Open-source Python module for the analysis of personalized light exposure data from wearable light loggers and dosimeters

Grégory Hammad[1, 2], Katharina Wulff[3, 4], Debra J. Skene[5], Mirjam Münch[6, 7], Manuel Spitschan[8, 9, 10, *]

1 Sleep & Chronobiology Group, GIGA – CRC in vivo imaging, University of Liège, *Belgium*
2 Chair of Neurogenetics, Institute of Human Genetics, University Hospital, Technical University of Munich, Munich, *Germany*
3 Departments of Radiation Sciences and Molecular Biology, Umea University, Umea, *Sweden*
4 Wallenberg Centre for Molecular Medicine (WCMM), Umea University, Umea, *Sweden*
5 Chronobiology, Faculty of Health and Medical Sciences, University of Surrey, Guildford, *UK*
6 Centre for Chronobiology, Psychiatric Hospital of the University of Basel, Basel, *Switzerland*
7 Transfaculty Platform for Molecular and Cognitive Neuroscience, University of Basel, Basel, *Switzerland*
8 Translational, Sensory & Circadian Neuroscience, Max Planck Institute for Biological Cybernetics, Tübingen, *Germany*
9 Chronobiology & Health, Department of Sport and Health Sciences (TUM SG), Technical University of Munich, Munich, *Germany*
10 TUM Institute for Advanced Study, Technical University of Munich, Garching, *Germany*

* Corresponding author

Abstract (250 words)

Light exposure fundamentally influences human physiology and behavior, with light being the most important *zeitgeber* of the circadian system. Throughout the day, people are exposed to various scenes differing in light level, spectral composition and spatio-temporal properties. Personalized light exposure can be measured through wearable light loggers and dosimeters, including wrist-worn actimeters containing light sensors, yielding time series of an individual's light exposure. There is growing interest in relating light exposure patterns to health outcomes, requiring analytic techniques to summarize light exposure properties. Building on the previously published Python-based *pyActigraphy* module, here we introduce the module *pyLight*. This module allows users to extract light exposure data recordings from a wide range of devices. It also includes software tools to clean and filter the data, and to compute common metrics for quantifying and visualizing light exposure data. For this tutorial, we demonstrate the use of pyLight in three examples: (1) loading, accessing and visual inspection of a publicly available dataset, (2) truncation, masking, filtering and binarization of the dataset, (3) calculation of summary metrics, including time above threshold (TAT) and mean light timing above threshold (MLiT). The *pyLight* module paves the way for open-source, large-scale automated analyses of light-exposure data.

Introduction

Light exposure profoundly affects human physiology and behaviour, including entrainment of the circadian clock, the production of the hormone melatonin, alertness and mood. These effects are mediated primarily by the intrinsically photosensitive retinal ganglion cells (ipRGCs) in the retina expressing the short-wavelength sensitive photopigment melanopsin (1–10). The ipRGCs project to a wide range of different brain areas, including the master biological clock in the hypothalamus, the suprachiasmatic nuclei (SCN) signalling timekeeping information (11–14).

The so-called 'non-visual 'effects of light are receiving attention from a variety of professionals, including neuroscientists, psychologists, lighting designers, architects, interdisciplinary scientists, regulators, and the general public (15–17). Moreover, negative consequences from potentially insufficient indoor illumination during daytime and excessive light exposure in the evening from light-emitting devices, namely light in the short-wavelength range, are increasingly recognized. Recently, recommendations for optimal ambient light exposure levels have been developed, proposing optimal light levels for daytime, evening and night-time light exposure (18) and exemplifying the translation of recent scientific findings in this field into practice.

In parallel to research uncovering the impact of light on human physiology and behaviour, small, light loggers, which are wearable devices measuring personalized light exposure over extended periods, have been developed (19). Light loggers include commercial wrist-worn light sensors built into actimetry devices (e.g., Actigraph wGT3X-BT, Actigraph Headquarters; Pensacola, FL, USA; CamNTech Actiwatch 4 / Motionwatch-8 CamNTech, Fenstanton, UK; Condor ActTrust1/2, Condor, Sao Pãolo, Brazil), brooches and pendants (e.g., Lys, Lys Technologies, Copenhagen, Denmark) and research-grade near-corneal-plane light loggers (e.g. LuxBlick (20,21), lido (22)). There is a large and growing set of studies using light loggers (20,21,23–37), differing in calibration properties, position, data pre-processing and recording intervals (19).

A dominant factor in light exposure is exposure to daylight (38), which is given by illumination due to the Earth's rotation. However, an individual's personal light exposure shows great variability over time (39), depending on light availability in the environment (indoors vs. outdoors; different lighting and window designs, types of light sources used), activities (outdoor and indoor activities at work, school, at home) and individual behaviour (eye movements). Due to this variability, light exposure data must be measured individually in a personalized fashion, and cannot be predicted simply from environmental measurements.

The availability of personalized light exposure data requires the development of analytical and statistical tools, for which a series of metrics have been proposed (19). While various open-source tools have been developed to perform analysis of light data in general, including the web-based *luox* platform (https://luox.app/, (40)), *LuxPy* (41), and *colour* (42) for the calculation of quantities from spectral and colorimetric data, none of these calculate exposure metrics from time-series light exposure data.

To facilitate the analysis of light exposure data, we introduce an open-source Python module for the analysis of time-series data. This module, termed pyLight, is part of and extends the previously published open-source *pyActigraphy* Python package (43), which implements functions for the loading, processing and analysis of actigraphy data. In this article, we will introduce the module, describe the contained functions and demonstrate the use of the module, with a specific focus on importing data, manipulating data, and calculating exposure metrics from the data. To our knowledge, pyLight is the only software package allowing for the convenient calculation of light metrics within a common API.

-
-
-
-
-

Overview of pyLight

Overall architecture

The *pyLight* module has been designed to be used independently within the *pyActigraphy* package. The module interfaces with the existing infrastructure of *pyActigraphy*. The basis of *pyLight* is a generic class holding the light exposure data. Via multiple inheritance, this class provides access to a list of analysis metrics dedicated to light exposure data analysis. Derived classes can then easily be implemented to support and read various native file formats from different light exposure devices. An example of such a class is provided by the '*GenLightDevice* ' class of *pyLight*.

Accessing data from different devices

In addition, for each device supported by *pyActigraphy* (e.g., Actigraph wGT3X-BT, Actigraph Headquarters; Pensacola, FL, USA; CamNTech Actiwatch 4 / Motionwatch-8 CamNTech, Fenstanton, UK; Condor ActTrust1/2, Condor, São Paolo, Brazil), the *pyLight* base class is able to handle the light exposure data recorded by these specific devices through a common API.

Calculation of light exposure metrics

pyLight implements a series of light exposure metrics. These exposure metrics can be applied to a range of different light logger-measured quantities, including photopic illuminance or melanopic equivalent daylight illuminance (mEDI), and other quantities derived from spectral or multi-channel light logger measurements. As the metrics are generally agnostic to the exact quantity, in the below, we use the placeholder term “light exposure”.

Aggregated statistics: Means, medians and other summary statistics can be calculated over the entire recording or over user-defined periods.

Threshold-based metrics: pyLight allows for the calculation of the time spent above a user-defined threshold (time above threshold; TAT) as well as the mean light timing above threshold (MLiT) developed by Reid and colleagues (44). The MLiT metric is defined as:

$$MLiT(C) = \frac{\sum_j^m \sum_k^n j \times I_{jk}(C)}{\sum_j^m \sum_k^n I_{jk}(C)}$$

Where I_{jk} is 1 if the light exposure intensity is above the threshold $C_{\square}$ in j-th daily period on the k-th day and 0 otherwise, j is the index of the j-th daily period, n is the number of daily period (e.g., 1440 for light exposure data measured every minute) and k is the number of days in the recording. This variable computes the time of day around which the mean light exposure above the threshold $C_{\square}$ is centred. The TAT is simply the number of minutes above the defined threshold $C_{\square}$. $C_{\square}$ is user-defined, thereby allowing for the probing of several different thresholds.

L5 and M10 metrics. Calculation of time of day and mean value of light exposure during the 5 hours window of least exposure or the 10 hours of maximal exposure (45). L5 and M10 metrics are extreme values within these periods, without regard to the average light exposure.

Inter-daily stability (IS) and intradaily variability (IV). These metrics have primarily been used to quantify rest-activity rhythms obtained from actigraphy studies (46). IS quantifies the stability of the daily pattern across days, while IV represents its fragmentation across the day. IS and IV have recently been applied to light exposure patterns and related to rest-rhythms (47).

Mathematically, IS and IV are are defined as:

$IS = \frac{n\sum_h^p(\bar{x}_h-\bar{x})^2}{p\sum_i^n(x_i-\bar{x})^2}$ and for interdaily stability (IS) and

$IV = \frac{n\sum_i^{n-1}(x_{i+1}-x_i)^2}{(n-1)\sum_i^n(x_i-\bar{x})^2}$ for intradaily variability (IV), where $\bar{x}_h$ is the average light exposure over all the h-th periods across all days, x_j is the light exposure during the j-th periods, $\bar{x}$ is the overall mean light exposure, n is the number of periods contained in the recording and p is the number of daily periods. IS is simply the 24-h value of the chi-square periodogram, normalised by the number of periods, n (48).

Transformations: Data can be transformed conveniently into logarithmic scales.

Masking and data selection

A crucial step prior to the analysis of the light exposure data is the processing of raw data, i.e., removing light data where the device was not worn, or covered by sleeves (for wrist worn devices). To implement these preprocessing steps, the *pyLight* module offers various methods to mask periods of data acquisitions, either by only reading a specific continuous period of data defined by a user-defined start and stop time, or by adding periods where the unwanted data are masked, thereby not contributing to any subsequent analysis. Such periods can either be defined manually or specified in a separate file for easier editing and storage (see online tutorial at https://ghammad.github.io/pyActigraphy/pyLight-DataManip.html#Masking). In addition summary statistics, such as mean, median, percentiles or standard deviations, as well as MLiT or TAT, can be obtained for consecutive or arbitrary time windows.

At present, there is no consensus on how light exposure data should be processed. Users of *pyLight* must understand that inclusion and exclusion of specific periods based on criteria may lead to biases of data, and we recommend an in-depth analysis of selection criteria.

Resampling and filtering

Another critical aspect of data processing covered by pyLight is resampling and filtering data before analysis. Often, fluctuations occurring at the acquisition frequency (e.g. tenths of a second) are considered irrelevant for the analysis of light exposure levels. To deal with these fluctuations, the *pyLight* module offers the possibility to resample the data to a specified frequency and aggregate periods with a custom function (sum, mean, median, etc). The module also allows users to digitally filter specific frequencies using a Butterworth filter.

Thresholding and binarization

Sometimes it is useful to only consider data above a specific threshold. Thresholded data can either be used a such, data below the threshold are simply discarded, or transformed into binary

data, where data above the threshold are replace with 1 and 0 otherwise. The *pyLight* module provides various methods to directly access raw, thresholded or binarized data.
For some metrics, (e.g. TAT and MLiT), it is possible to directly specify the threshold used for the computation of such metrics.

Documentation

The documentation of the *pyLight* module is integrated into the documentation of the *pyActigraphy* package, which contains installation and "Quick Start" instructions for users, information about the authors, a code of conduct and the code license. The documentation is generated automatically from source code annotations and published. The list of online tutorials for *pyActigraphy* has been extended with specific tutorials for the *pyLight* module. Such tutorials are particularly useful for teaching users with various levels of programming expertise how to use all the functionalities available in the module. They start with basic instructions about how to read and visualize light exposure data, progress with examples on how to manipulate light exposure data (masking, resampling, thresholding, etc) and finish with more advanced code lines to compute specific light exposure metrics.

Code availability

The code, documentation and two additional tutorials are open-source and available on GitHub (https://github.com/ghammad/pyActigraphy). The code base repository is licensed under the GNU General Public License v3.0. When the module is used for calculations, please cite this paper along with the original pyActigraphy publication (43).

Contributing

Researchers wishing to contribute to the pyLight module are welcome to do so by issuing pull requests on the pyActigraphy GitHub repository (https://github.com/ghammad/pyActigraphy).

A worked example

Basics

The following worked example will guide the reader on how to use the *pyLight* module by performing the analysis of a publicly available data set of actigraphy data licensed under the CC0 1.0 Universal (CC0 1.0) Public Domain Dedication license (49). The data, collected with the

Respironics Actiwatch Spectrum Pro (Respironics, Bend, OR, USA), were analysed in two other publications (50,51).

Requirements

1. To follow this example, basic knowledge and a working installation of Python is a prerequisite. Many operating systems (including macOS and Linux) already come with a Python installation, but for others, it needs to be installed. The reader is pointed to the official Python website (https://wiki.python.org/moin/BeginnersGuide/Download) for instructions, but this information can be conveniently obtained through any web search engine. In addition, the pyActigraphy package must be installed (see https://ghammad.github.io/pyActigraphy/index.html#installation for instructions). This can be done using *pip*, the Python package management system.
2.
3.
4.
5.

Example

As in any Python script, the first step consists in importing the necessary modules. As already mentioned, *pyLight* is actually an independent module of the pyActigraphy package. Therefore, we simply start by importing it. Other packages are used for convenience:

```
import pyActigraphy
# Import the logarithm base 10 function from the default python math package
from math import log10
# Package for tabular data manipulation
import pandas as pd
# Package for statistical analysis
import pingouin as pg
# Package for interactive plotting
import plotly.graph_objects as go
```

Now, we define the path to the data to analyse:

```
# Adapt the path to the actual path
fpath = '/path/to/data'
```

The data files are stored in two different directories. One, CLIENT, is for data from chronic insomnia participants and the other, PARTNERS, is for data from their respective partners.

Individual data analysis

Since these data were acquired with Respironics devices, we use the dedicated reader function, *read_raw_rpx*, from the IO module of pyActigraphy to read the input data file:

```
raw = pyActigraphy.io.read_raw_rpx(
    fpath+'CLIENT/C1025_Acti1_Treatment_6_09_2016_2_52_00_PM_New_Analysis.csv',
    language='ENG_UK',
    period='6D', # Restrict data to the first 6 days.
)
```

As usual in python, more information about this function can be obtained with:

```
help(pyActigraphy.io.read_raw_rpx)
```

The input file contains both locomotor activity and light data. The latter can easily be accessed through the attribute 'light' which holds an object of class 'LightRecording':

```
raw.light
```

To inspect which light channels were found in this recording:

```
raw.light.get_channel_list()
```

returns a list with the names of the light channels.

To visualize the data, we can plot all the light channels contained in the recording (Fig.1):

```
layout = go.Layout(
    title="Light exposure data",
    xaxis=dict(title="Date time"),
    yaxis=dict(title="$\log_{10}(\mathrm{Light~intensity}+1)$"),
    showlegend=True
)
fig = go.Figure(
    data=[
        go.Scatter(
            x=raw.light.get_channel(channel).index.astype(str),
            y=raw.light.get_channel(channel),
            name=channel,
        )
        for channel in raw.light.get_channel_list()
    ],
    layout=layout
)
fig.show() # Interactive figure display
```

To save the figure to a file for later use, the function write_image can be used:

```
fig.write_image('fig_ind_light.png', scale=6)
```

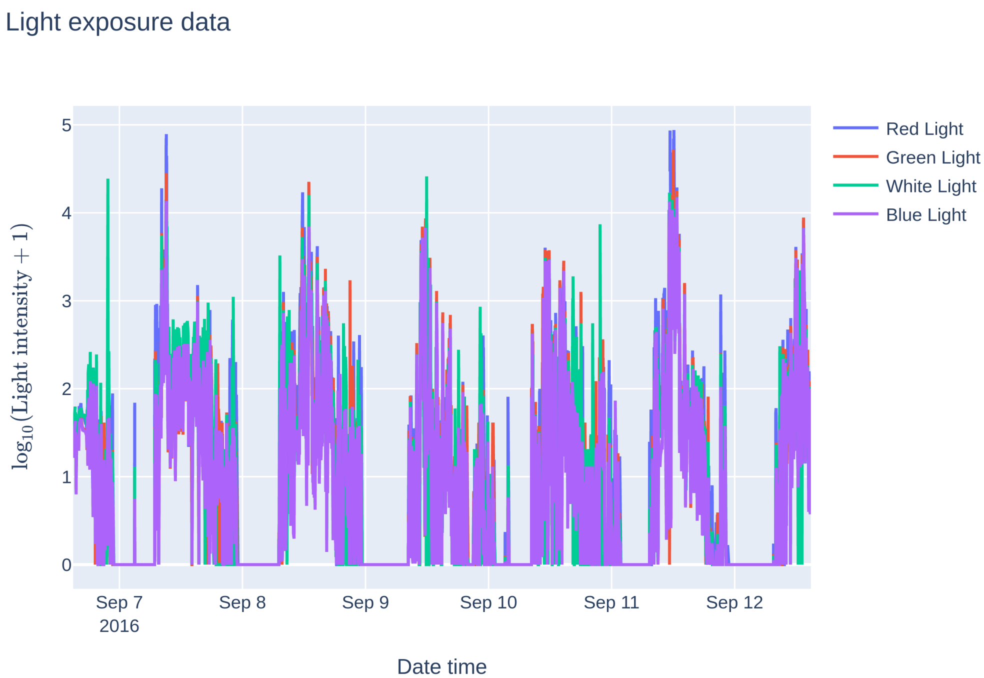

Fig. 1. Time series of light exposure levels

Now that we have visually inspected our data, we can compute various light exposure metrics as follows:

Exposure Levels with data thresholded at $log_{10}(100+1)$.

light_expo_lvl = raw.light.light_exposure_level(threshold=log10(100+1))

light_expo_lvl.name = ‘Level_100' # Set the name for latter re-use

Time above threshold (TAT), setting the threshold at $log_{10}(100+1)$ and time in minutes

light_tat = raw.light.TAT(threshold=log10(100+1), oformat='minute')

light_tat.name = ‘TAT_100'

Mean light timing (MLiT), setting the threshold at $log_{10}(500+1)$

light_mlit = raw.light.MLiT(threshold=log10(500+1))

light_mlit.name = 'MLit_500'

These function outputs are stored in pandas.Series objects that can easily be manipulated and concatenated into a summary table (pandas.DataFrame) that can be used for further statistical analysis or saved to a file:

```
results = pd.concat([light_expo_lvl, light_tat, light_mlit],axis=1)

results.to_csv(‘tab1.csv')
```

Group-level analysis

Visualisation and inspection of individual data are an import step in any analysis. However, this step is performed and the data are deemed suitable to analysis, it might be useful to read individual files by batch and compute metrics at the group level.

Here, we will show how to read all data files from bother clients and partners, compute various metrics and compare both groups.

To read multiple files at once, we can use the *read_raw* function from the IO module of *pyActigraphy*:

```
clients = pyActigraphy.io.read_raw(
    fpath+'CLIENT/C*.csv', reader_type='RPX', period='6D', language='ENG_UK', n_jobs=5
)
partners = pyActigraphy.io.read_raw(
    fpath+'PARTNER/P*.csv', reader_type='RPX', period='6D', language='ENG_UK', n_jobs=5
)
```

Both the ‘clients’ and ‘partners’ objects store data, extracted from each individual files. Therefore, it is possible to loop over this individual data and compute the requested metrics.

Here, we will save the metric outputs to separate lists and then concatenate them to form a summary table:

```
# Declare empty lists
light_expo_lvls = []
light_tats = []
light_mlits = []

# Loop over all the LightRecording objects contained in ‘clients’:
for iread in clients.readers:
    # Compute light exposure levels:
    light_expo_lvl = iread.light.light_exposure_level(threshold=log10(100+1))
    light_expo_lvl.name = iread.name # set name to participant’s name
    light_expo_lvls.append(light_expo_lvl) # store output in its dedicated list

    # Compute time above threshold:
    light_tat = iread.light.TAT(threshold=log10(100+1), oformat='timedelta')
    light_tat.name = iread.name # set name to participant’s name
    light_tats.append(light_tat) # store output in its dedicated list

    # Compute mean light timing:
    light_mlit = iread.light.MLiT(threshold=log10(500+1))
    light_mlit.name = iread.name # set name to participant’s name
    light_mlits.append(light_mlit) # store output in its dedicated list
```

Once the loop is completed, individual results are concatenated into group-level summary tables:

```
clients_light_expo_lvl_results = pd.concat(light_expo_lvls,axis=1).T
clients_light_tat_results = pd.concat(light_tats,axis=1).T
clients_light_mlit_results = pd.concat(light_mlits,axis=1).T
```

Again, since the summary tables are pandas.DataFrame, it is possible to save them to .csv files for further use:

```
clients_light_expo_lvl_results.to_csv('tab_clients_expo_100.csv')
clients_light_tat_results.to_csv('tab_clients_tat_100.csv')
clients_light_mlit_results.to_csv('tab_clients_mlit_500.csv')
```

To analyse the partner’s data, it simply requires to substitute the ‘clients’ object by the ‘partners’ object and then re-use the same code for iterating over individual files:

```
# Reset lists before storing individual results:
light_expo_lvls = []
light_tats = []
light_mlits = []
for iread in partners.readers: # here, clients has been changed to partners.
    light_expo_lvl = iread.light.light_exposure_level(threshold=log10(100+1))
    light_expo_lvl.name = iread.name
    light_expo_lvls.append(light_expo_lvl)

    light_tat = iread.light.TAT(threshold=log10(100+1), oformat='minute')
    light_tat.name = iread.name
    light_tats.append(light_tat)

    light_mlit = iread.light.MLiT(threshold=log10(500+1))
    light_mlit.name = iread.name
    light_mlits.append(light_mlit)

# Concatenate individual results for the partners
partners_light_expo_lvl_results = pd.concat(light_expo_lvls,axis=1).T
```

```
partners_light_tat_results = pd.concat(light_tats,axis=1).T
partners_light_mlit_results = pd.concat(light_mlits,axis=1).T
# Save results to .csv files
partners_light_expo_lvl_results.to_csv('tab_partners_expo_100.csv')
partners_light_tat_results.to_csv('tab_partners_tat_100.csv')
partners_light_mlit_results.to_csv('tab_partners_mlit_500.csv')
```

These summary files can now serve as input for statistical analyses, for example, or for visual representation of the results (Fig. 2):

```
fig = go.Figure()
fig.add_trace(go.Box(
    y=clients_light_expo_lvl_results.loc[:,'White Light'],
    name='Clients',
    marker_color='darkblue',
    #boxmean=True
))
fig.add_trace(go.Box(
    y=partners_light_expo_lvl_results.loc[:,'White Light'],
    name='Partners',
    marker_color='royalblue',
    #boxmean=True
))
fig.update_layout(yaxis_title=r'Mean light exposure level', height=500,width=500);
# Display box plot
```

```
fig.show()
```

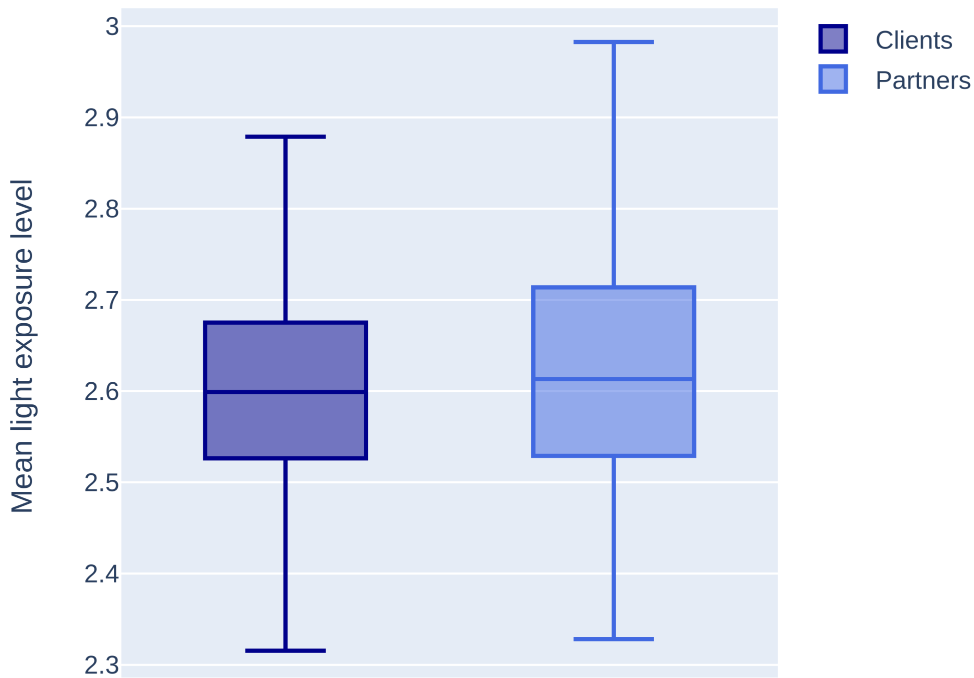

Fig. 2. Boxplot of the mean light exposure level for clients and partners.

```
# Save
fig.write_image('fig_grp_explevel.png', scale=6)
```

Future directions

As more light loggers and dosimeters are being developed, the pyLight module will serve as a useful software entry point for the analysis of data produced by these devices. pyLight is future-proof in that it can perform its calculations in a device-agnostic manner, as long as the data stored on the device are accessible and use an open format. Using a programmatic approach to light exposure facilitates sensitivity analyses in which thresholds in threshold-based metrics (such as TAT and MLiT) are varied systematically and the effect on a response variable is observed (52). As the field of light logging and dosimetry matures, pyLight can be expanded to account for newly developed metrics, and can serve as a benchmark for alternative software solutions.

Conclusion

In conclusion, we presented pyLight, an extension to pyActigraphy, designed for the analysis of light exposure data. The module reports a series of light exposure metrics, which can be applied on a range of different existing file formats. We have presented a worked example demonstrating the use of the pyLight module on a previously published actigraphy data set containing light exposure.

References

1. Provencio I, Rodriguez IR, Jiang G, Hayes WP, Moreira EF, Rollag MD. A novel human opsin in the inner retina. J Neurosci. 2000 Jan 15;20(2):600–5.

2. Berson DM, Dunn FA, Takao M. Phototransduction by retinal ganglion cells that set the circadian clock. Science. 2002 Feb 8;295(5557):1070–3.

3. Hattar S, Liao HW, Takao M, Berson DM, Yau KW. Melanopsin-containing retinal ganglion cells: architecture, projections, and intrinsic photosensitivity. Science. 2002 Feb 8;295(5557):1065–70.

4. Lucas RJ, Hattar S, Takao M, Berson DM, Foster RG, Yau KW. Diminished pupillary light reflex at high irradiances in melanopsin-knockout mice. Science. 2003 Jan 10;299(5604):245–7.

5. Rollag MD, Berson DM, Provencio I. Melanopsin, ganglion-cell photoreceptors, and mammalian photoentrainment. J Biol Rhythms. 2003 Jun;18(3):227–34.

6. Lucas RJ, Peirson SN, Berson DM, Brown TM, Cooper HM, Czeisler CA, et al. Measuring and using light in the melanopsin age. Trends Neurosci. 2014 Jan;37(1):1–9.

7. Do MTH. Melanopsin and the Intrinsically Photosensitive Retinal Ganglion Cells: Biophysics to Behavior. Neuron. 2019 Oct 23;104(2):205–26.

8. Mure LS. Intrinsically photosensitive retinal ganglion cells of the human retina. Front Neurol. 2021 Mar 25;12:636330.

9. Schmidt TM, Chen SK, Hattar S. Intrinsically photosensitive retinal ganglion cells: many subtypes, diverse functions. Trends Neurosci. 2011 Nov;34(11):572–80.

10. Spitschan M. Melanopsin contributions to non-visual and visual function. Current Opinion in Behavioral Sciences. 2019 Dec;30:67–72.

11. Hannibal J, Hindersson P, Østergaard J, Georg B, Heegaard S, Larsen PJ, et al. Melanopsin Is expressed in PACAP-containing retinal ganglion cells of the human retinohypothalamic tract. Invest Ophthalmol Vis Sci. 2004 Nov 1;45(11):4202.

12. Weaver DR. The suprachiasmatic nucleus: a 25-year retrospective. J Biol Rhythms. 1998 Apr;13(2):100–12.

13. Welsh DK, Takahashi JS, Kay SA. Suprachiasmatic nucleus: cell autonomy and network properties. Annu Rev Physiol. 2010;72:551–77.

14. Hastings MH, Maywood ES, Brancaccio M. Generation of circadian rhythms in the suprachiasmatic nucleus. Nat Rev Neurosci. 2018 Aug;19(8):453–69.

15. Stefani O, Cajochen C. Should We Re-think Regulations and Standards for Lighting at Workplaces? A Practice Review on Existing Lighting Recommendations. Front Psychiatry. 2021 May 13;12:652161.

16. Houser KW, Esposito T. Human-Centric Lighting: Foundational Considerations and a Five-Step Design Process. Front Neurol. 2021 Jan 27;12:630553.

17. Vetter C, Pattison PM, Houser K, Herf M, Phillips AJK, Wright KP, et al. A review of human physiological responses to light: Implications for the development of integrative lighting solutions. LEUKOS. 2022 Jul 3;18(3):387–414.

18. Brown TM, Brainard GC, Cajochen C, Czeisler CA, Hanifin JP, Lockley SW, et al. Recommendations for daytime, evening, and nighttime indoor light exposure to best support physiology, sleep, and wakefulness in healthy adults. PLoS Biol. 2022 Mar;20(3):e3001571.

19. Hartmeyer S, Webler F, Andersen M. Towards a framework for light-dosimetry studies: Methodological considerations. Lighting Research & Technology. 2022 Jul 19;147715352211032.

20. Hubalek S, Brink M, Schierz C. Office workers' daily exposure to light and its influence on sleep quality and mood. Lighting Research & Technology. 2010;42(1):33–50.

21. Hubalek, S, Zöschg, D., Schierz, C. LuxBlick – A measurement device for recording corneal illuminance and effective irradiance regarding unspecific biological effects [Abstracts from the 17th annual meeting of the society for light treatment and biological rhythms (Eindhoven, the Netherlands)]. Chronobiology International. 2006 Jan;23(3):695–746.

22. Stampfli J, Schrader B, di Battista C, Häfliger R, Schälli O, Wichmann G, et al. The Light-Dosimeter: A new device to help advance research on the non-visual responses to light. Lighting Research & Technology. 2023 Feb 13;147715352211471.

23. Woelders T, Beersma DGM, Gordijn MCM, Hut RA, Wams EJ. Daily Light Exposure Patterns Reveal Phase and Period of the Human Circadian Clock. J Biol Rhythms. 2017 Jun;32(3):274–86.

24. Wams EJ, Woelders T, Marring I, van Rosmalen L, Beersma DGM, Gordijn MCM, et al. Linking Light Exposure and Subsequent Sleep: A Field Polysomnography Study in Humans. Sleep. 2017 Dec 1;40(12).

25. Aarts MPJ, van Duijnhoven J, Aries MBC, Rosemann ALP. Performance of personally worn dosimeters to study non-image forming effects of light: Assessment methods. Building and Environment. 2017;117:60–72.

26. Markvart J, Hansen ÅM, Christoffersen J. Comparison and Correction of the Light Sensor Output from 48 Wearable Light Exposure Devices by Using a Side-by-Side Field Calibration Method. Leukos. 2015;11(3):155–71.

27. Smolders KCHJ, de Kort YAW, van den Berg SM. Daytime light exposure and feelings of vitality: Results of a field study during regular weekdays. Journal of Environmental Psychology. 2013;36:270–9.

28. Figueiro MG, Hamner R, Bierman A, Rea MS. Comparisons of three practical field devices used to measure personal light exposures and activity levels. Light Res Technol. 2013 Aug;45(4):421–34.

29. Jardim AC, Pawley MD, Cheeseman JF, Guesgen MJ, Steele CT, Warman GR. Validating the use of wrist-level light monitoring for in-hospital circadian studies. Chronobiol Int. 2011 Nov;28(9):834–40.

30. Scheuermaier K, Laffan AM, Duffy JF. Light exposure patterns in healthy older and young adults. J Biol Rhythms. 2010 Apr;25(2):113–22.

31. Thorne HC, Jones KH, Peters SP, Archer SN, Dijk DJ. Daily and Seasonal Variation in the Spectral Composition of Light Exposure in Humans. Chronobiology International. 2009 Jan;26(5):854–66.

32. Dumont M, Beaulieu C. Light exposure in the natural environment: relevance to mood and sleep disorders. Sleep Med. 2007 Sep;8(6):557–65.

33. Bierman A, Klein TR, Rea MS. The Daysimeter: a device for measuring optical radiation as a stimulus for the human circadian system. Measurement Science and Technology. 2005;16(11):2292–9.

34. Okudaira N, Kripke DF, Webster JB. Naturalistic studies of human light exposure. Am J Physiol. 1983 Oct;245(4):R613-615.

35. Campbell SS, Kripke DF, Gillin JC, Hrubovcak JC. Exposure to light in healthy elderly subjects and alzheimer's patients. Physiology & Behavior. 1988;42(2):141–4.

36. Savides TJ, Messin S, Senger C, Kripke DF. Natural light exposure of young adults. Physiology & Behavior. 1986;38(4):571–4.

37. Spitschan M, Smolders K, Vandendriessche B, Bent B, Bakker JP, Rodriguez-Chavez IR, et al. Verification, analytical validation and clinical validation (V3) of wearable dosimeters and light loggers. DIGITAL HEALTH. 2022 Jan;8:205520762211448.

38. Münch M, Wirz-Justice A, Brown SA, Kantermann T, Martiny K, Stefani O, et al. The Role of Daylight for Humans: Gaps in Current Knowledge. Clocks Sleep. 2020 Mar;2(1):61–85.

39. Spitschan M. Time-Varying Light Exposure in Chronobiology and Sleep Research Experiments. Frontiers in Neurology [Internet]. 2021 [cited 2022 Oct 20];12. Available from: https://www.frontiersin.org/articles/10.3389/fneur.2021.654158

40. Spitschan M, Mead J, Roos C, Lowis C, Griffiths B, Mucur P, et al. luox: novel validated open-access and open-source web platform for calculating and sharing physiologically relevant quantities for light and lighting. Wellcome Open Res. 2021 Jun 3;6:69.

41. Smet KAG. Tutorial: The LuxPy Python Toolbox for Lighting and Color Science. LEUKOS. 2020 Jul 2;16(3):179–201.

42. Mansencal, Thomas, Mauderer, Michael, Parsons, Michael, Shaw, Nick, Wheatley, Kevin, Cooper, Sean, et al. Colour 0.4.1 [Internet]. Zenodo; 2022 [cited 2022 Nov 17]. Available from: https://zenodo.org/record/605791

43. Hammad G, Reyt M, Beliy N, Baillet M, Deantoni M, Lesoinne A, et al. pyActigraphy: Open-source python package for actigraphy data visualization and analysis. Schneidman-Duhovny D, editor. PLoS Comput Biol. 2021 Oct 19;17(10):e1009514.

44. Reid KJ, Santostasi G, Baron KG, Wilson J, Kang J, Zee PC. Timing and Intensity of Light Correlate with Body Weight in Adults. Mistlberger RE, editor. PLoS ONE. 2014 Apr 2;9(4):e92251.

45. Van Someren EJ, Kessler A, Mirmiran M, Swaab DF. Indirect bright light improves circadian rest-activity rhythm disturbances in demented patients. Biol Psychiatry. 1997 May 1;41(9):955–63.

46. Witting W, Kwa IH, Eikelenboom P, Mirmiran M, Swaab DF. Alterations in the circadian rest-activity rhythm in aging and Alzheimer's disease. Biol Psychiatry. 1990 Mar 15;27(6):563–72.

47. Kim SJ, Lim YC, Kwon HJ, Lee JH. Association of rest–activity and light exposure rhythms with sleep quality in insomnia patients. Chronobiology International. 2020 Mar 3;37(3):403–13.

48. Sokolove PG, Bushell WN. The chi square periodogram: its utility for analysis of circadian rhythms. J Theor Biol. 1978 May 8;72(1):131–60.

49. Angelova M, Kusmakar S, Karmakar C, Zhu Y, Shelyag S, Drummond S, et al. Chronic insomnia and bed partner actigraphy data [Internet]. Dryad; 2020 [cited 2023 Sep 5]. p. 18036133 bytes. Available from: https://datadryad.org/stash/dataset/doi:10.5061/dryad.b8gtht7bh

50. Kusmakar S, Karmakar C, Zhu Y, Shelyag S, Drummond SPA, Ellis JG, et al. A machine learning model for multi-night actigraphic detection of chronic insomnia: development and validation of a pre-screening tool. R Soc open sci. 2021 Jun;8(6):202264.

51. Mellor A, Hamill K, Jenkins MM, Baucom DH, Norton PJ, Drummond SPA. Partner-assisted cognitive behavioural therapy for insomnia versus cognitive behavioural therapy for insomnia: a randomised controlled trial. Trials. 2019 Dec;20(1):262.

52. Peeters ST, Smolders KCHJ, Kompier ME, De Kort YAW. Let Me Count the Light. Accounting for Intensity, Duration and Timing of Light When Predicting Sleep and Subjective Alertness in Field Studies. LEUKOS. 2022 Oct 2;18(4):417–37.

1.
2.