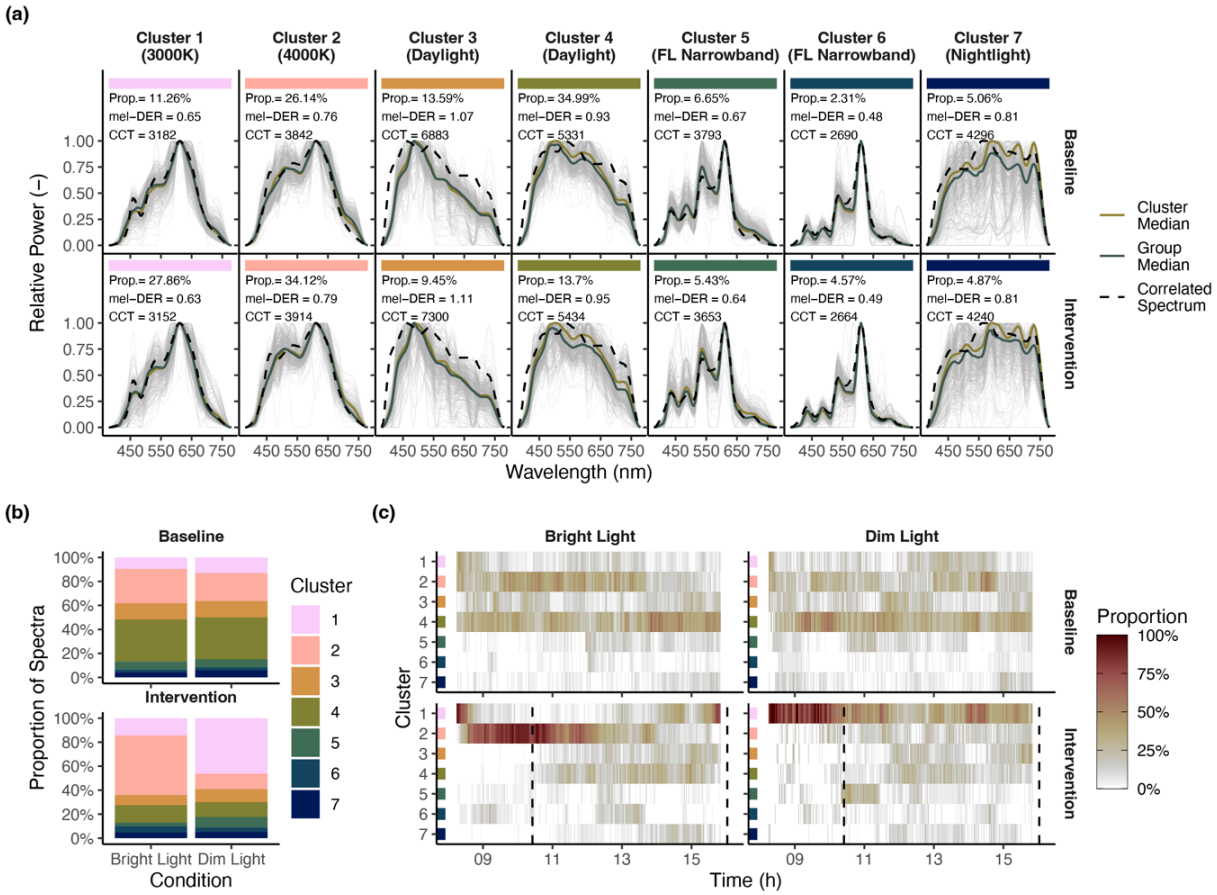

Figure 4 – Clustering of spectral power distributions (SPDs) during school hours: (a) Clusters with respective cluster median and correlated reference SPD, as well as median of cluster subset per measurement period (group median). Only a random subset of 500 SPDs per plot is shown. The proportion of SPDs, median melanopic DER and median CCT are indicated. (b) Proportion of cluster SPDs per group (condition × measurement period). (c) Proportion of cluster SPDs per group over time. Dashed lines indicate average sunrise and sunset.

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 5a 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 mel-DERs (0.51 and 0.52). In contrast, participants were exposed to very little light from fluorescent light sources (4 % – 7 % of SPDs).

The distribution of clusters (Figure 5b) 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 = .001) and the intervention period (25 % vs. 10 %, p < .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 < .001). This difference is also reflected in the distribution of clusters over time (Figure 5c), with the 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.

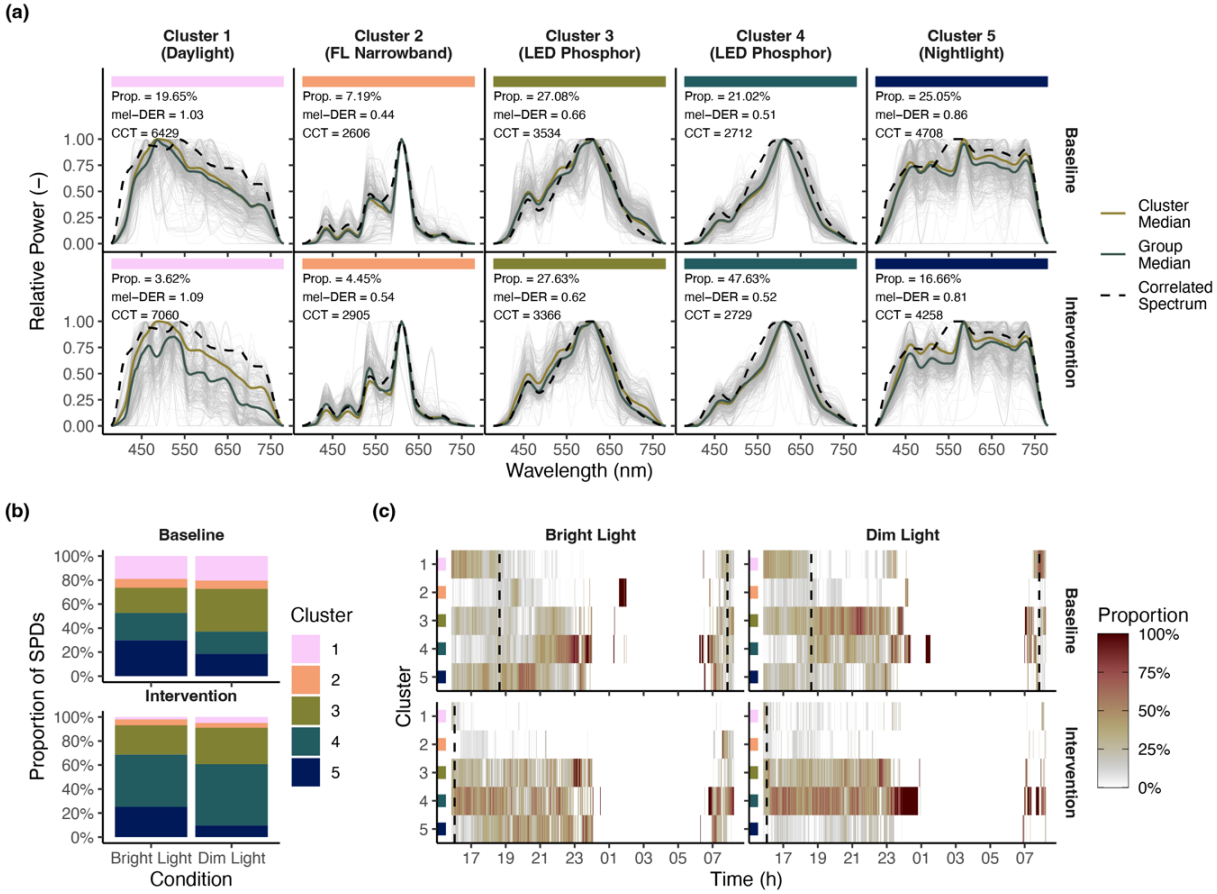

Figure 5 – Clustering of spectral power distributions (SPDs) outside school hours: (a) clusters with respective cluster median and correlated reference SPD, as well as median of cluster subset per measurement period (group median). Only a random subset of 500 SPDs per plot is shown. The proportion of SPDs, median mel-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 average sunrise and sunset.

3.2.3 Melanopic EDI and CCT

To relate the spectral diet to quantities of light, we calculated the median mel-EDI and median CCT[4] in 10min bins across all school days and participants (Figure 6), revealing, for instance, that during the intervention period, levels of median mel-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 mel-EDI increased after 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 is in line with a significantly higher proportion of daylight in the bright light group. During night-time, median mel-EDI levels and CCTs were generally low in both periods (~3000K, ~35 lx). Interestingly, neither in the bright nor dim light condition did the median mel-EDI levels reach the target levels of the intervention (cf. Table 1).

[4] Calculated using McCamy's approximation.

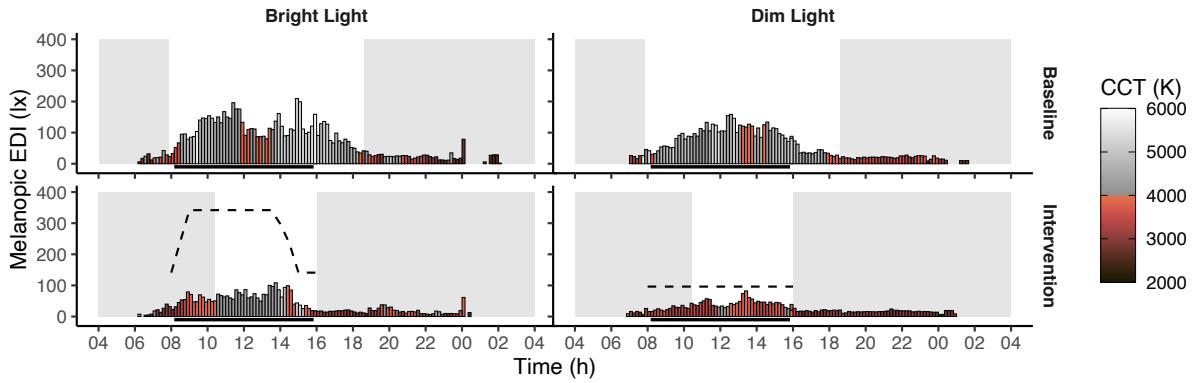

Figure 6 – Median melanopic equivalent daylight illuminance (mel-EDI) and median correlated colour temperature (CCT) in 10min bins across all school days. The shaded regions indicate night, the solid line school hours, and the dashed lines the mel-EDI settings of the intervention.

4 Discussion

In this work we used a 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, with the aim 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 What insights were 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 spectral types that were recorded depended on other factors, in particular, the presence of daylight. Specifically, the proportion of SPDs related to daylight increased after sunrise, with participants in the dim light group being exposed to significantly less daylight than those in the bright light group, possibly due to the use of window shading (e.g., curtains). These results indicate that daylight might have been a confounding factor in this study since daylight in the classrooms was not controlled.

Given the high latitude of Reykjavik, the average daylength during the baseline period was nearly double the daylength during the intervention period (10.8h vs. 5.6h). This substantial difference was 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 allowed the experimental conditions to be clearly visible in the morning and afternoon. However, in the presence of daylight, indoor lighting conditions were much harder to discern, as observed during the baseline period, where it was difficult to determine whether the lighting conditions were similar between experimental groups as intended.

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 mel-EDI levels measured with a reference spectrometer at eye-level and the median mel-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 turned off or were set at the wrong CCT can be excluded. 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 shading of the sensor by the head. But 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 on their desk 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 mel-EDI levels across participants and schooldays was very high, making it difficult to draw conclusions.

Beside verifying the experimental conditions, the data also allowed insights into the spectral diets outside of the “controlled” conditions. Here, the results how that the lighting environment of participants outside school hours was characterised by mostly warm white LED light sources with a low mel-DER and little fluorescent light, corresponding to current recommendations for lighting practices (Brown *et al*., 2022). Nevertheless, the data also shows substantial variation, indicating that this trend does not hold for all participants. As a comparison, a previous study using spectrally resolved light-dosimetry in Australia has found a much higher proportion of fluorescent light and higher mel-DERs in the three hours before bedtime (Cain *et al.*, 2021).

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 dosimeter, or too low measured light levels. In addition, the number of participants was not balanced between conditions and measurement periods. Consequently, some data points only reflect measurements from a few participants, thus biasing the results.

While it is remarkable that a 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 that 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 accurate the response curves characterise the underlying mechanisms of the spectral sensor. Furthermore, due to 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 (Webler, 2022). Since current standards for characterisation and calibration of photometry devices (e.g., ISO/CIE 19476:2014; CIE, 2014), are not directly applicable to light logging dosimeters with multiple spectral channels, updated recommendations for calibration and performance characterisation of dosimeters are urgently needed (Hartmeyer *et al.*, 2022).

For clustering the data, we used PCA, which is a commonly used method for dimensionality reduction that is both robust and computationally efficient. However, PCA in Euclidian space disregards 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 median resulted in a better match to the known intervention SPDs. 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 (Deborah *et al.* 2015). 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. Currently, we are developing a semi-supervised clustering and classification approach using autoencoder networks, aiming to achieve a better clustering and classification performance that would allow to estimate the composition of clusters in terms of different spectral types.

5 Conclusion

This study is one of 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 for 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 were able to verify the experimental conditions of the study and identify dominant types of light sources participants were exposed to outside of the experimental conditions. Our findings also 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 allows to get novel insights into spectral diets, which we hope contributes to an advancement of our understanding and consequently improvement of our modern life with light.

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