OPTICA
Advancing Optics and Photonics Worldwide

Technical Groups

Measuring light, color, spectrum and personalized light exposure using wearable light sensors

Featuring John Maule, Janine Stampfli, Björn Schrader, Forrest webler, Vineetha Kalavally

11 February 2022

Technical Group Executive Committee

Francisco Imai
Chair of the Color Technical Group

Rigmor C. Baraas
University of South-Eastern Norway

Javier Hernandez-Andres
Universidad de Granada

About the Color Technical Group

Our technical group focuses on all aspects related to the physics, physiology, and psychology of color in biological and machine vision.

Our mission is to connect the 900+ members of our community through technical events, webinars, networking events, and social media.

Our past activities have included:

- Special webinar on display calibration
- Vision science in times of social distancing bi-weekly coffee breaks
- Incubator meetings

Connect with the Color Technical Group

Join our online community to stay up to date on our group's activities. You also can share your ideas for technical group events or let us know if you're interested in presenting your research.

Ways to connect with us:

- Our website at www.optica.org/VC
- On Twitter at #OSAColorTG
- On LinkedIn at www.linkedin.com/groups/13573604
- Email us at TGactivities@optica.org

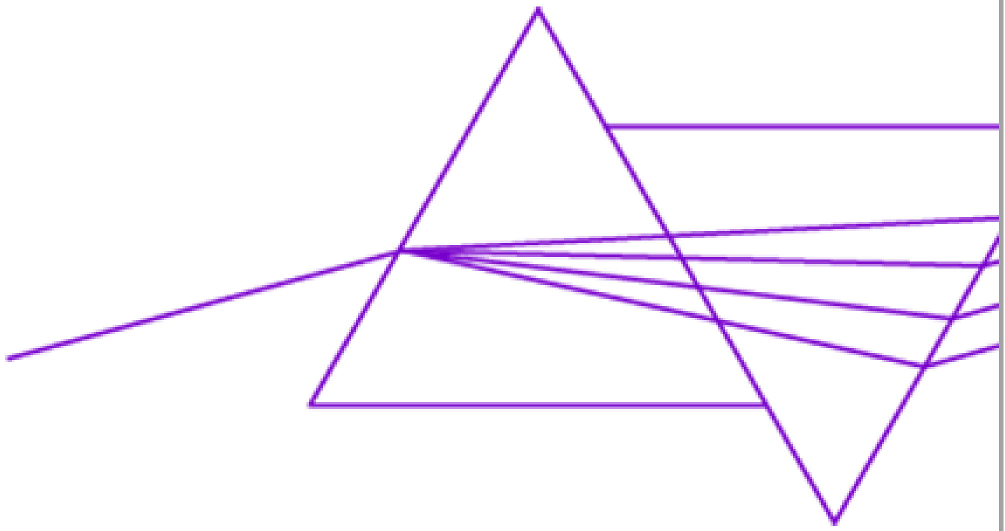
OPTICA

Advancing Optics and Photonics Worldwide

Color

WEBINAR

Measuring Light, Color, Spectrum and Personalized Light Exposure Using Wearable Light Sensors



11 February 2022 | 11:00 — 12:30 EST (UTC-05:00)

John Maule, Sussex University

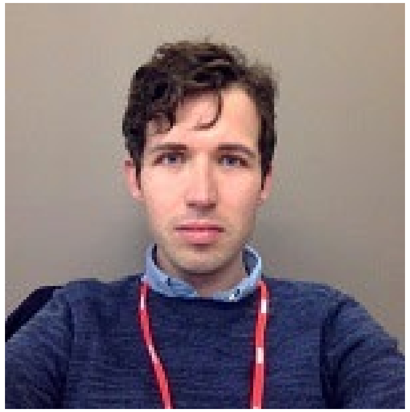
Dr. John Maule is a senior research fellow in the Sussex Colour Group. His research covers a range of topics in colour vision and perception including visual averaging and ensemble statistics of colour, colour perception in autism, and adaptation. His current work seeks to quantify the chromatic statistics of different environments and measure their effect on colour perception and aesthetics.

Janine Stampfli, Lucerne University of Applied Sciences and Arts

After studying business and economics at the University of Basel (Switzerland), Janine Stampfli went abroad in 2004 and worked as a project manager for an NGO and later for a private sector company. She got a MSc in Light and Lighting from University College London (United Kingdom) in 2017 and has been part of an interdisciplinary research team focused on light and lighting at the Lucerne School of Engineering and Architecture (Switzerland) since 201

Björn Schrader, Lucerne University of Applied Sciences and Arts

Björn Schrader studied at the Technical University of Braunschweig (Germany) and at the Technical University of Ilmenau (Germany), specialising in media technology/lighting technology. After graduating, he worked as a lighting designer at Zumtobel AG and later as a senior lighting consultant at Amstein & Walthert – both in Zurich (Switzerland). He has been a full-time lecturer at the Lucerne School of Engineering and Architecture (Switzerland) since 2011 and heads the interdisciplinary research team Licht@hslu.



Forrest Webler, EPFL

Forrest Webler is a PhD student at the laboratory of integrated performance in design (LIPID). His work relates to spectral sensing and will be discussing his work towards the development of a wearable sensor for spectral monitoring.

Vineetha Kalavally, Monash University

Dr. Vineetha is currently leading a research group focused on Solid State Lighting (SSL) at Monash University Malaysia. She applies light and color science fundamentals to Intelligent control of SSL systems with an industry focus and the goal of realizing energy-efficient human-centric lighting systems.

HSLU Hochschule Luzern

The Light-Dosimeter – a novel, portable device to record an individual's light exposure

Optica Webinar, 11 February 2022

Prof. Björn Schrader
Janine Stampfli
Lucerne School of Engineering and Architecture

Funding
VELUX STIFTUNG

Light-Dosimeter

Photo: Licht@hslu

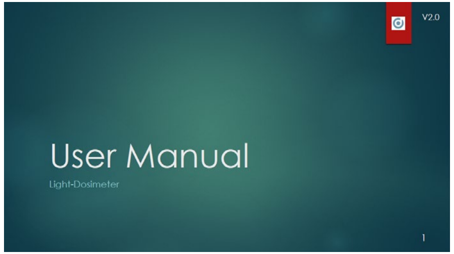
Light-Dosimeter

Photo: Licht@hslu

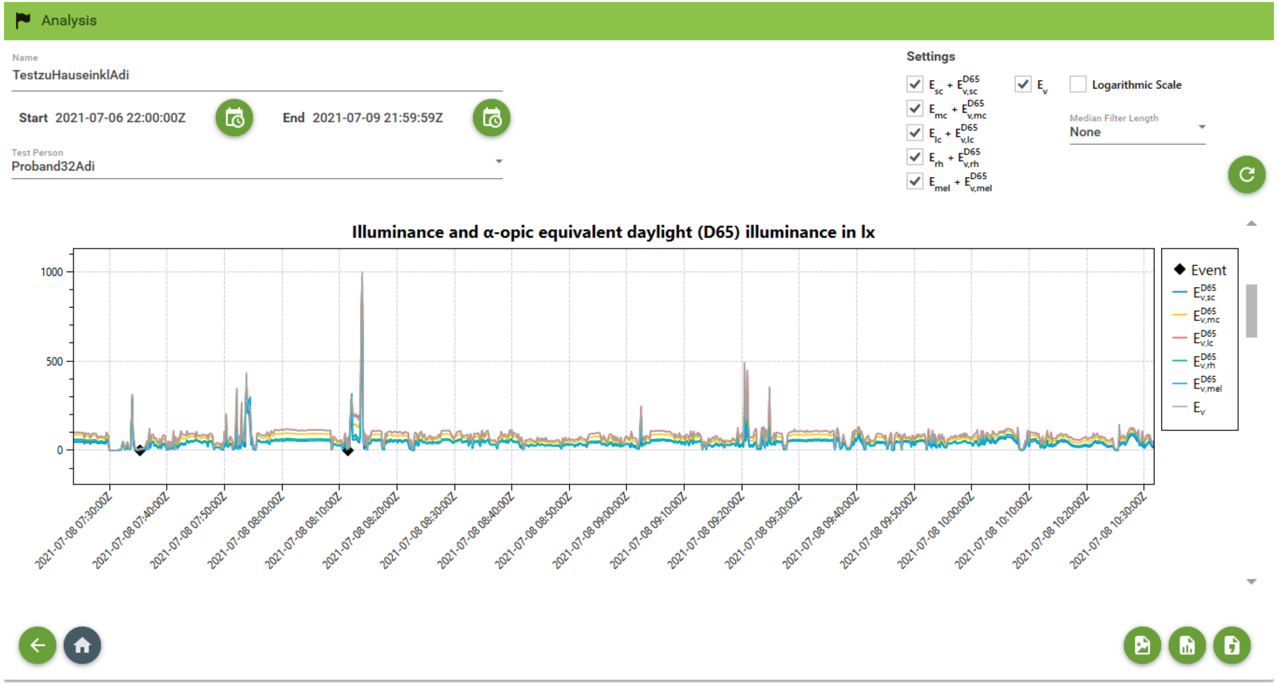
Light-Dosimeter

Specifications

Size of the casing	58 mm × 20,6 mm × 16 mm
Weight of the device	~27 g
Recording interval	10 sec
Wavelength range	380 nm to 780 nm
Measurement range	~5 lx to 100k lx
Battery life	~7 days
Battery charging time	~2 hours
Memory size	~300 days
Interface	Micro USB
Ingress protection	IP20



Light-Dosimeter



Source: Licht@hslu

Custom-made software «Lido Studio»

Light-Dosimeter

Metrics:

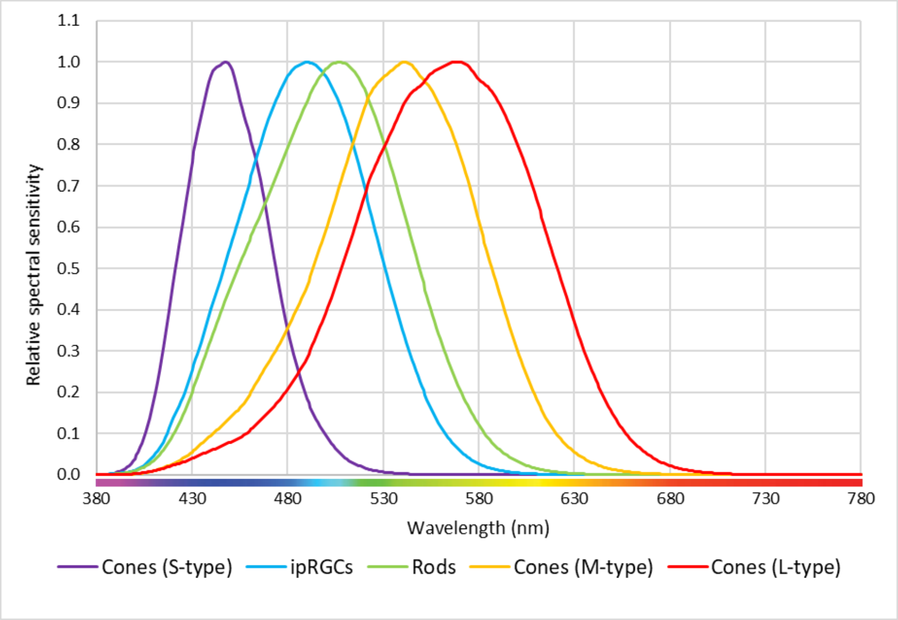
α-opic irradiance ($E_{\mathrm{e},\alpha}, E_{\alpha}$)
→ S-cone, M-cone, L-cone, rhodopic and melanopic

α-opic equivalent daylight (D65) illuminance ($E_{\mathrm{v},\alpha}^{\mathrm{D65}}$)
→ S-cone, M-cone, L-cone, rhodopic and melanopic

Illuminance (E_v)

Correlated Colour Temperature (CCT) / Duv

Tilt angle



Graphic: Licht@hslu

Light-Dosimeter

Photo: @espenbibow – Bergen Stress and Sleep Group

Tyndall National Institute Institiúid Náisiúnta

Technische Hochschule Rosenheim

University of Oxford

UPK Universitäre Psychiatrische Kliniken Basel

University of Bergen

Light-Dosimeter

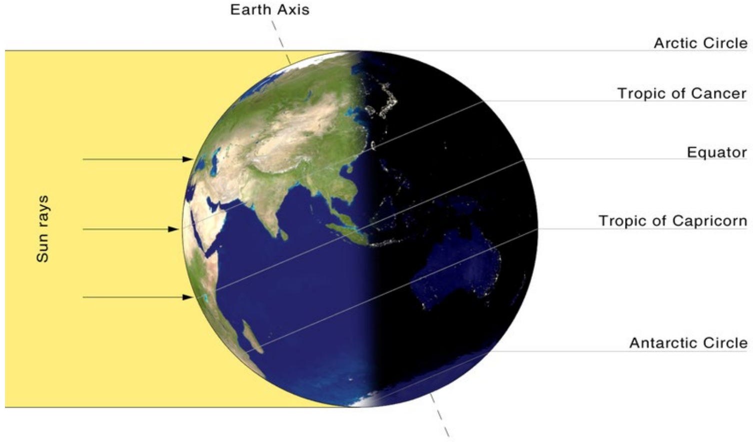
Graphic: Licht@hslu

Thank you for your attention.

Contact details: T +41 (0)41 349 35 75, janine.stampfli@hslu.ch, www.light-dosimeter.ch

Optica Webinar - 11th February 2022

J.Maule@sussex.ac.uk



Measuring geographical and seasonal variation in colour and light exposure

Dr John Maule

University of Sussex

European Research Council
Established by the European Commission
COLOURMIND (772193)
PI: Prof. Anna Franklin

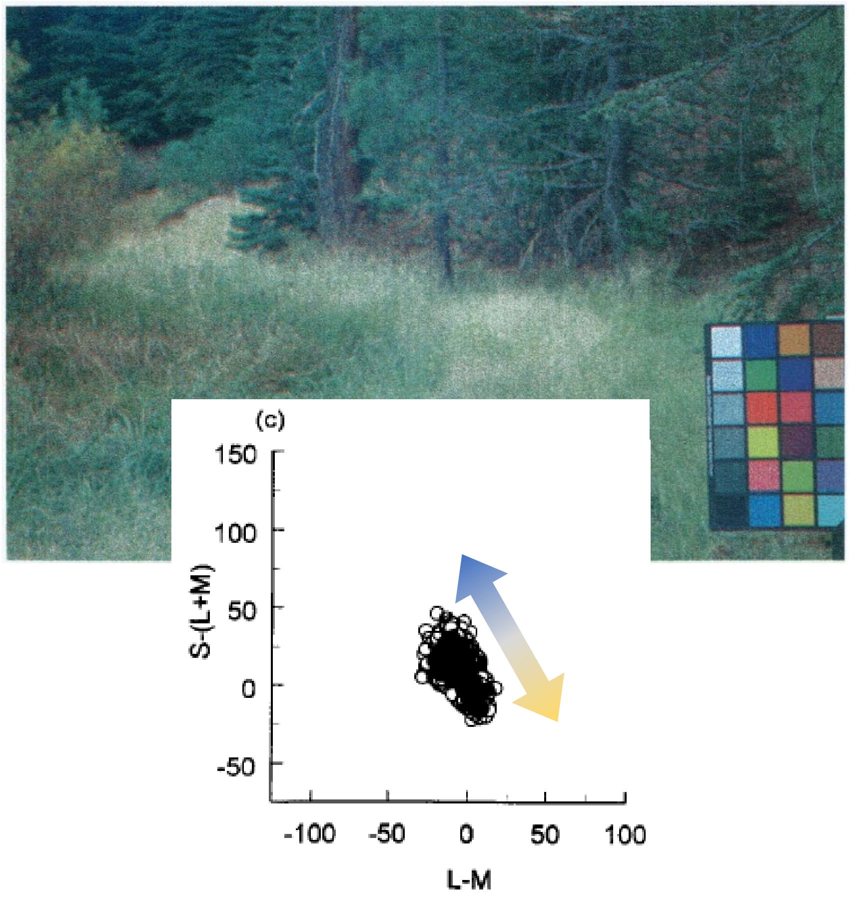
The Sussex Colour Group

How does the environment affect colour perception?



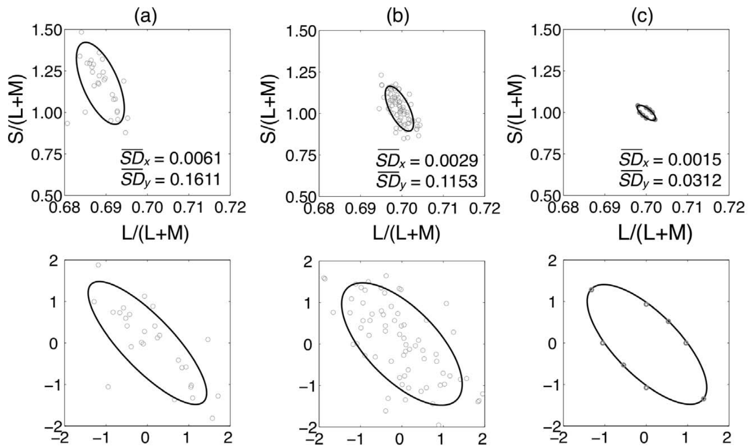



How does the environment affect colour perception?



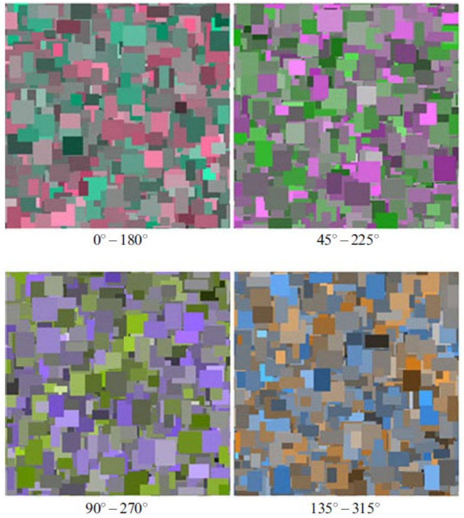
Webster & Mollon (1997) *Vis. Res.*

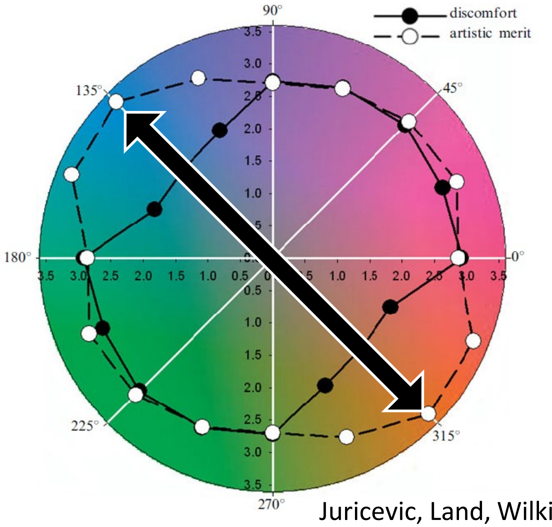
Chromatic sensitivity / white settings



Bosten, Beer & MacLeod (2015) *Journal of Vision*

Aesthetic judgments

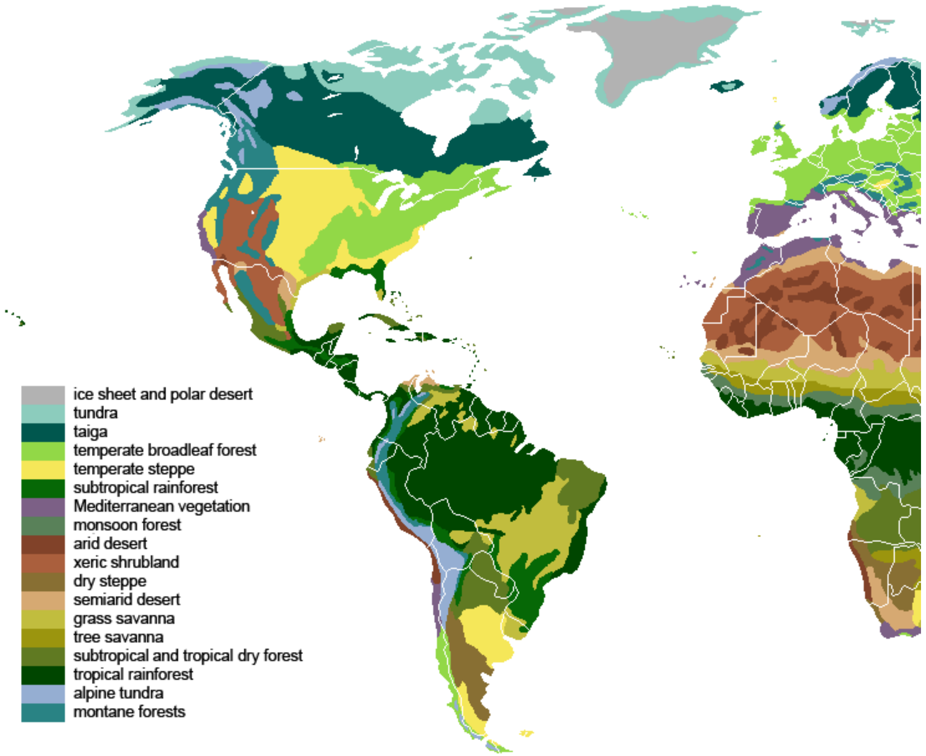




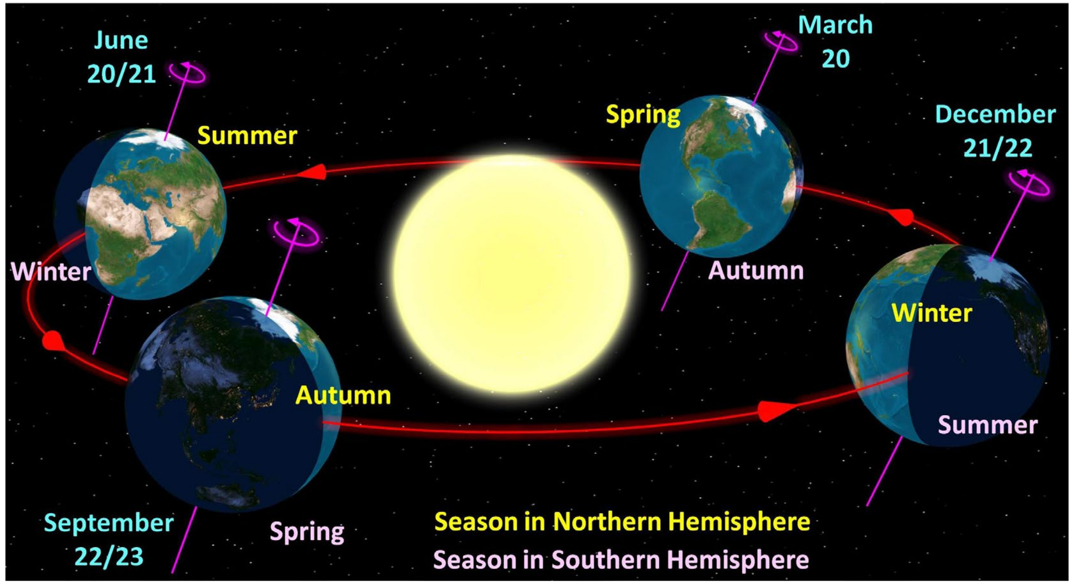
Juricevic, Land, Wilkins & Webster (2010) *Perception*

How does the environment affect colour perception?

1. Across different geographical locations



2. Across seasons



Fieldwork locations

Esmeraldas:
Rainforest-based, settled agricultural lifestyle spent mostly outdoors.

Quito:
City-based, lifestyles as those living in a capital city.

United Kingdom

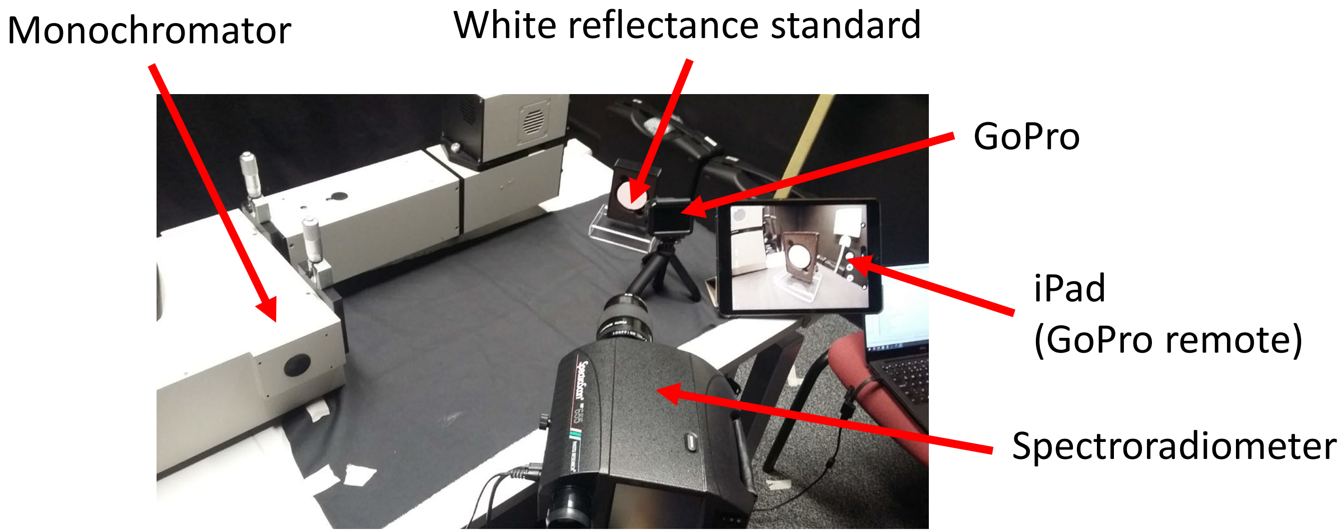
Sussex:
City-based, lifestyles as those living in an urban area.

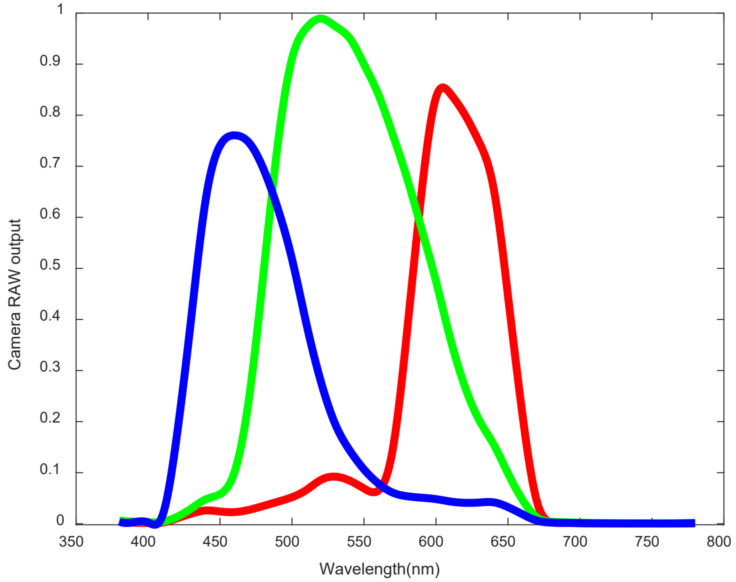
Ecuador data collection: Simeon Floyd, University of Quito

Measuring “chromatic diet”

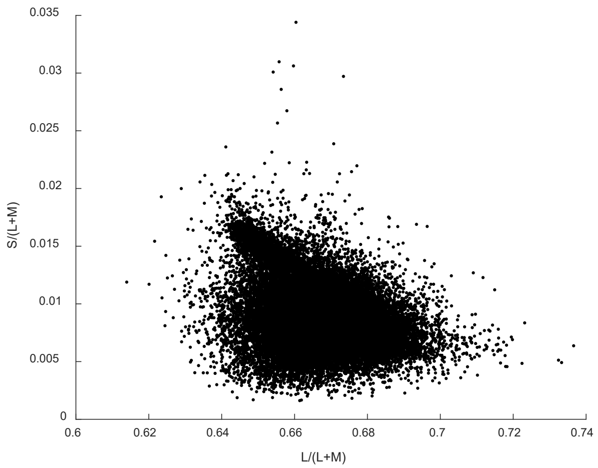
- Aim to capture and measure the lived “chromatic diet”.
- Colour-calibrated head-mounted GoPro cameras worn as people go about daily life
- Automatic time-lapse captures an image every 30 seconds.

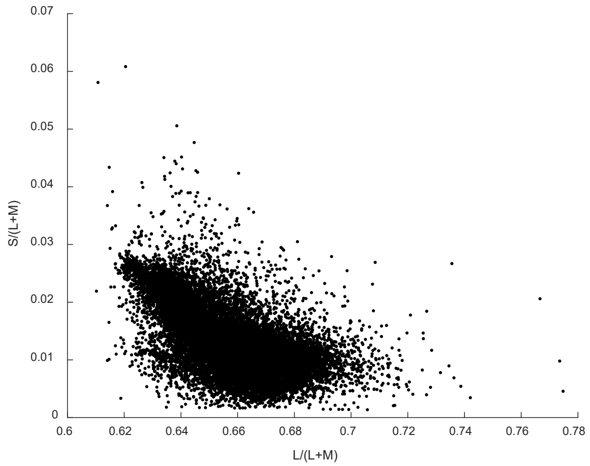
RAW sensor data → **Camera R/G/B sensitivities** → LMS cone activations → Chromatic statistics (Macleod & Boynton)





Measuring "chromatic diet"





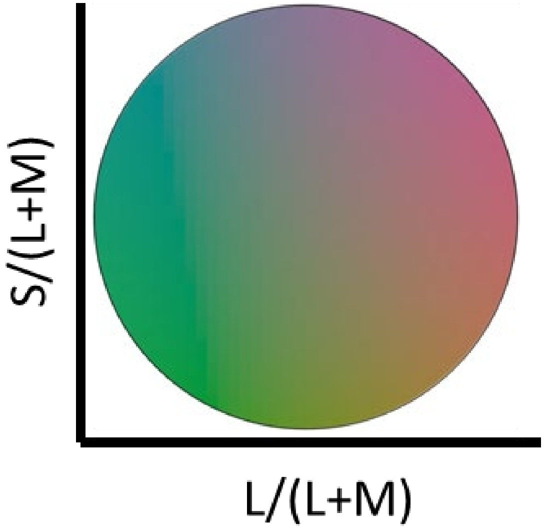


Image montages

Esmeraldas

Quito

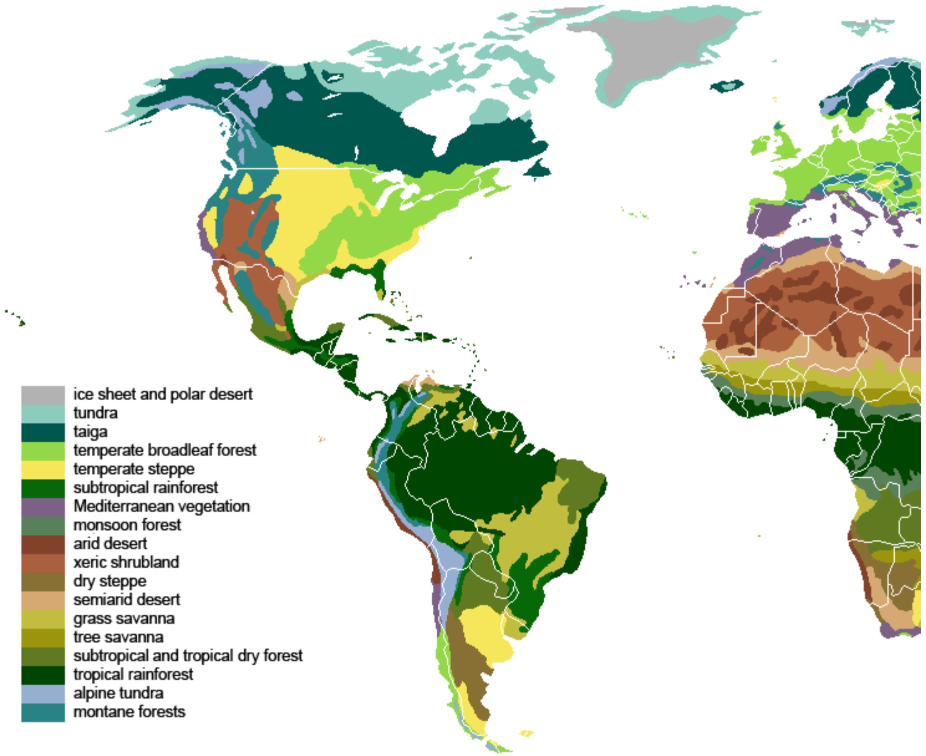
Sussex

Chromatic image statistics (e.g. mean chromaticity, variance in cone-opponent mechanisms, distribution of hues, mean saturation for different hues…)

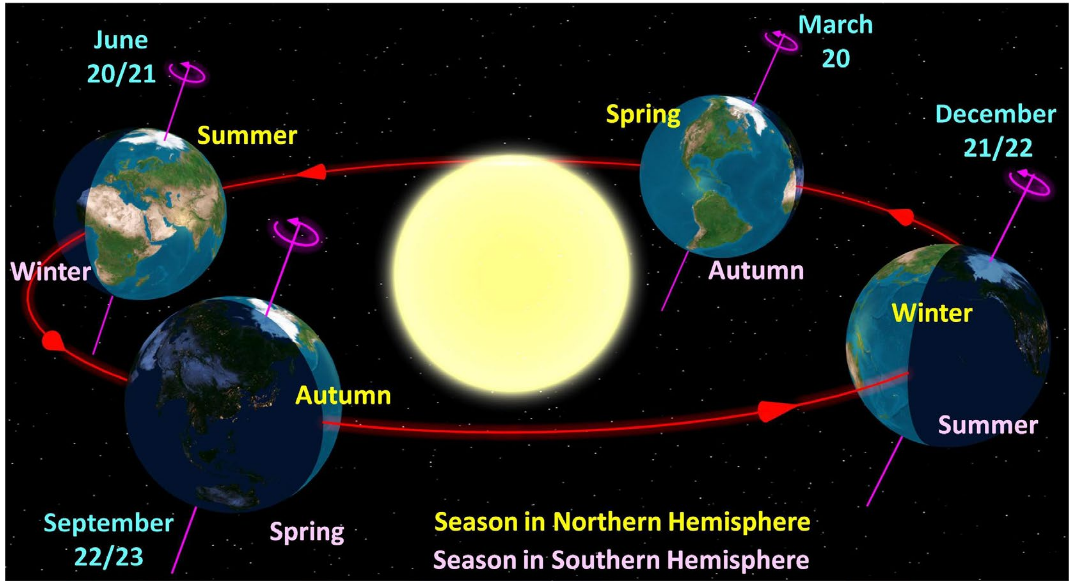
Maule et al. (2021) *Journal of Vision* [VSS 2021]
Skelton et al. (2021) *Journal of Vision* [VSS 2021]

How does the environment affect colour perception?

1. Across different geographical locations



2. Across seasons



How does the environment affect colour perception?

<u>Unique yellow</u> shifts with the seasons
(York, UK – approx. 54°N)

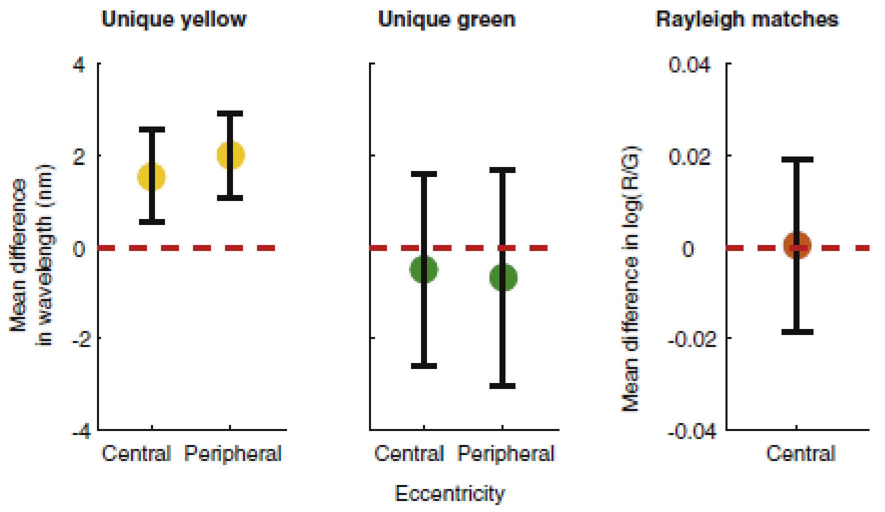
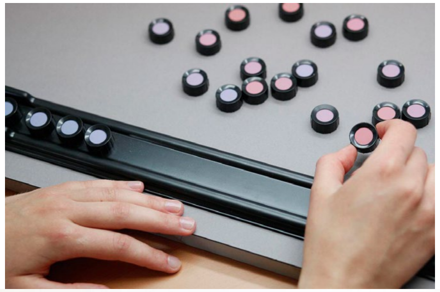
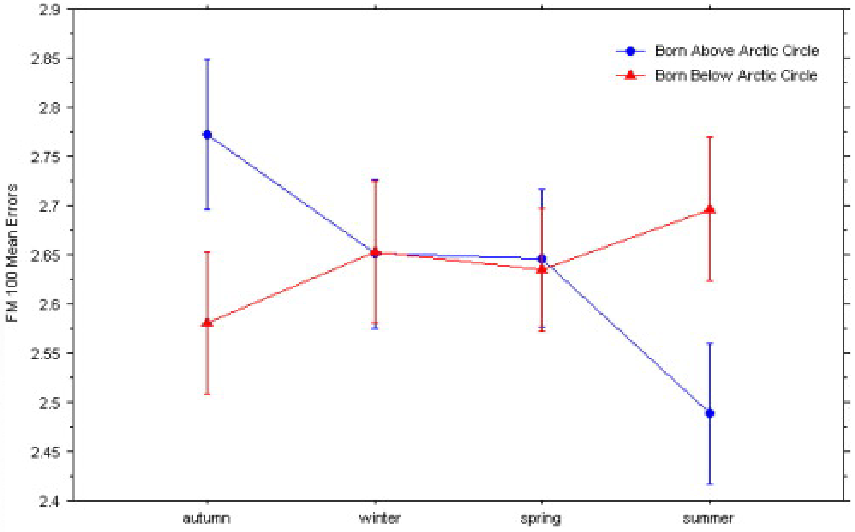


Figure 1. Mean differences between seasons for UY, UG and Rayleigh matches.
Mean differences between winter and summer (winter–summer) for the two eccentricities (central and peripheral) measured for UY (central = 1.55 nm, peripheral = 2.01 nm) and UG (central = –0.50 nm, peripheral = –0.66 nm), and for central Rayleigh matches (0.0005 log(R/G)). Error bars are ±95% confidence intervals, and the zero crossing (where the mean difference is zero) is highlighted with the dashed red line.

Welbourne, Morland & Wade (2015) *Current Biology*

Differences in **<u>FM100HT performance</u>** with latitude and season of birth.
(Tromsø, Norway – approx. 69°N)





Laeng et al. (2007)
Vision Research

How does the environment affect colour perception?

Location 1: Tromsø (latitude approx. 69°N)

- Winter *mørketid* (dark time) – the sun does not rise (Nov-Jan)
- Summer *midnatssol* (midnight sun) – the sun does not set (May-July)

Location 2: Oslo (latitude approx. 60°N)

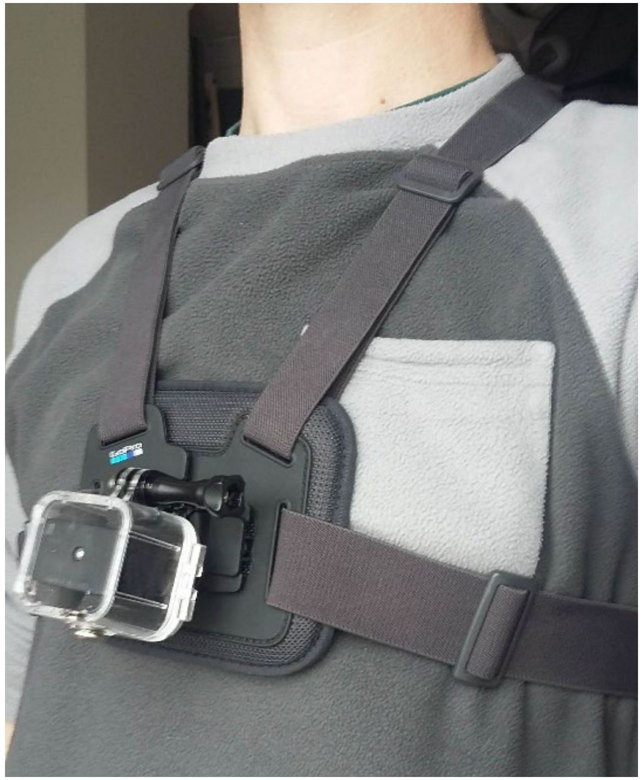
- Winter solstice approx. 6h daylight
- Summer solstice approx. 18h daylight

With Bruno Laeng (Oslo)
& Mikolaj Hernik (Tromsø)

Measuring “spectral diet”
(after Webler, Spitschan *et al*., 2019)

<u>nanoLambda XL-500 BLE Spectroradiometer</u> (NanoLambda Korea Inc.)

- Portable spectrometer with Bluetooth connectivity
- Android/iOS app
- 390-760nm



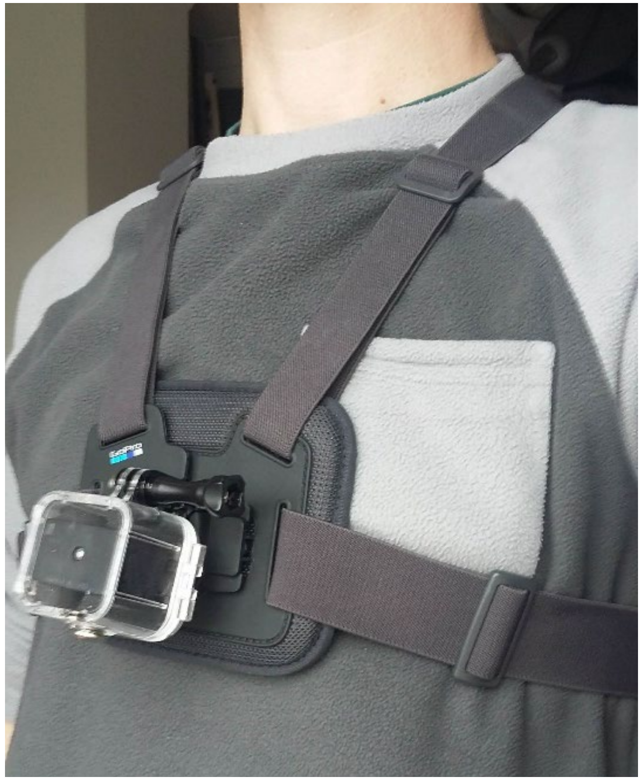
Measuring “spectral diet”

(after Webler, Spitschan *et al.*, 2019)

Aim:

- Capture the spectral diet for participants in both locations (Oslo & Tromsø) each season.

- 10 to 15 participants per season and location
- Two days recording of waking hours
- One sample every 15 seconds

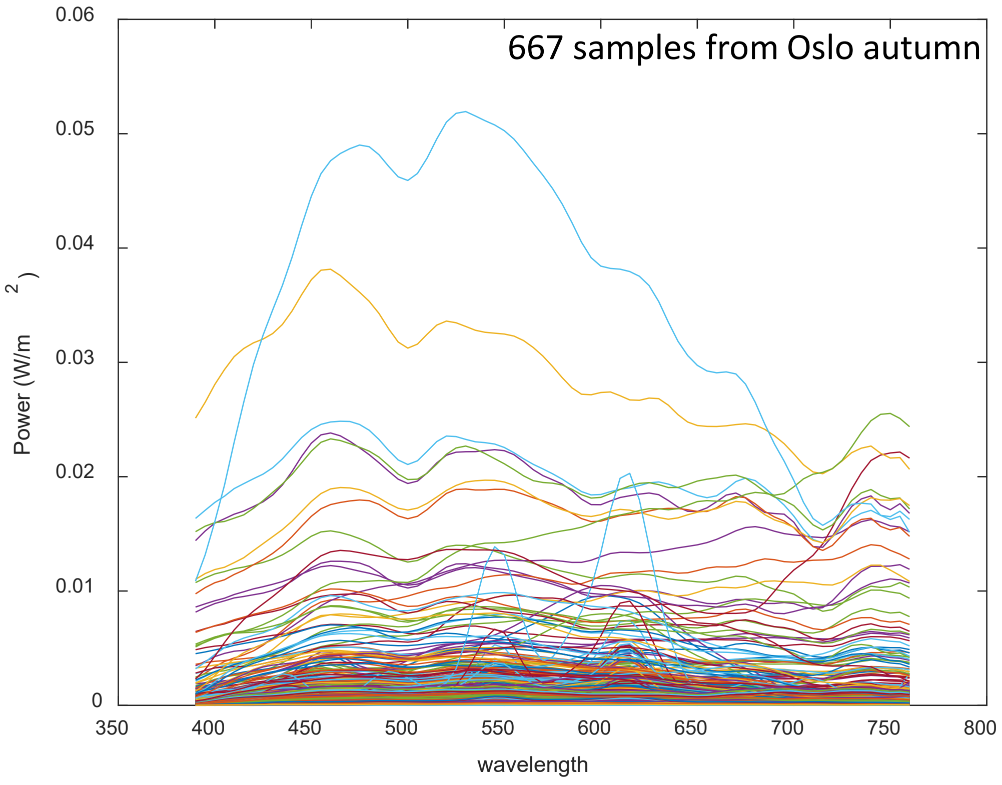


Data collection:

Tromsø: Mahdis Jafari / Sarjo Kuyateh

Oslo: Shaoib Nabil

Data analysis

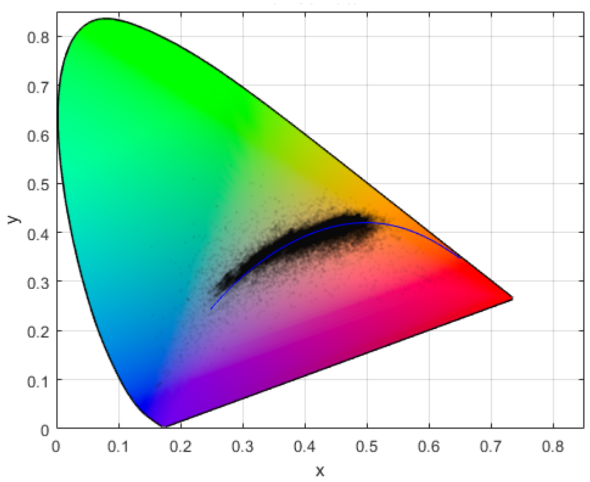


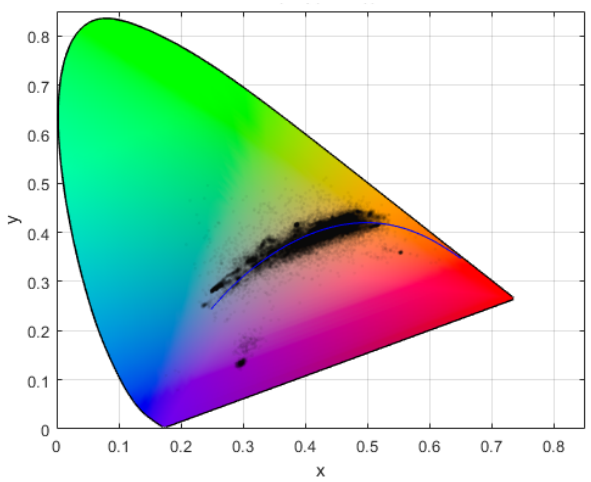
- Rich spectral diet data (approx. 40k samples per location per season)
- After filtering to remove noisy measurements, spectra can be converted into human vision colour spaces (e.g. CIE spaces, Macleod-Boynton)
- Spectra can be analysed using multivariate methods, such as cluster analysis (see Webler et al., 2019), or machine learning techniques to classify illumination types.

Example data - chromaticity

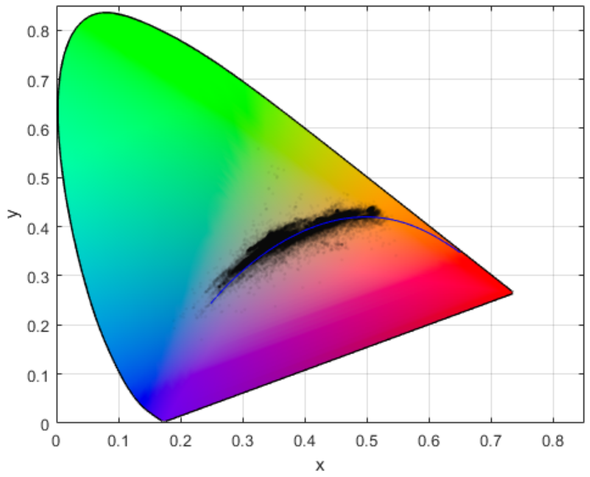
Autumn | Winter

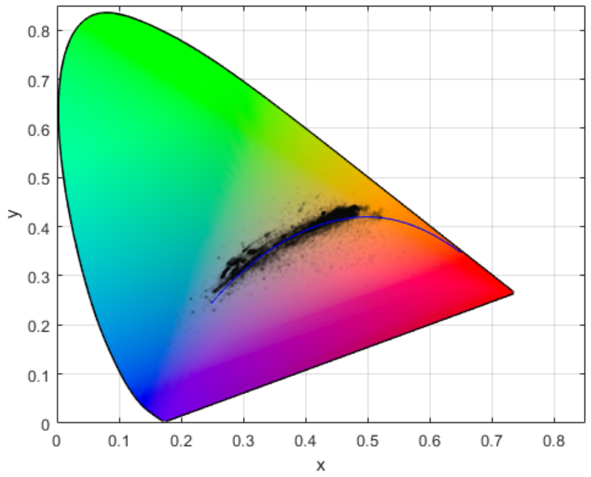
Tromsø





Oslo





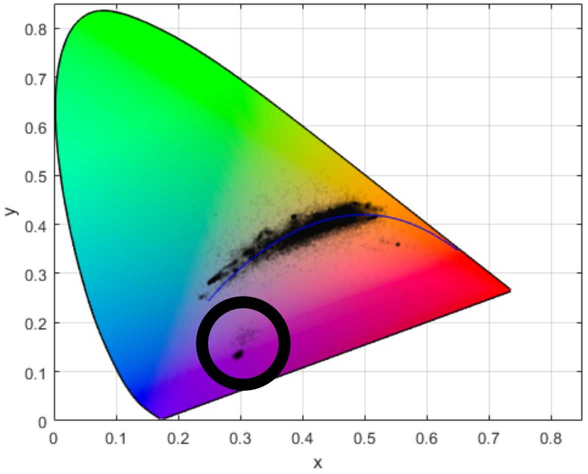
Example data - chromaticity

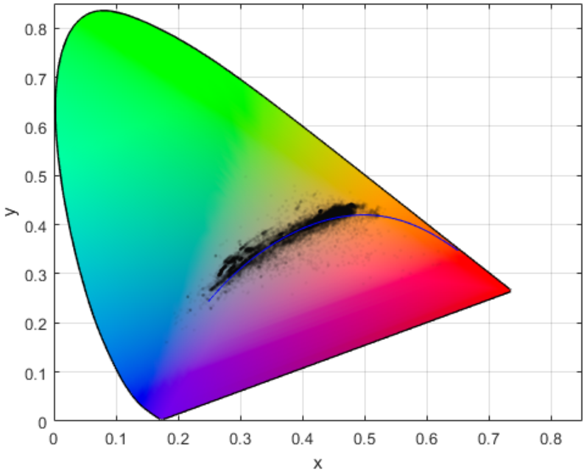
Autumn

Winter

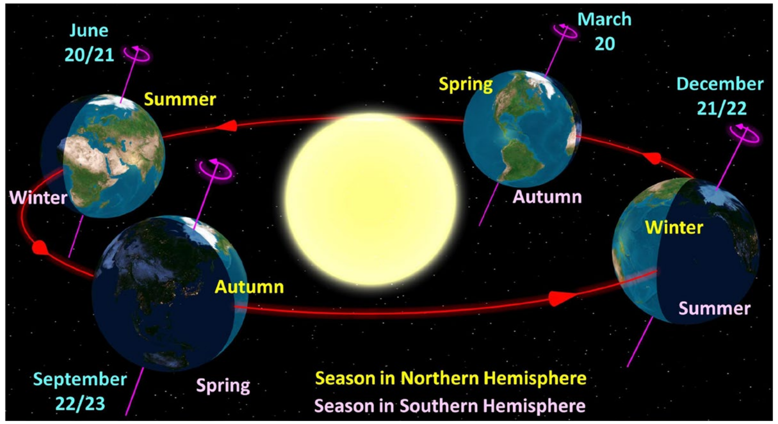
Tr

C

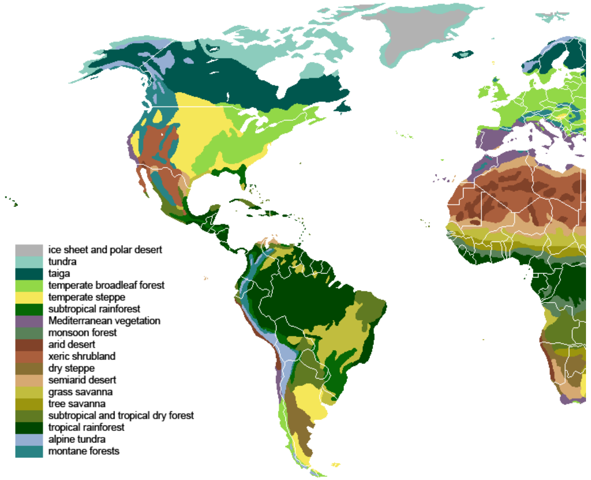




Summary



Wearable sensors can be used to estimate the visual diet and quantify differences between locations/seasons.



- Head-mounted RGB cameras can be used for gathering image databases which are both ego-centric and colour-calibrated.
- Wearable spectral sensors can provide data on the diet of illumination and chromaticity experienced where there is extreme seasonal variation in day length.
- Combining this data with psychophysical/behavioural experiments we are investigating developmental and life-long calibration to the chromatic statistics of the visual environment.

Acknowledgments

European Research Council

Established by the European Commission

COLOURMIND (772193)

PI: Prof. Anna Franklin

Sussex Colour Group

Prof. Anna Franklin

Dr. Alice Skelton

Beata Wozniak

Martina Guido

University of Sussex

The Sussex Colour Group

Universidad San Francisco de Quito — Simeon Floyd

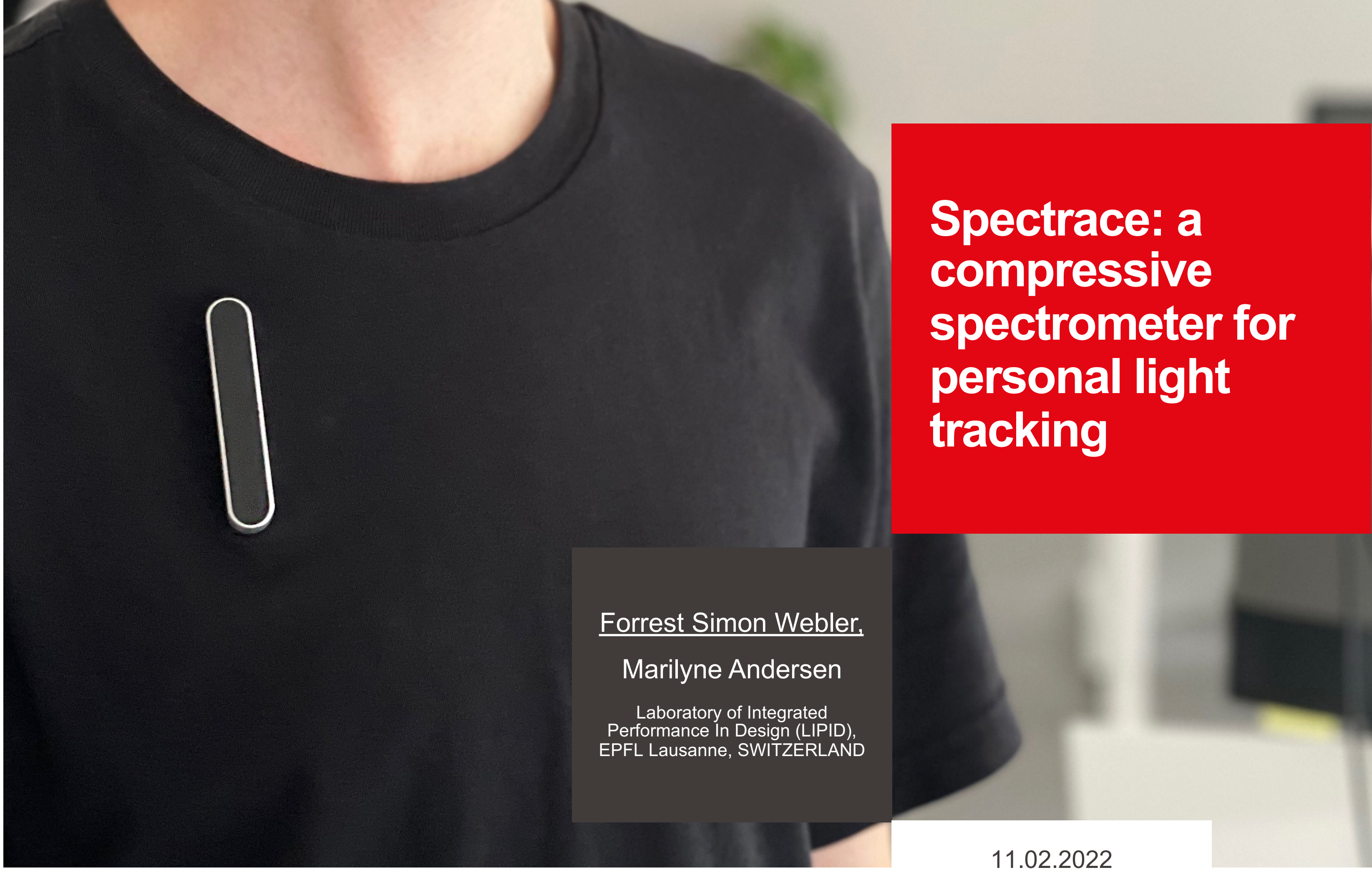
University of York — Asifa Majid

Universitas Osloensis MDCCCXI — Bruno Laeng

UiT The Arctic University of Norway — Mikolaj Hernik

Sussex vision lab

Jenny Bosten



Spectrace: a compressive spectrometer for personal light tracking

Forrest Simon Webler,

Marilyne Andersen

Laboratory of Integrated Performance In Design (LIPID), EPFL Lausanne, SWITZERLAND

11.02.2022

Approaches in conventional spectrometry

Stochastic phenomena

↓

Multiplicative processes

↓

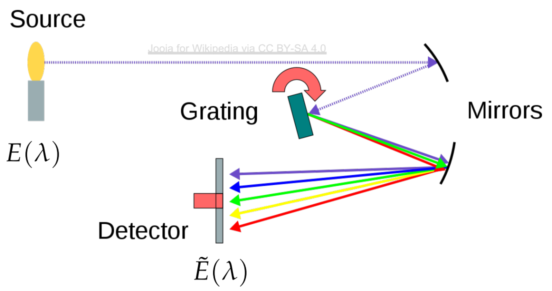
Observable (natural signal)

$E(\lambda)$

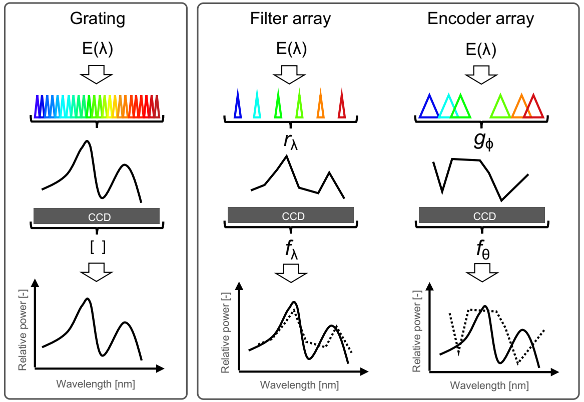
$\mathbf{N} : \mathbb{R}^\infty \rightarrow \mathbb{R}^n$

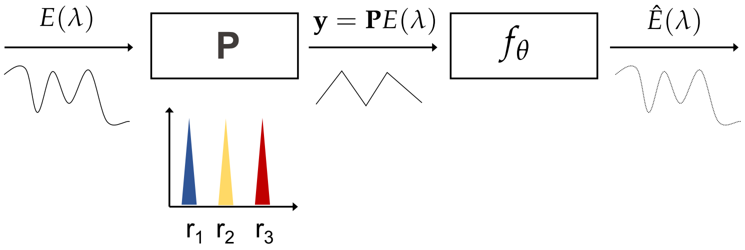
Target measurement

$\tilde{E}(\lambda) = \mathbf{N}E(\lambda)$

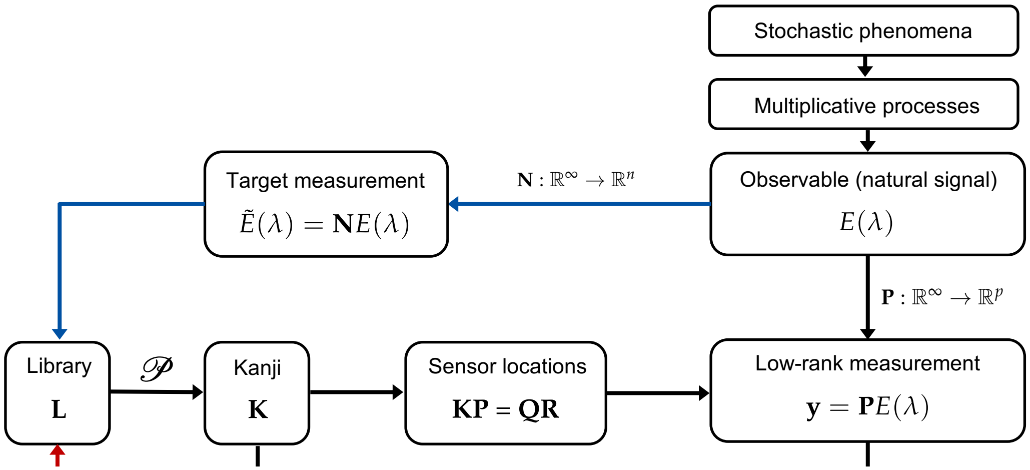


"calibration free"
Encoder-array (reconstructive) spectrometry

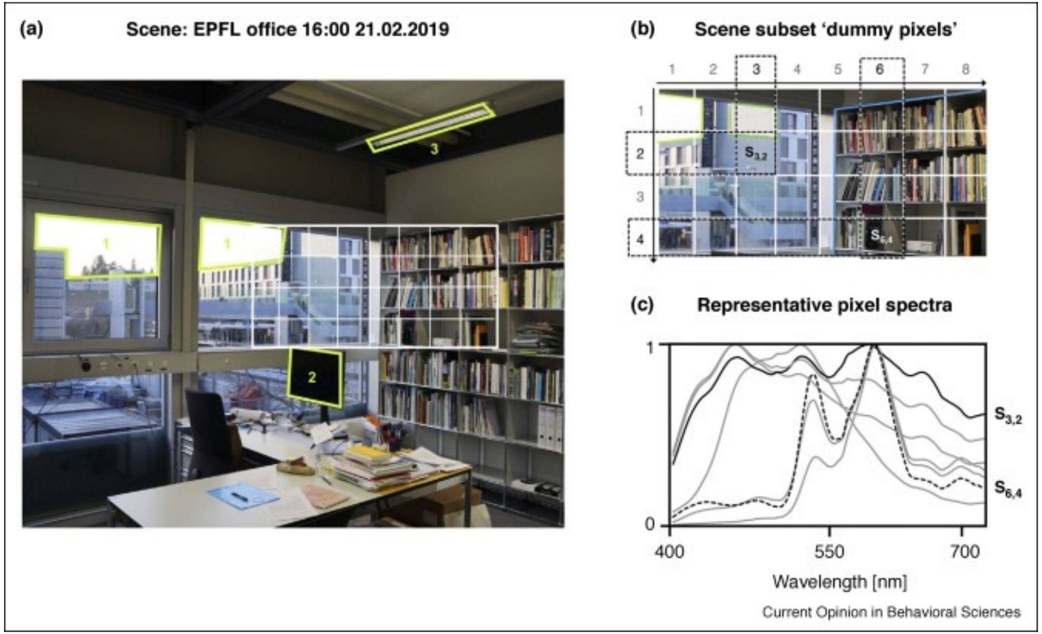




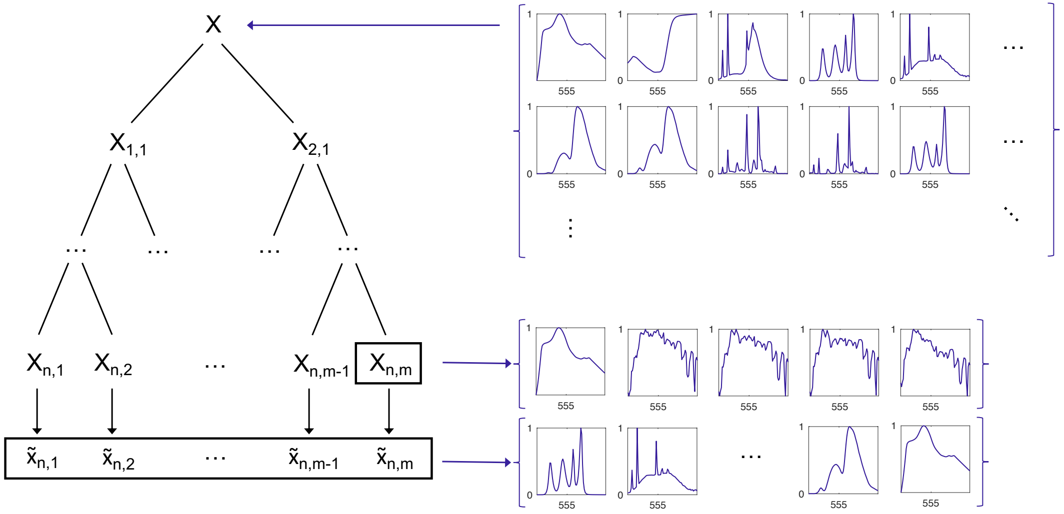
Encoder-array (reconstructive) spectrometry



The world is full of patterns

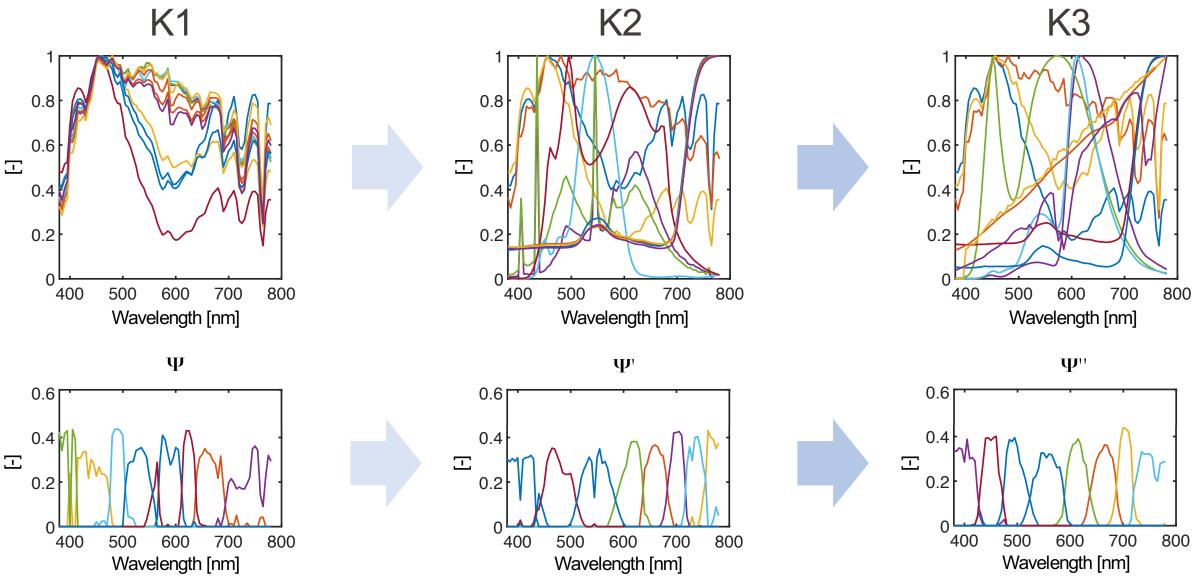


Encoder-array (reconstructive) spectrometry

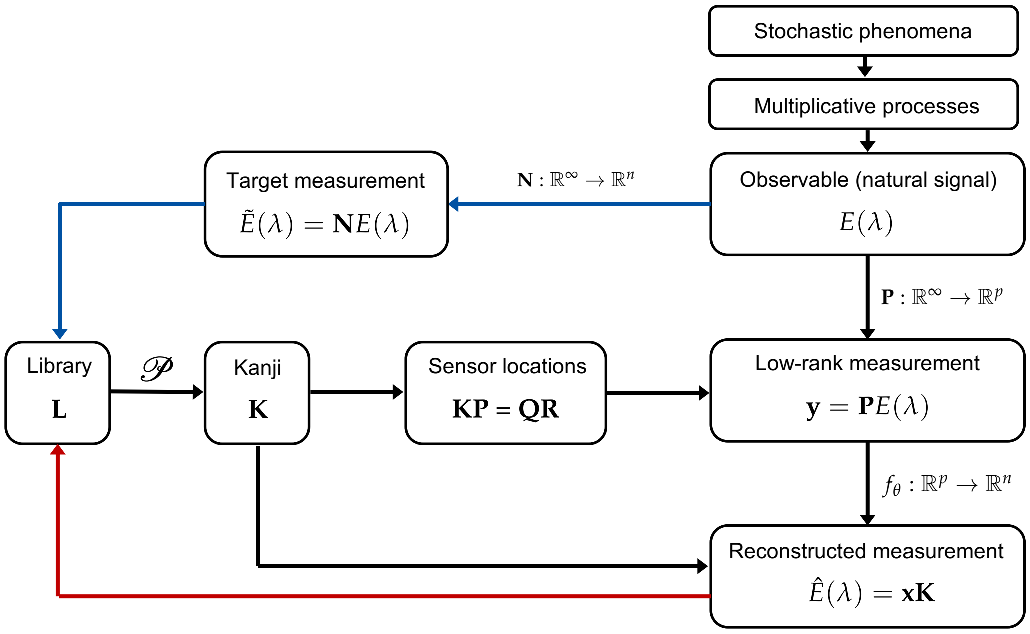


$\mathbf{K} = [\tilde{\mathbf{X}}, \mathbf{X}_{i,m}]$ "Kanji"

Encoder-array (reconstructive) spectrometry

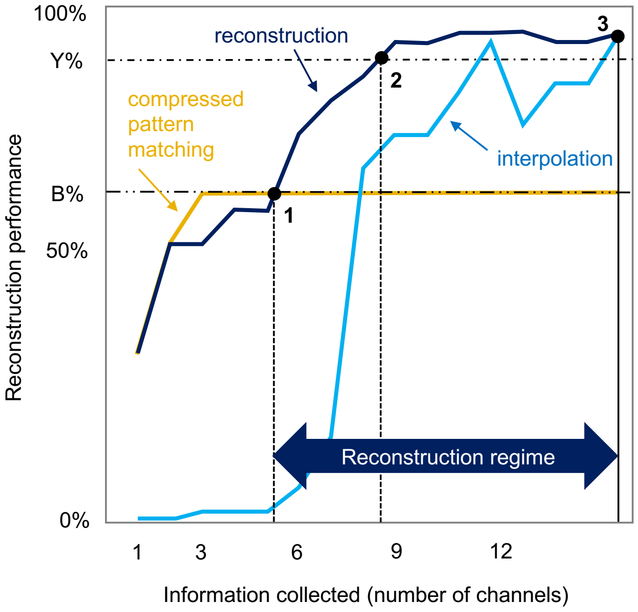


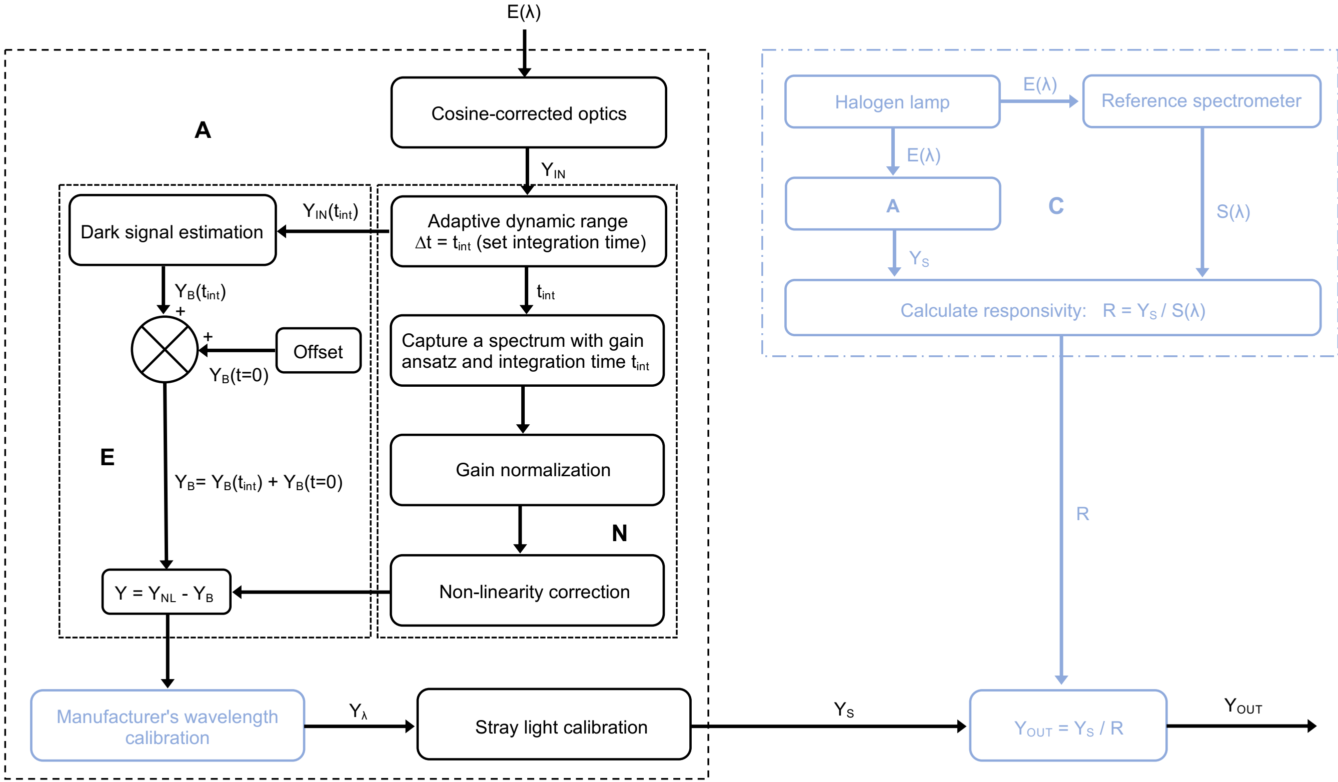
Encoder-array (reconstructive) spectrometry



Reconstructed measurement

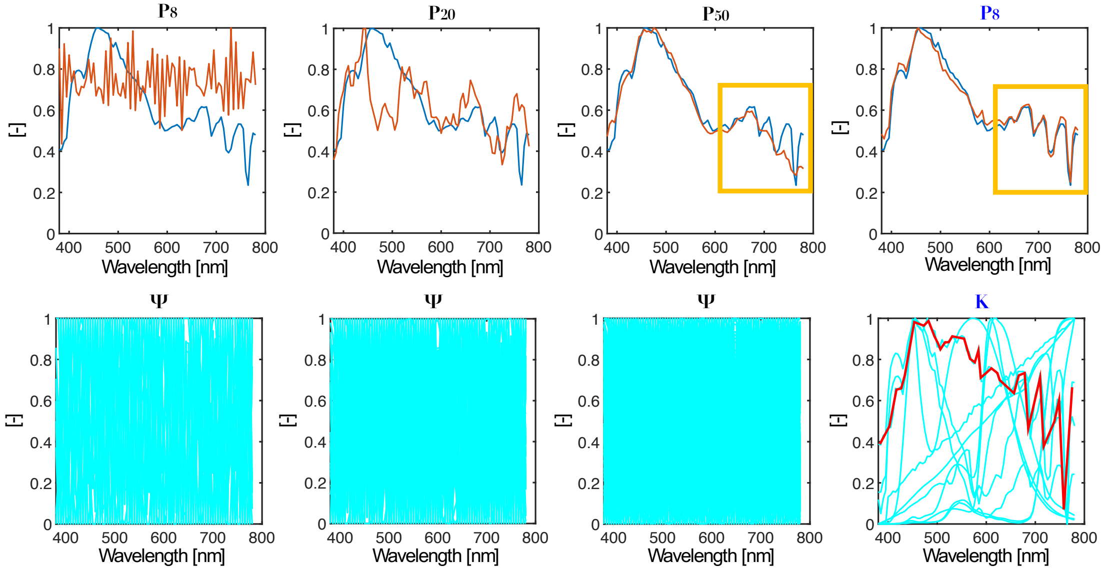
$$\hat{E}(\lambda) = \mathbf{xK}$$




E(λ)
Cosine-corrected optics
A
Y_IN
Y_IN(t_int)
Dark signal estimation
Adaptive dynamic range
Δt = t_int (set integration time)
Y_B(t_int)
+
+
t_int
Offset
Y_B(t=0)
Capture a spectrum with gain
ansatz and integration time t_int
E
Y_B= Y_B(t_int) + Y_B(t=0)
Gain normalization
N
Y = Y_NL - Y_B
Non-linearity correction
Manufacturer's wavelength
calibration
Y_λ
Stray light calibration
Y_S
Y_OUT = Y_S / R
Y_OUT
Halogen lamp
E(λ)
Reference spectrometer
E(λ)
A
C
S(λ)
Y_S
Calculate responsivity: R = Y_S / S(λ)
R

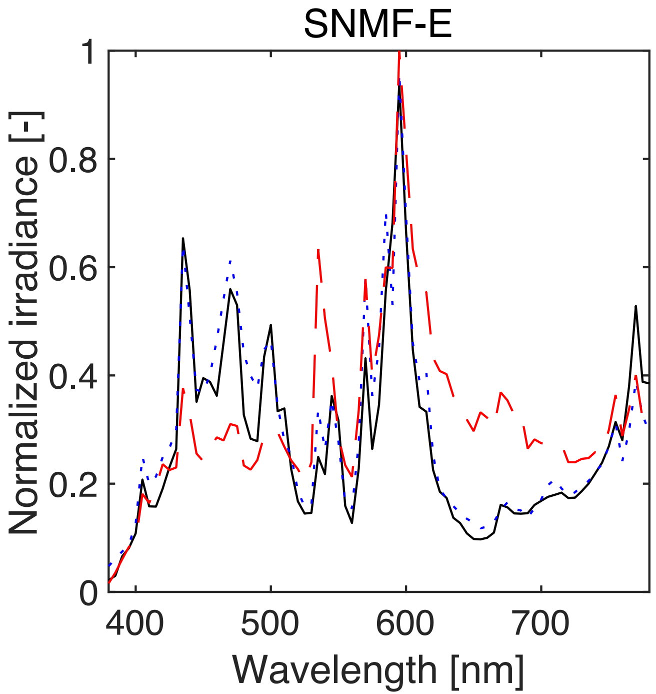
Reconstructed measurement

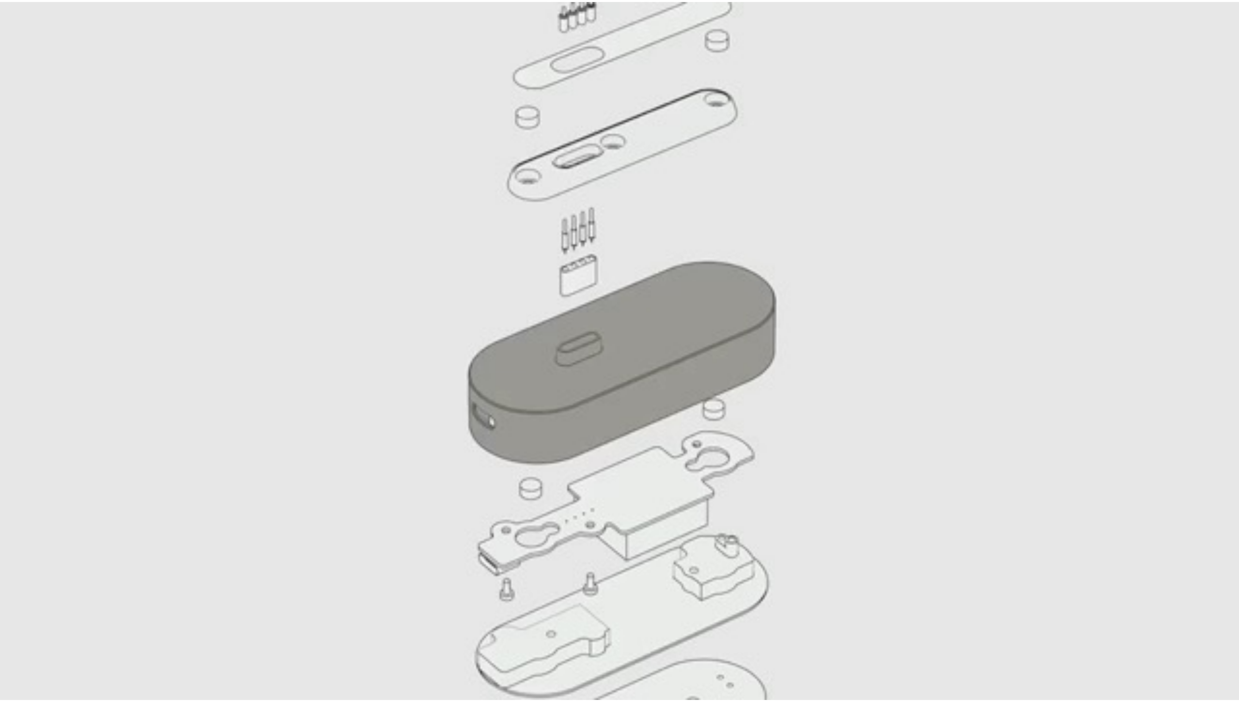
$$\hat{E}(\lambda) = \mathbf{xK}$$



Reconstructed measurement

$$\hat{E}(\lambda) = \mathbf{xK}$$






Merci!

Towards a global database of daily corneal light exposure using wearable spectral sensors

Date Time: Feb 11, 2022 11:00 Eastern Time (US and Canada)
Topic: Measuring Light, Color, Spectrum and Personalized Light Exposure Using Wearable Light Sensors

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Director, Intelligent Lighting Laboratory

Monash University

Webinar Agenda

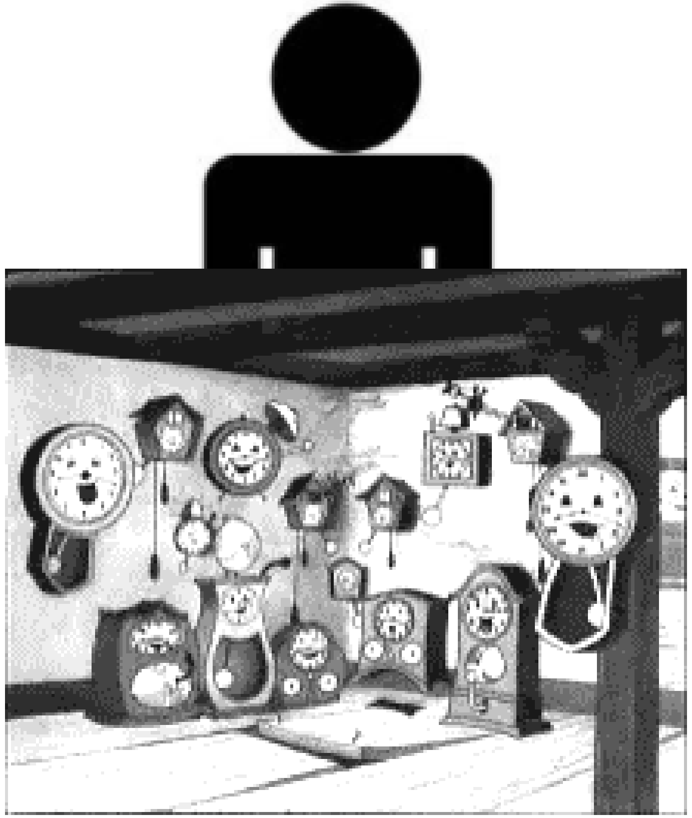
- Enhance the understanding of metrology of optical radiation for human photoreception using wearables
- Creation of a global database of personal light exposure data
- Exploiting such a data base to improve human wellbeing

Webinar Outline

- Significance of measuring personalised light exposure
- The device – wearable light spectral sensors
- The data collection framework
- Case studies - The prediction of human physiology and psychology using light as stimulus

Significance of ambulatory light exposure measurements

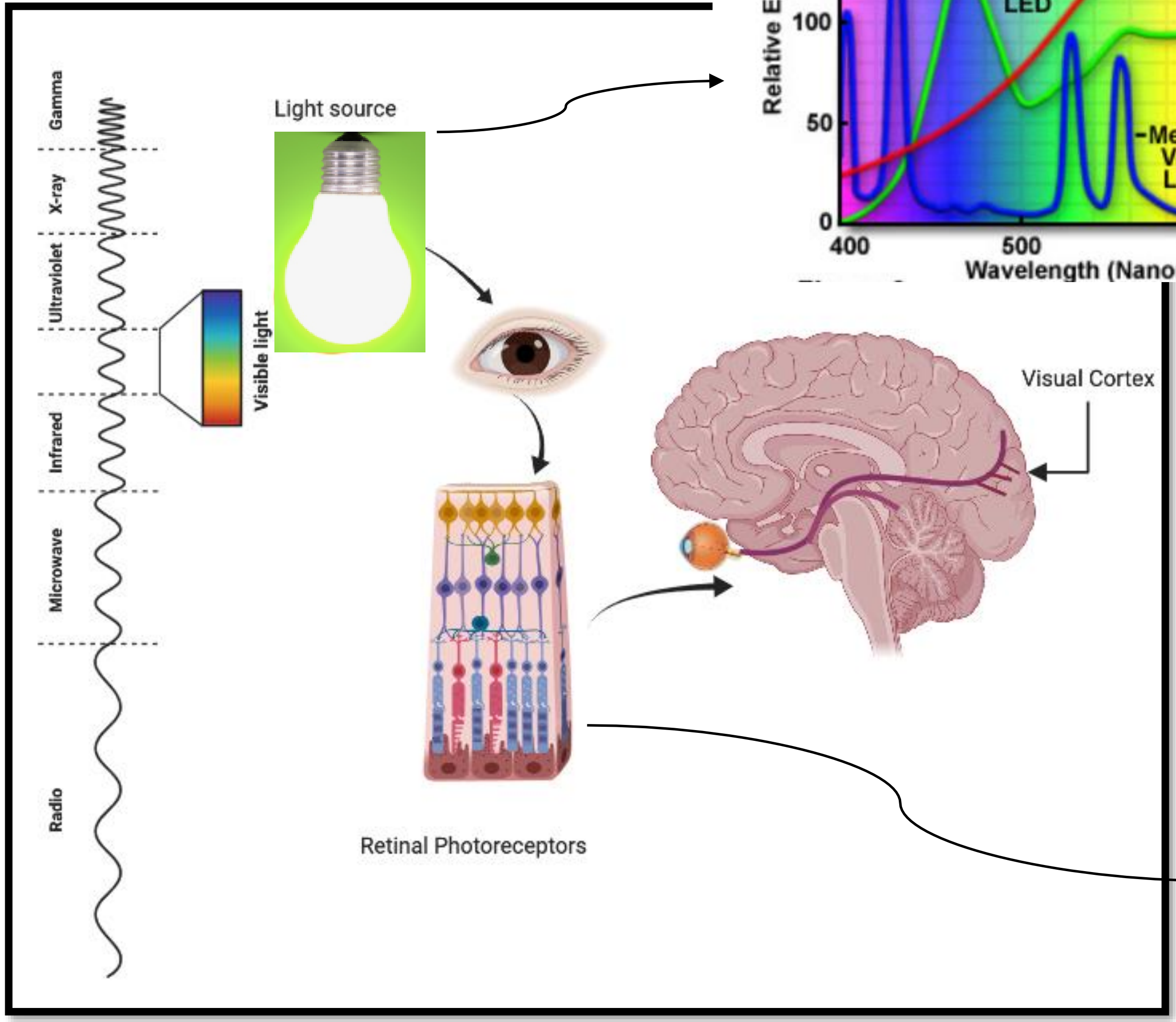
Disruptions in Human biological rhythms

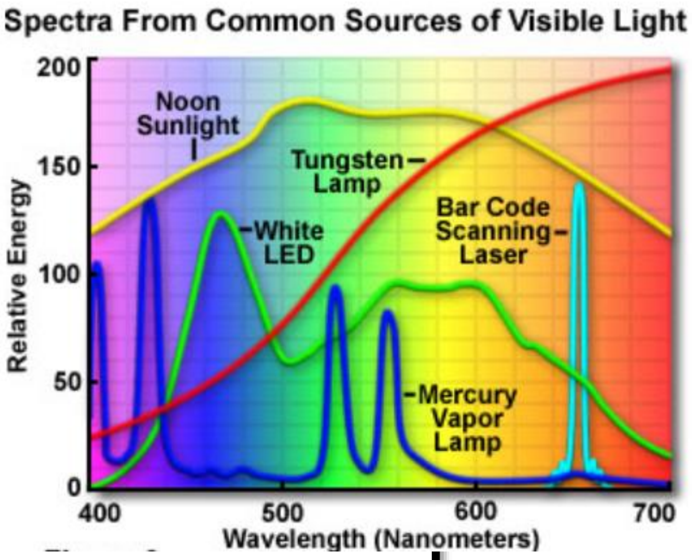


A wearable light sensor can help

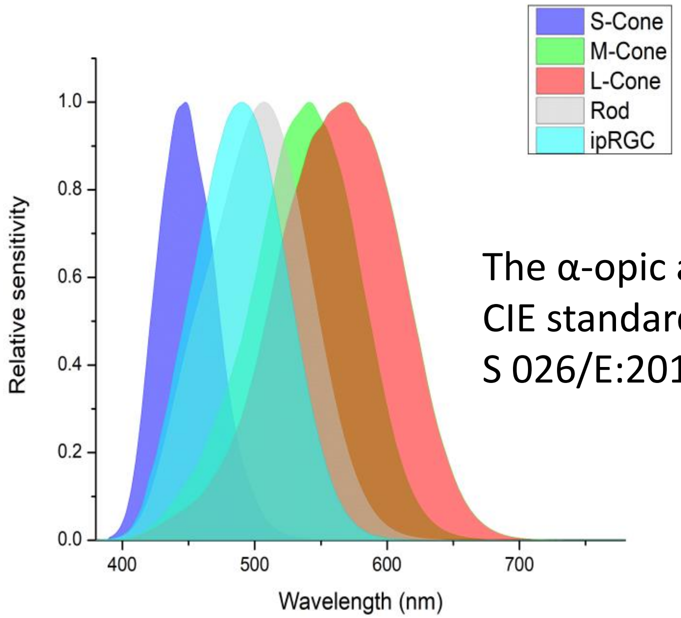
- Non-Visual Effects of Light
- Light is an external cue
- Light-dark cycles
- Modern-day disruptions
- Diseases on the rise

Spectrum is important!





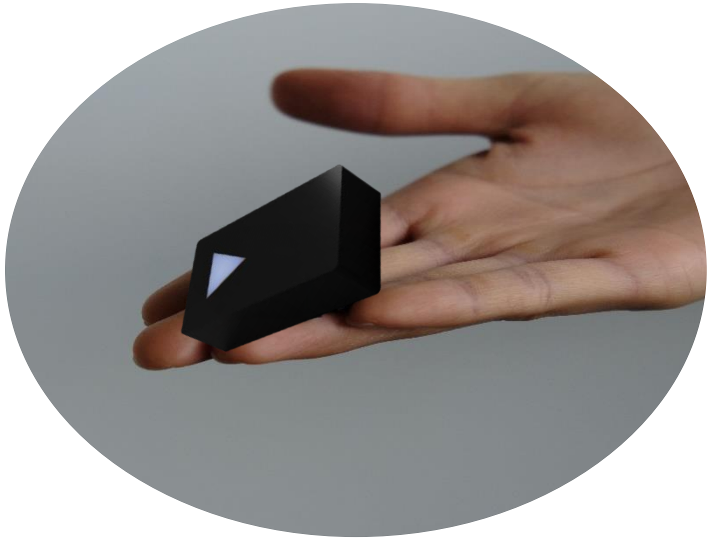
Action spectra for the 5 photoreceptors, the rods, the S, M and L cones and the ipRGCs, peak at different wavelengths spanning the entire visible wavelength range. Hence if optical radiation for human photoreception is what we are targeting to measure, such measurements require a wearable spectrophotometer that can record the full spectrum of light.



The α-opic action spectra following the CIE standard S 026/E:2018.

Some images from: https://www.olympus-lifescience.com/en/microscope-resource/primer/lightandcolor/lightsourcesintro/

A Wearable Light Spectral Sensor – Device Design



Why Wearable?

Ecologically valid measurements of light exposure an absolute must!

- The pathways of the Visual and Non-visual effects of light
- Lack of sleep is the next pandemic
- Alertness, cognition, mood, executive functioning, decision making
- Light therapy

Steps in the Design of a Wearable Light Spectral Sensor

- Sensor Selection
- Characterisation and calibration
- Spectral reconstruction and α-opic illuminance computation
- Hardware integration
- Software integration - App and Cloud Storage
- Testing and Validation

Sensor Selection

Spectral sensing can be done using many types of CMOS-based sensors. There are 2 categories, one where light enters through an optical slit and uses a reflective grating to direct the light on to different parts of a CMOS sensor (mini spectrophotometer). And the other (spectral sensors) that integrate filters on to standard CMOS silicon, taking advantage of the cheaper and more robust surface mount packaging.

Mini Spectrophotometers

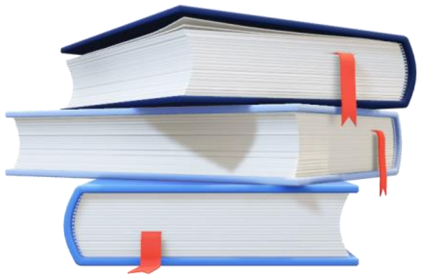
- Expensive
- Sensitive to rough movements
- High resolution
- High Accuracy
- Heavy
- Power hungry
- Shorter battery life
- Wearable, heavy
- Easier spectral reconstruction

Spectral sensors

- Cheap
- Robust Packaging
- Low resolution
- Low Accuracy
- Light
- Power efficient
- Longer battery life
- Wearable, light
- Complex spectral reconstruction

Sensor Calibration – Mini spectrophotometers

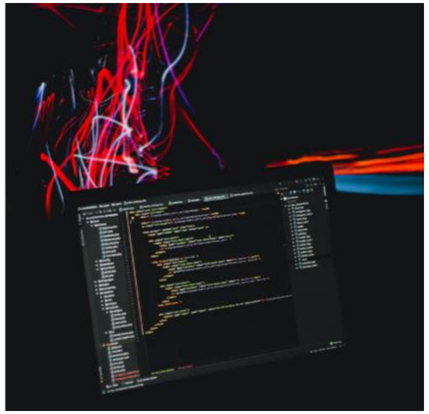
Baseline	Electronic offset	Dark signal
Stray Light	wavelengths other than those intended to be measured	In range / Out of range
Spectrum	wavelength	irradiance
Nonlinearity	Sensor saturation	Integration time



Based on CIE 233: 2019
Calibration,
Characterisation,
and use of array
spectroradiometers

Sensor Calibration – Data-driven approach

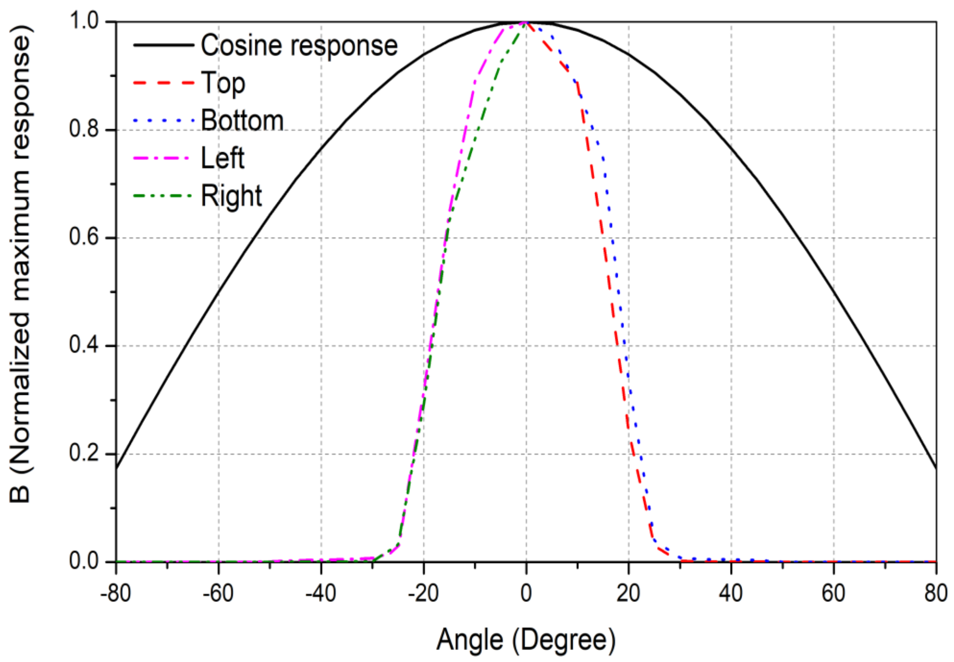
Simple Interpolation	Responsivity Standard spectrophotometer	Interpolation	Low computational cost and low accuracy
Regression Models	Data Collection Standard spectrophotometer	Best fit	Medium computational cost and improved accuracy
Machine Learning	Data Collection Standard spectrophotometer	algorithm for most accurate prediction	Optimised computational cost and high accuracy



Based on data driven methods

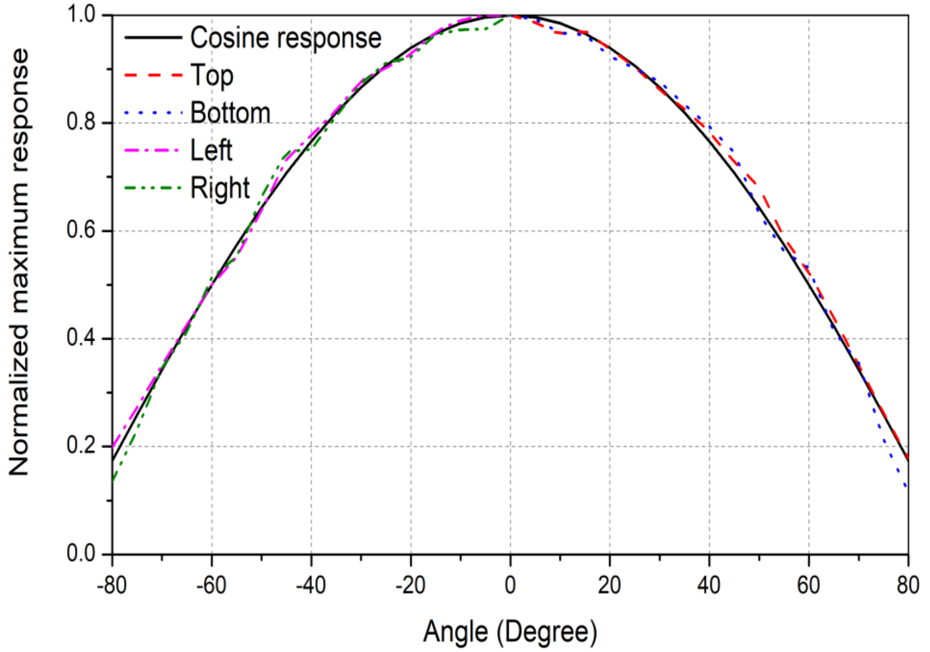
Simple interpolation
Regression (e.g. polynomial least-square) is straightforward, limited calibration data
Machine Learning (e.g. neural networks) needs large training data

Directional Response



(a)

f_2	Without optical modification	With optical modification
Top	51.37	1.11614
Bottom	51.31	0.49177
Left	50.89	0.577516
Right	50.51	0.428236
f_2 index	51.02	0.653416



(b)

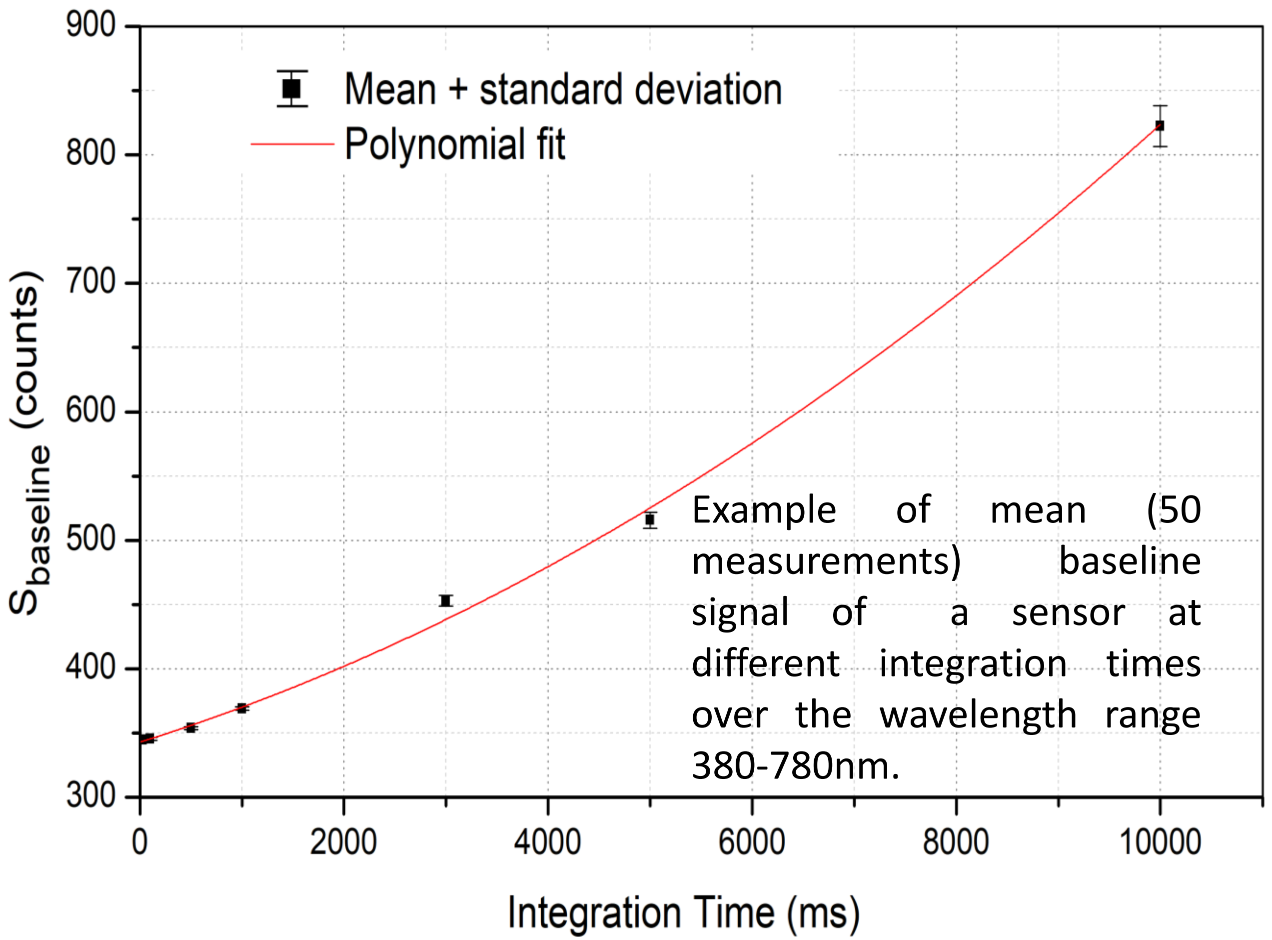
Directional response of the device compared with the ideal cosine response: (a) with no optical modification; (b) after optical modification.

Spatial response must also be similar to that of the eye, which is Lambertian

Use CIE directional response mismatch function to evaluate the error

A. Mohamed, V. Kalavally, S. W. Cain, A. J. Phillips, E. M. McGlashan, and C. P. Tan, "Wearable light spectral sensor optimized for measuring daily α-opic light exposure," *Optics Express*, vol. 29, no. 17, pp. 27612-27627, 2021.

Baseline Calibration

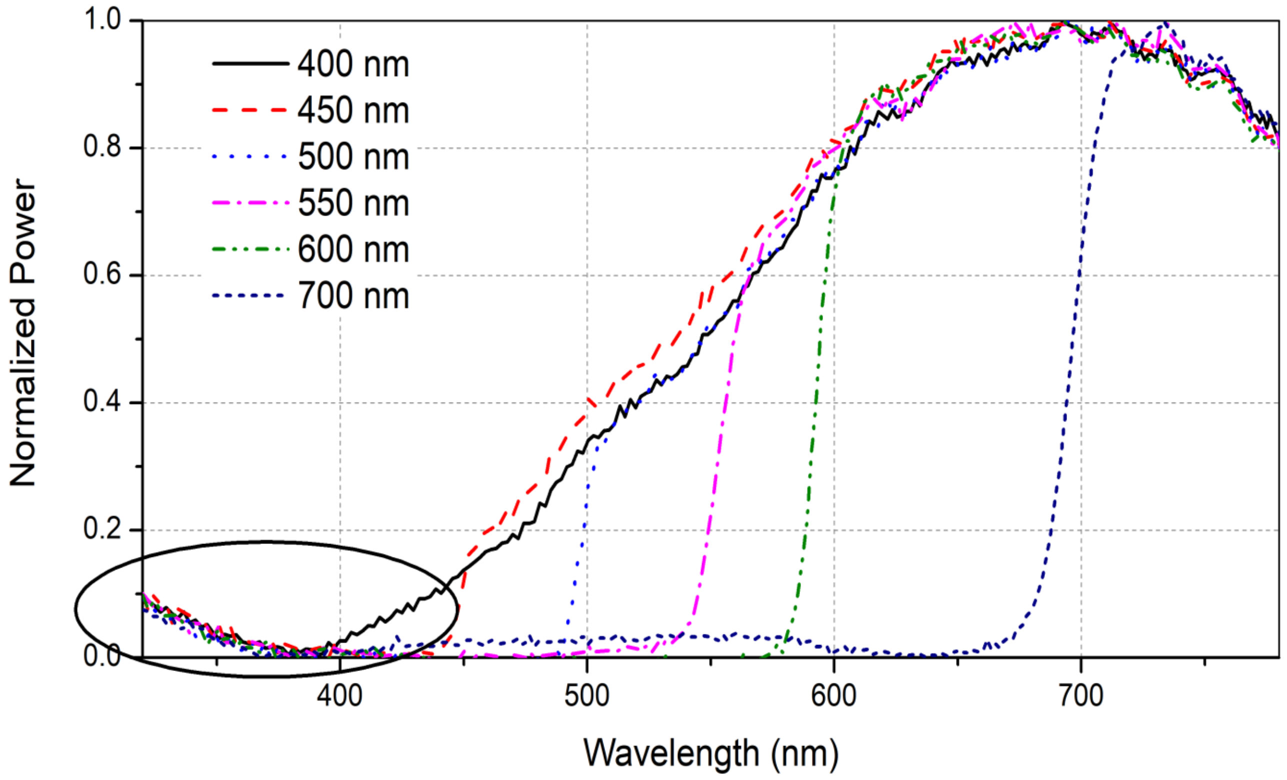


Example of mean (50 measurements) baseline signal of a sensor at different integration times over the wavelength range 380-780nm.

Most array spectroradiometers have a baseline signal that is present even in the absence of a light input, which must be characterized and subtracted from measurements.

Baseline signals are measured with the sensor in complete darkness.

Straylight Calibration



(a)

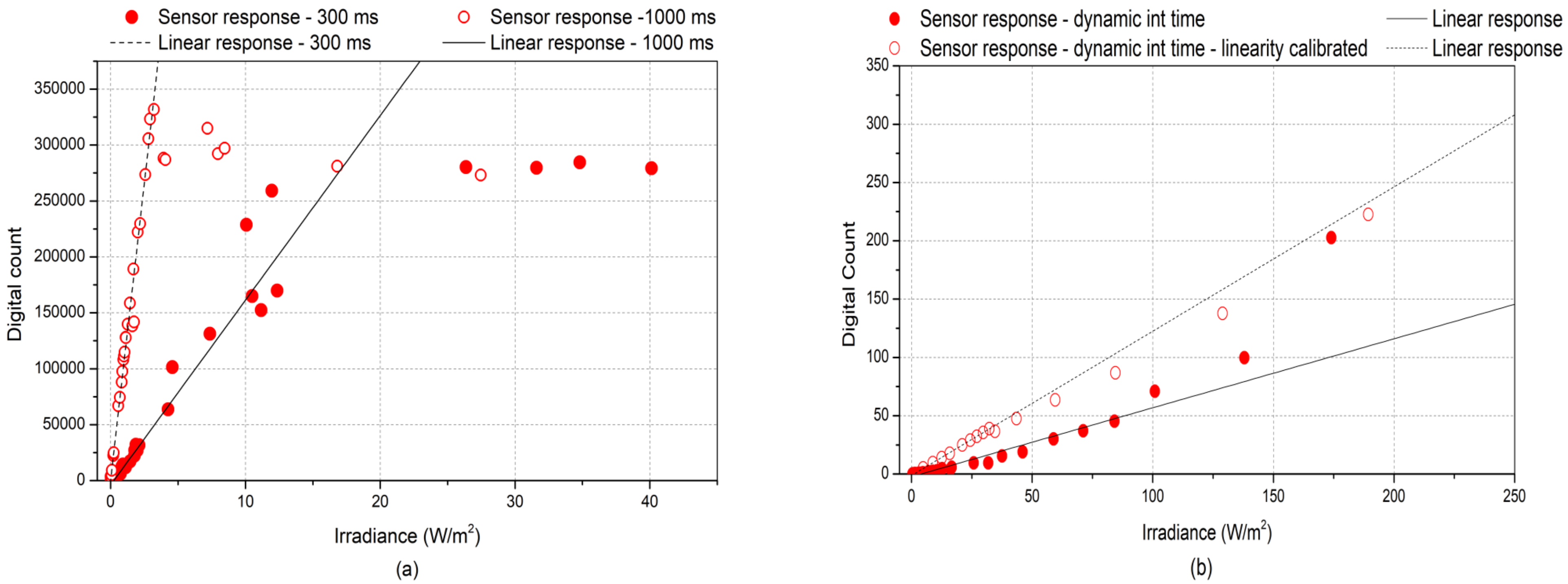
Characterization of the effect of stray-light contribution from light outside the specified spectral range of the device: (a) The device was exposed to a halogen light source transmitted through a long pass filter blocking signals below the wavelengths stated in the legend of the figure. The signal detected (circled) below the cut-on wavelength is due to stray-light and requires correction.

Stray light refers to light that reaches the detector at wavelengths other than the wavelength intended to be measured

There is a response at wavelengths below 400 nm that is due to stray light

An elevated level of stray light at shorter wavelengths.

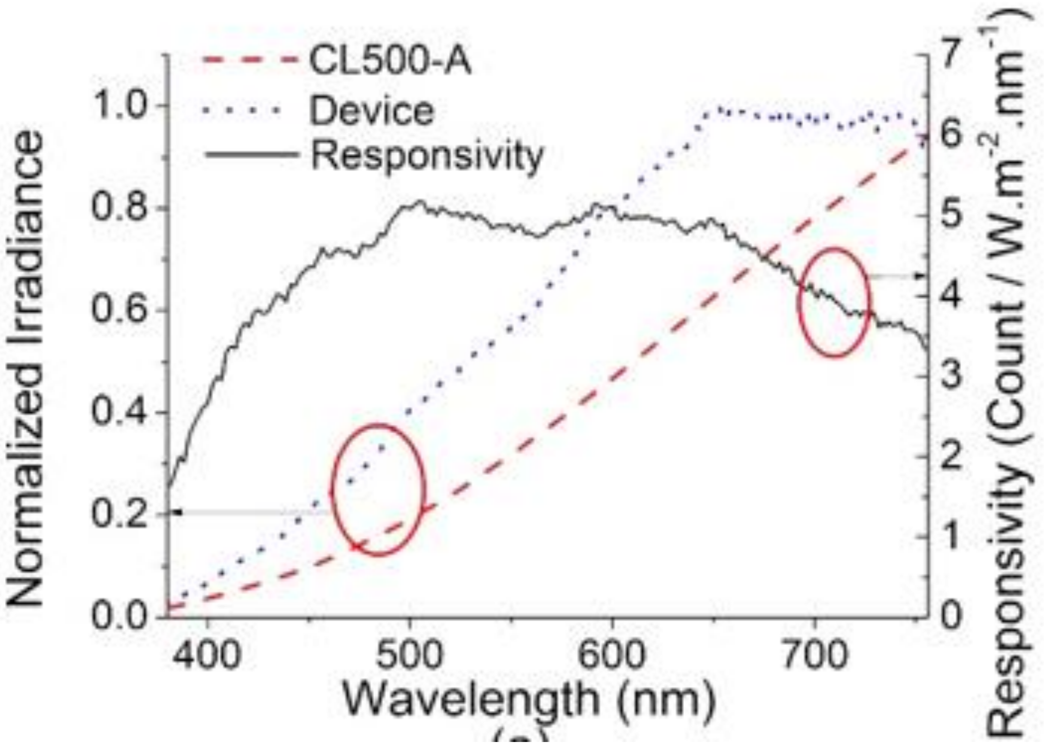
Non-linearity Calibration



Linearity characterization of the device related to the amplitude response of the sensor with (a) constant integration times of 300 ms and 1000 ms; and (b) dynamic integration time with linearity calibration.

Two forms of non-linearity have to be considered for irradiance calibration, one related to the amplitude response of the sensor to irradiance and the other to the integration time of the sensor.

Irradiance Calibration

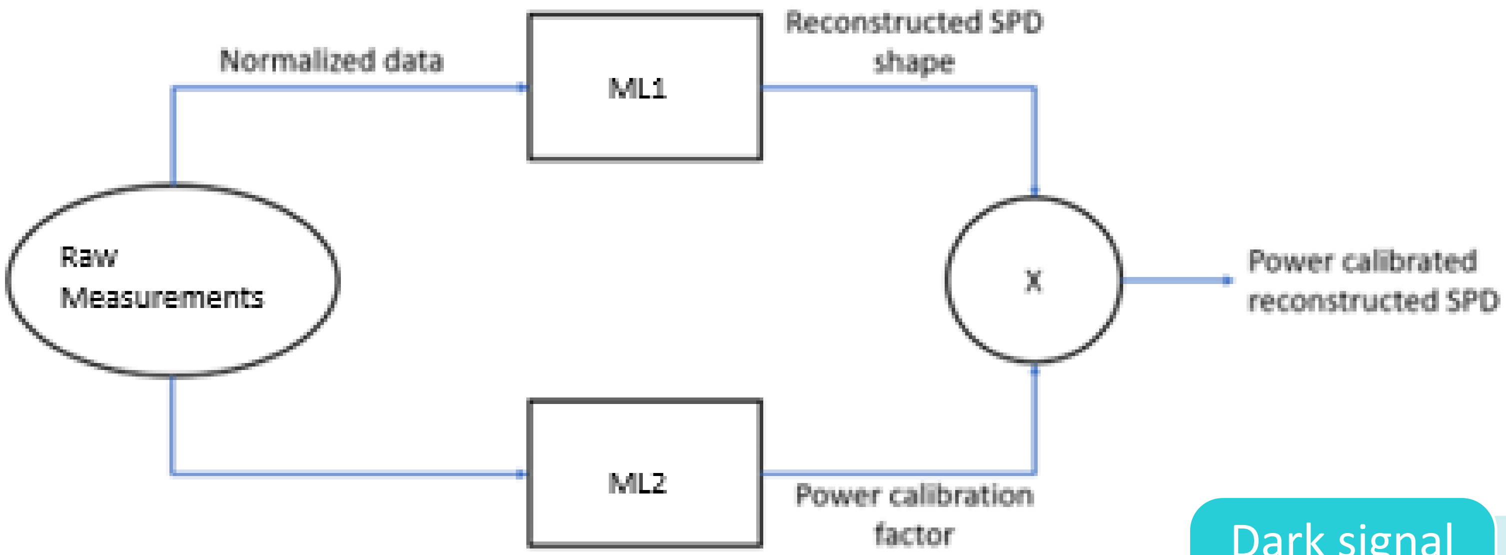


Responsivity of device calibrated against a standard spectroradiometer with a Halogen lamp.

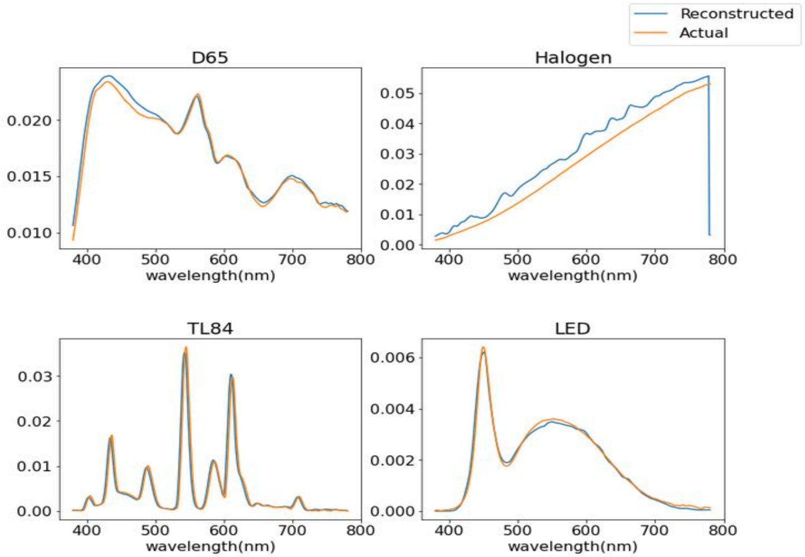
Irradiance calibration allows for the determination the spectral responsivity of the device

NIST traceable, calibrated light source to be used for calibration

Data-driven spectral reconstruction



High-level view of the proposed approach



Dark signal and Straylight	• May not require correction
Directional response	• No change in approach
Linearity calibration	• Constant integration time – associated nonlinearity correction is not required

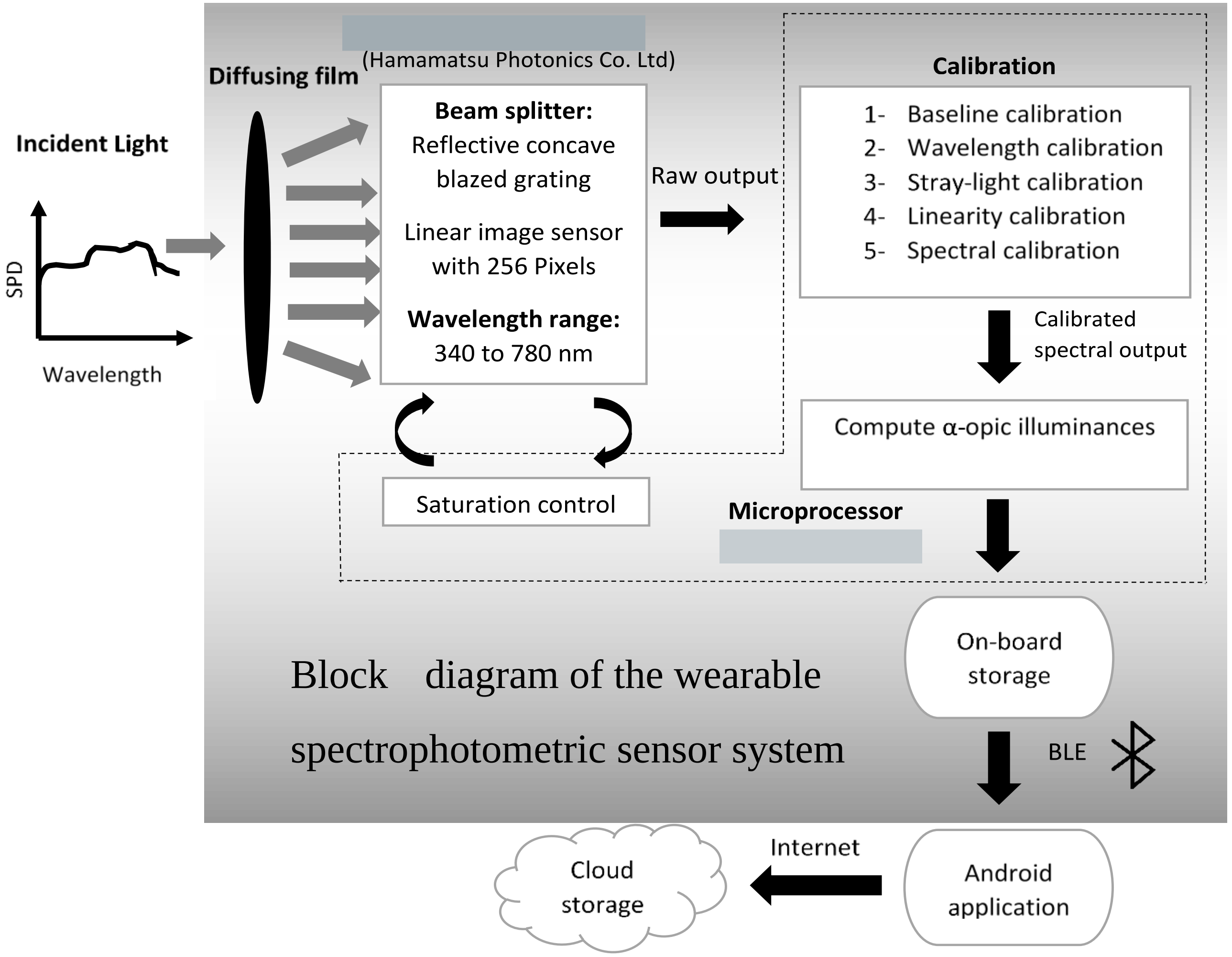
Hardware - Device Miniaturisation

Device Memory
- Sensor type - Number of sensor outputs
- Days of uninterrupted operation

Battery
- Depends on power consumption of sensor
- Frequency of measurements
- size

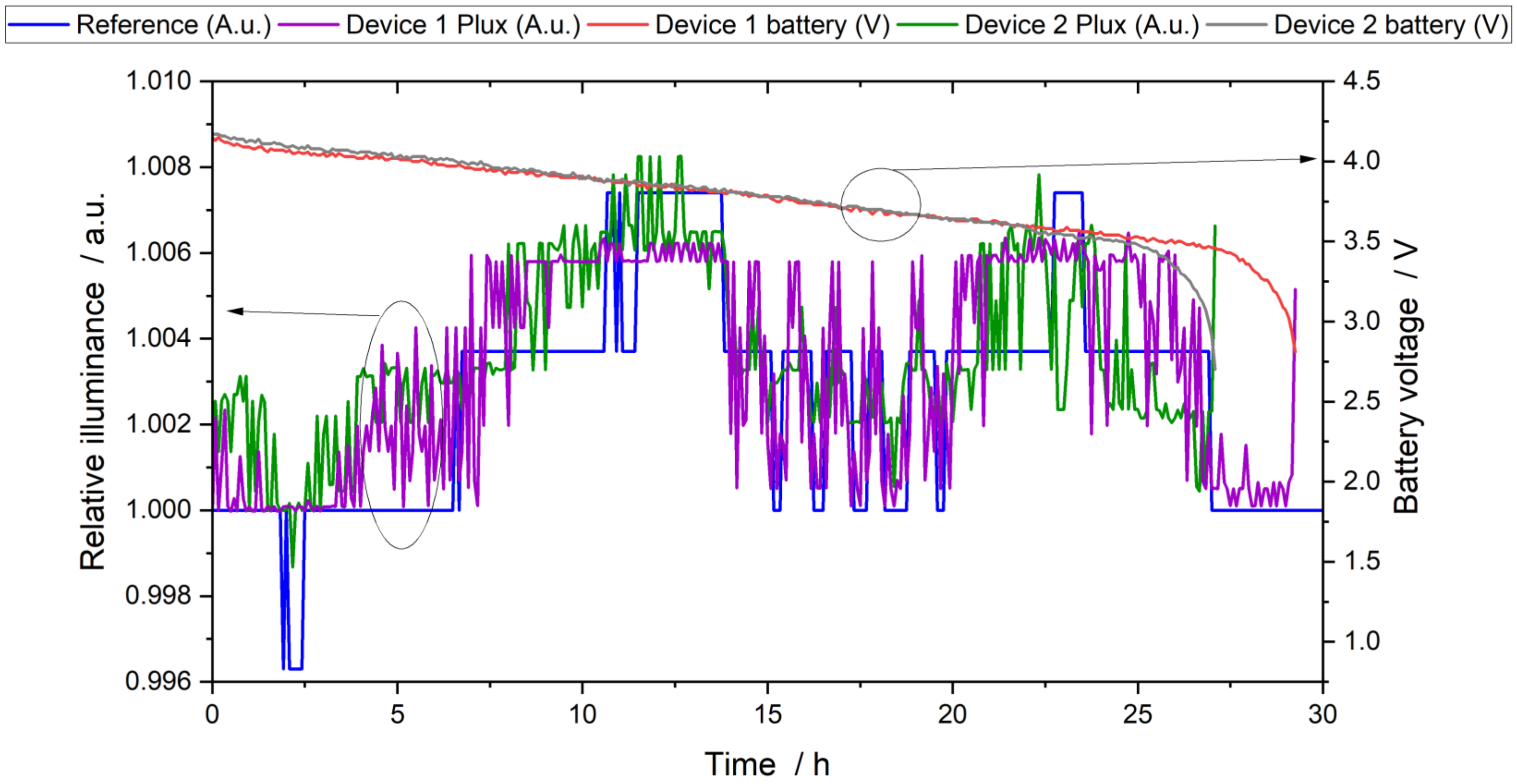
Microprocessor
- Computational power
- Speed

Antenna
- Lower energy
- Range



Block diagram of the wearable spectrophotometric sensor system

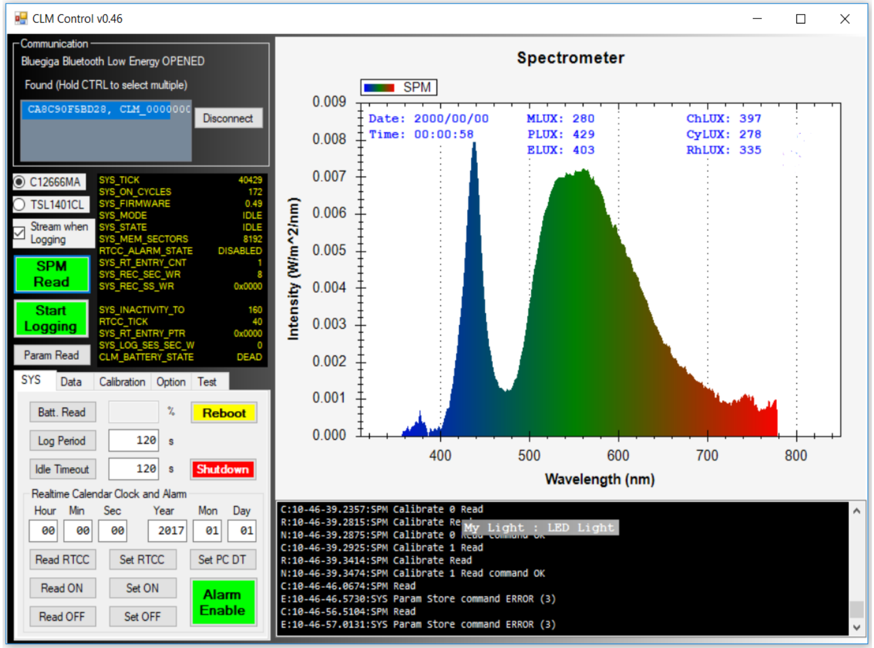
Effect of Battery Voltage on Sensor Performance



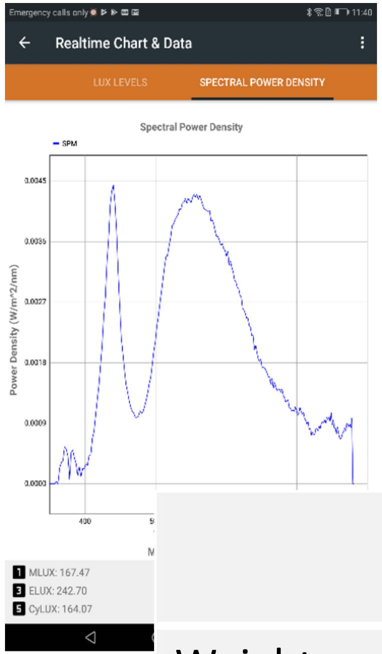
Declared battery life must be tested against the voltage thresholds below which the sensor stops tracking the spectrum accurately

Software – App and Cloud Storage

(a)



(b)



(c)

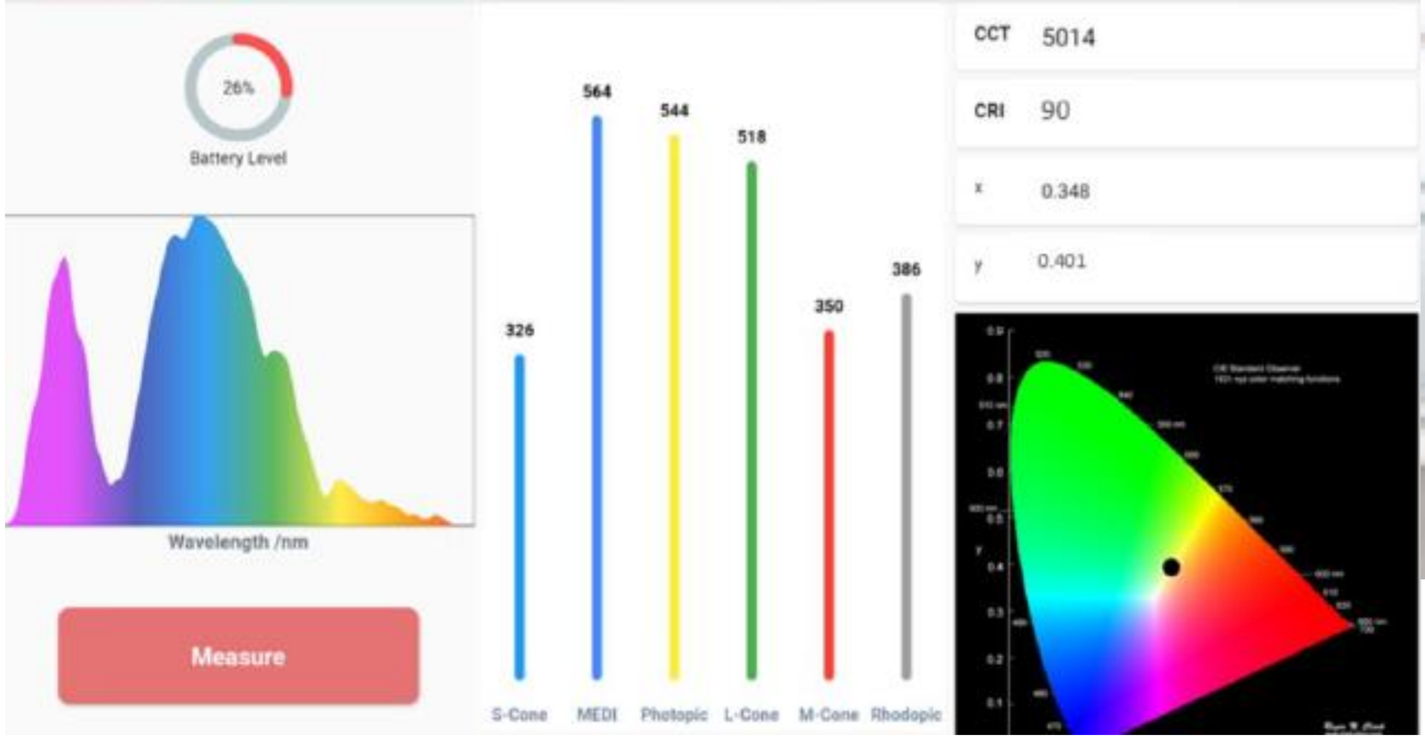
User interfaces developed to operate the device: (a) PC GUI developed with Visual Studio; (b) Android application developed for the device (c) wearable form factor (d) typical specs

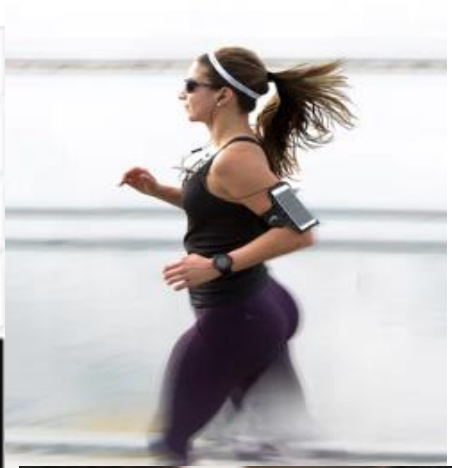
	Mini Spectro photometer	Spectral sensor
Weight	~30g	~20g
Size	~45x20x17 mm	~45x20x15 mm
Battery life	1 day (110 maH)	3 days (200mAH)
Memory	5 days	90 days

* at 1 sample/min

(d)

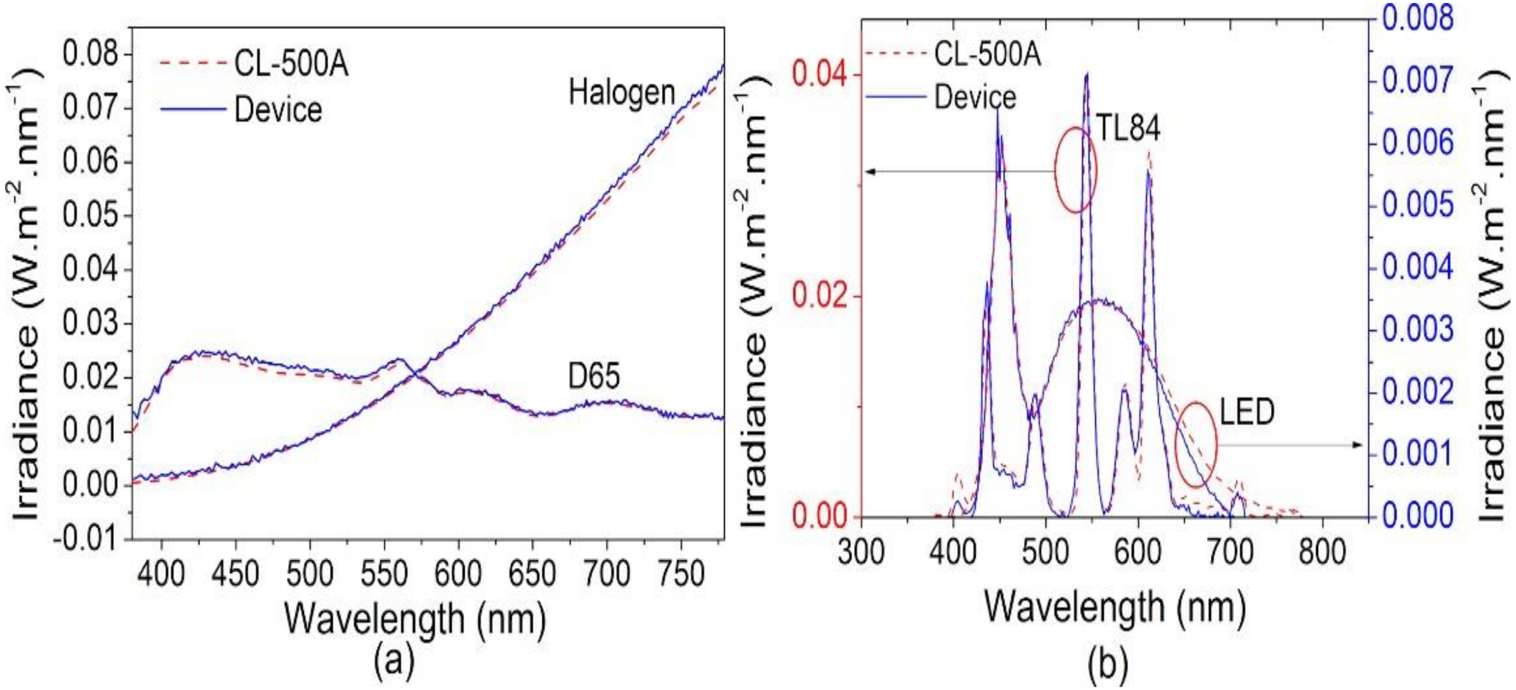
Additional Features





Color, CCT and light quality information
Recognition of light type
Recommendations for a light diet
Accelerometers to record actigraphy data
Temperature sensor

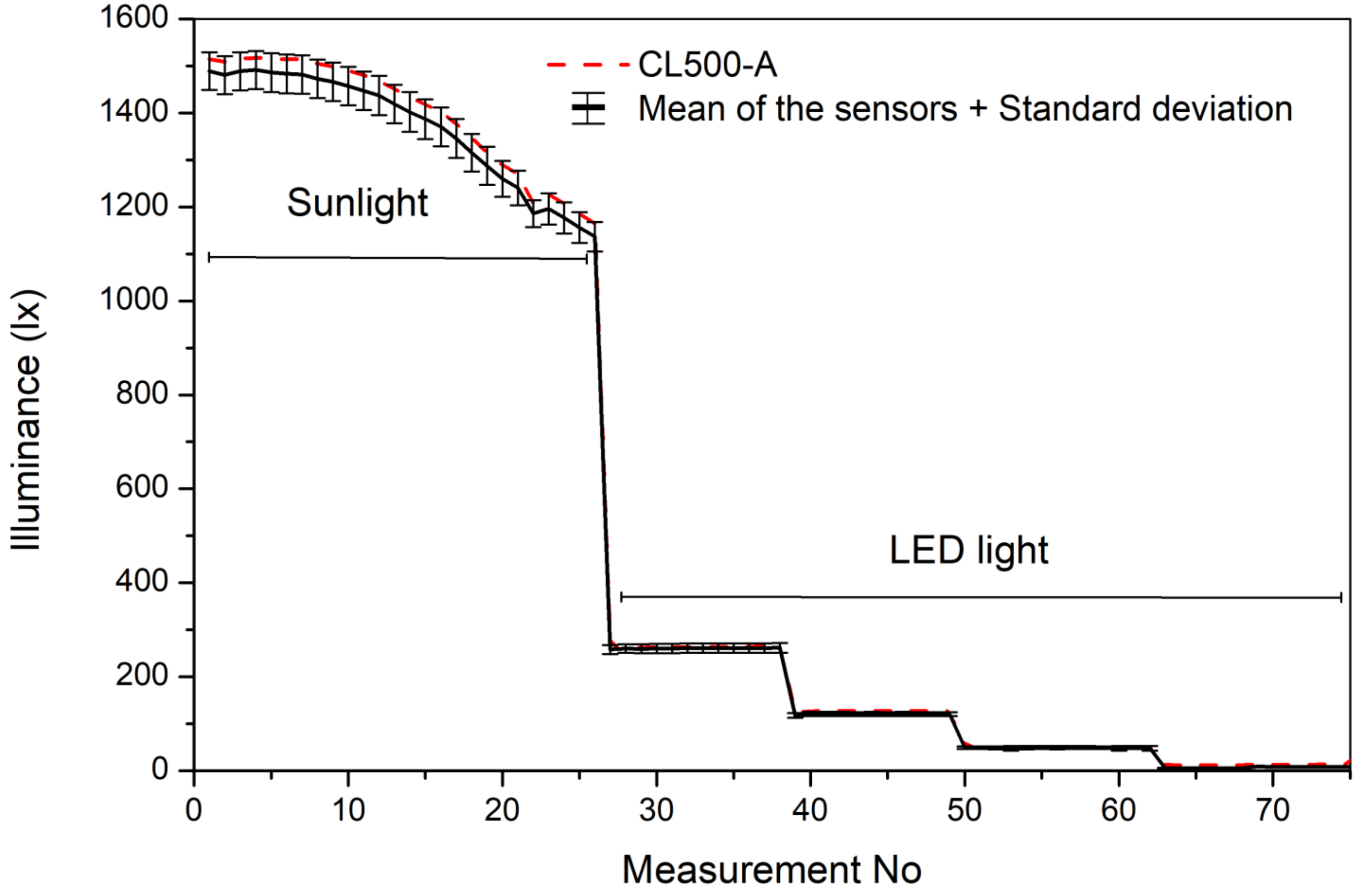
Testing and Validation



	Illuminance error (%)			
Illuminant	D65	A	TL84	LED
Photopic	0.23	2.24	4.70	0.17
Melanopic	1.80	2.51	0.77	0.67
L-Cone	1.87	2.20	4.04	0.27
S-Cone	1.06	4.36	6.96	3.25
M-Cone	0.13	2.39	4.68	0.81
Rhodopic	0.08	2.56	1.75	0.12
NRMSE	0.04	0.03	0.03	0.03

The percentage difference between the α-opic EDI values calculated by using the irradiance spectra obtained by this mini spectrophotometer type device (from our lab) compared to a laboratory standard spectroradiometer was less than 7% for all light sources.

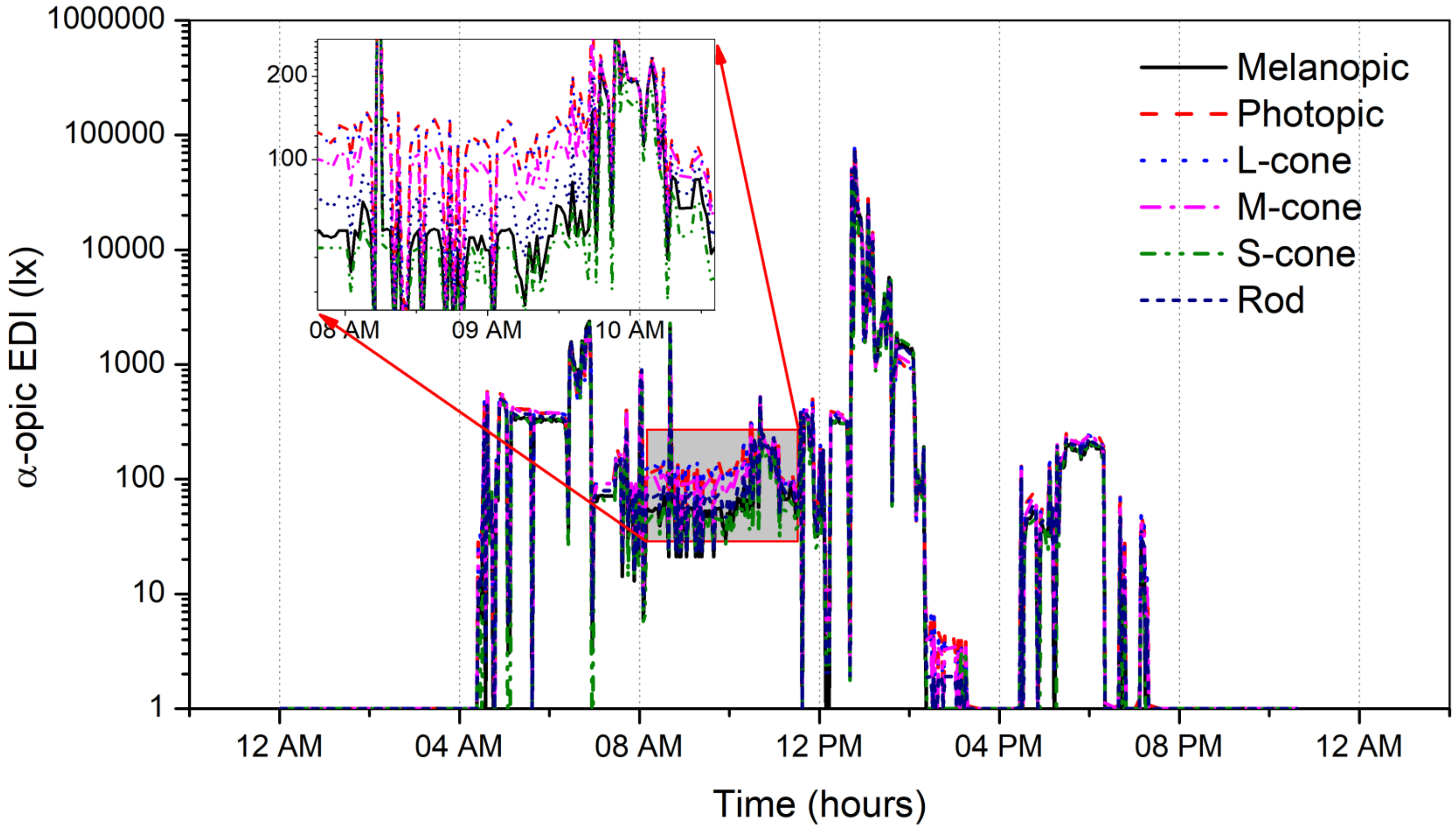
Inter-device variability



Inter-device variability in outdoor and LED indoor lighting

Measurements taken with 5 sensor units for several lighting conditions. This was done for typically observed illuminance levels of sunlight and indoor LED lighting. The mean and standard deviation for 5 sensors are in close proximity to each other and with measurements taken using a reference spectrophotometer.

Measured α-opic EDI data



α-opic EDI data measured for an individual wearing the device for a day

Data logged from a real-world participant who wears the device for 24 hours except when sleeping.
The α-opic EDIs and the photopic illuminance exposures of this participant in a typical day varies significantly in magnitude and relative to each other.
There is a need to monitor them separately in studies sensitive to an individual's retinal photoreception using a personal wearable sensor.

Chest/Eye-Worn Wearable Light Spectral Sensors in Use

Some Research Prototypes

- Wearable Light Spectral Sensor by Intelligent Lighting Laboratory and Turner Institute of Brain and Mental Health, Monash University

- Lido by Lucerne School of Engineering and Architecture

  Image source: https://light-dosimeter.ch/

- Spectrace by EPFL Swiss Federal Institute of Technology in Lausanne

  Image source: https://actu.epfl.ch/news/combining-science-and-design-to-measure-our-exposu/

- Daysimeter by RPI
  Image source:
  https://www.lrc.rpi.edu/programs/lightHealth/img/oldDaysimeter.jpg

Chest/Eye-Worn Wearable Light Spectral Sensors in Use

Commercially Available

- Lys Button
  image source:
  https://www.gadgenda.com/lys-button-10-wearable

- Condor

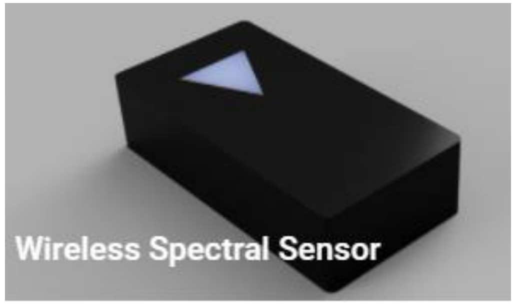
  Image source:
https://www.condorinst.com.br/en/contato/

- Others..

Not all sensors in both categories are full spectrum sensors

Choices made depend on the objectives of the data collection

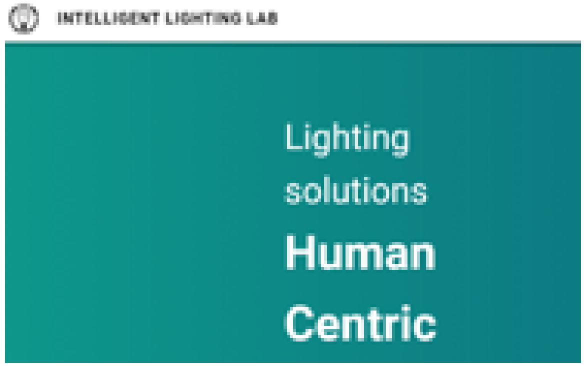
Framework Development



Light Data

Actigraphy Watch

Actigraphy Data



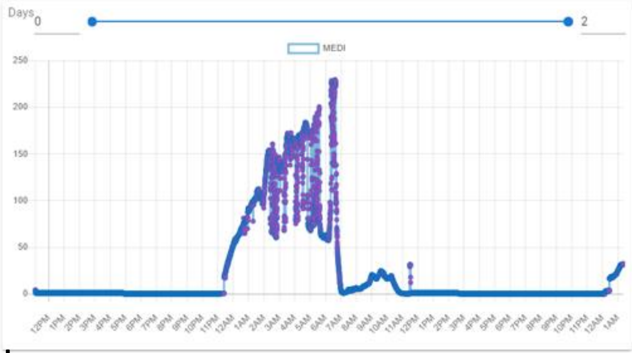
Web-based Application

Upload

Download

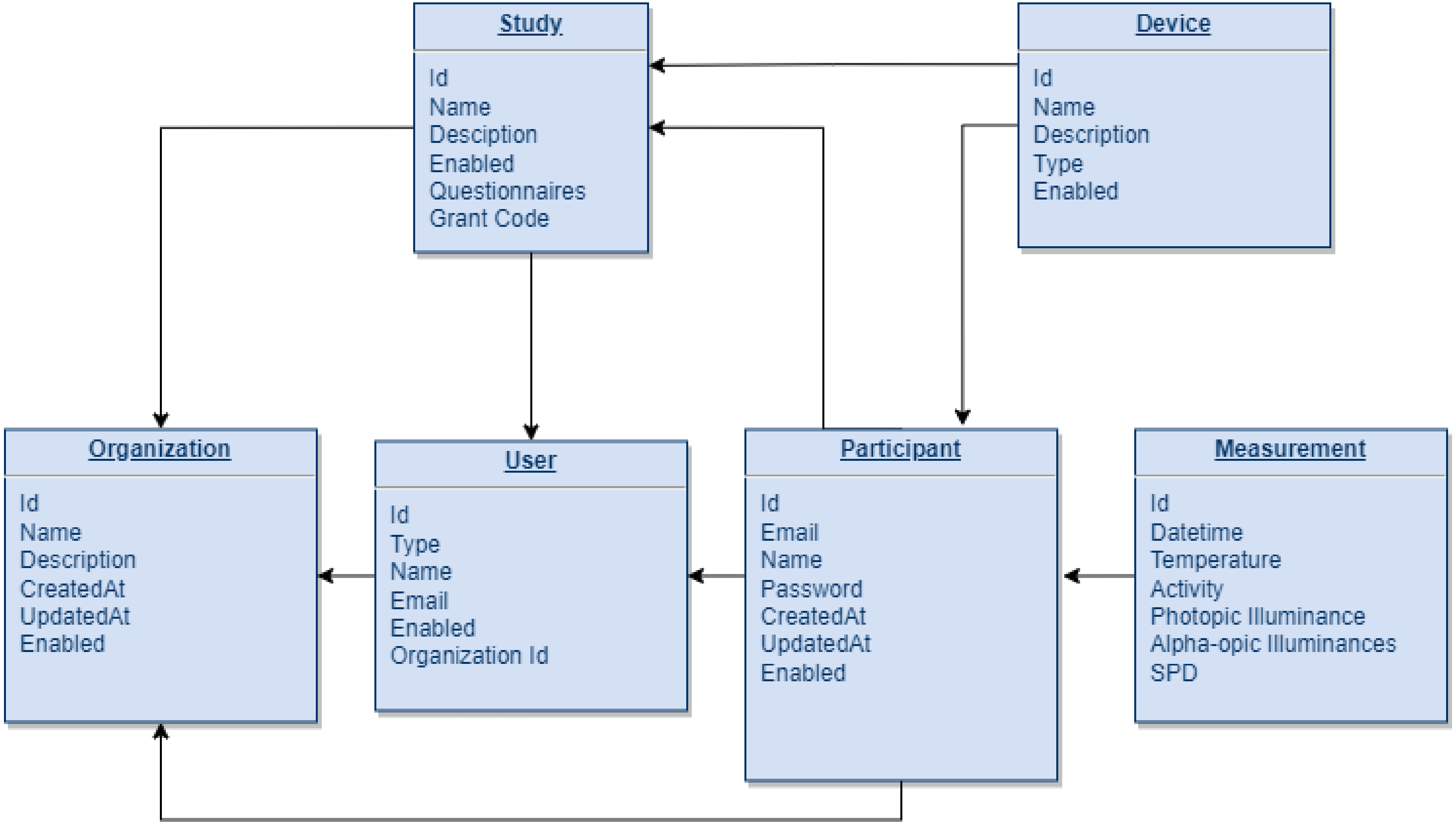
Cloud Database

Analysis



A framework to facilitate the uploading data from the light spectral sensor and other sensors involved in the study to a cloud-based database

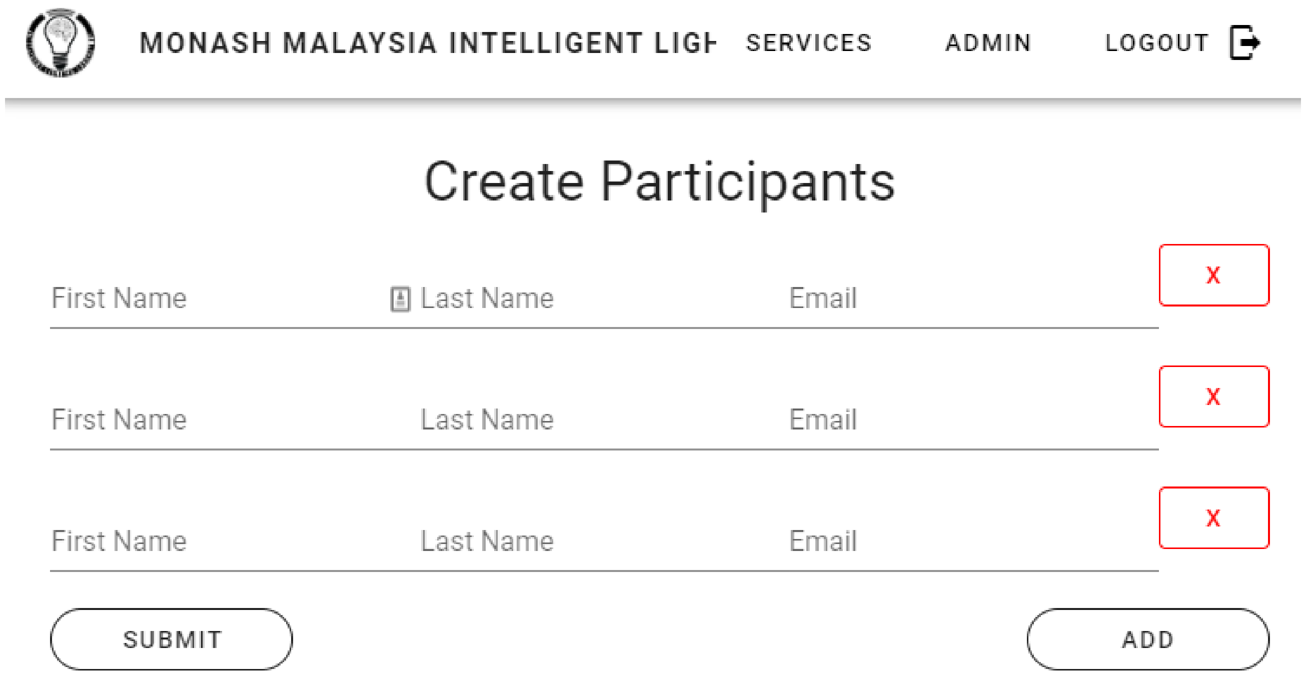
Database Overall Schema

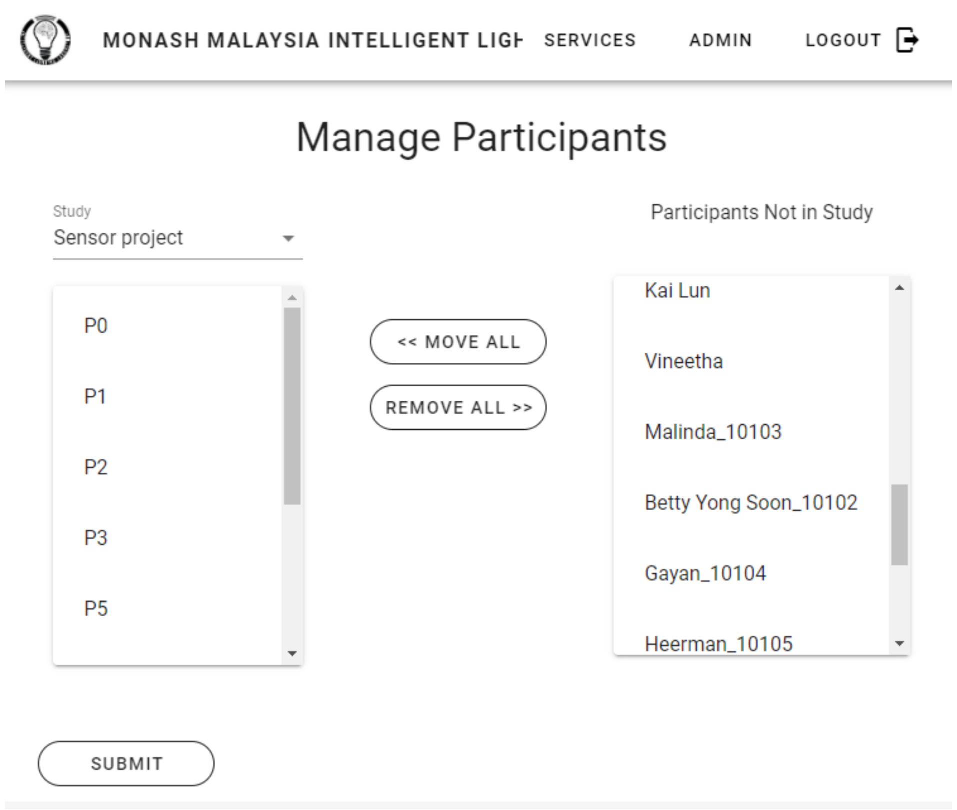


Have a standard format for reporting a time series spectral data based on the FAIR (Findeable, Accessible, Interoperable and Reusable) guiding principle

The Process

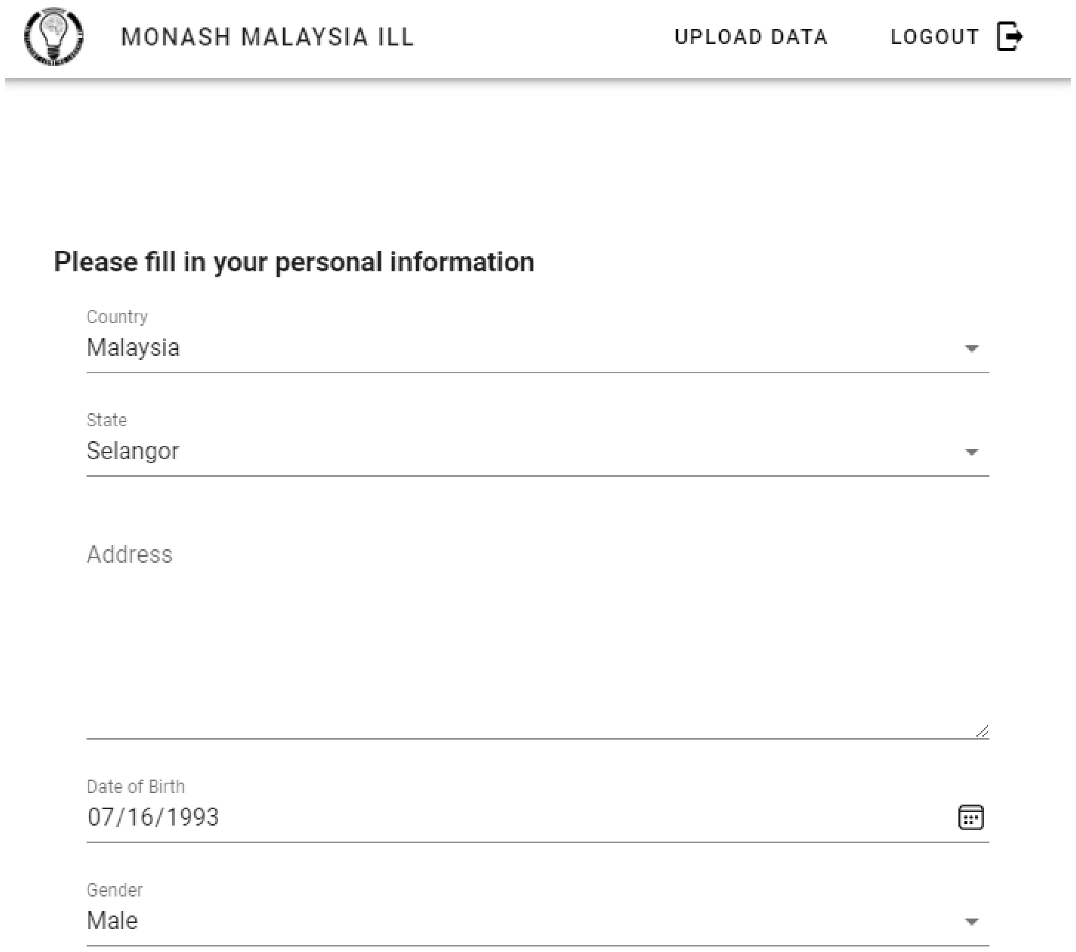
- Participant Registration and data acquisition
  - Participants are created in the database
  - Studies and devices are assigned to the participant





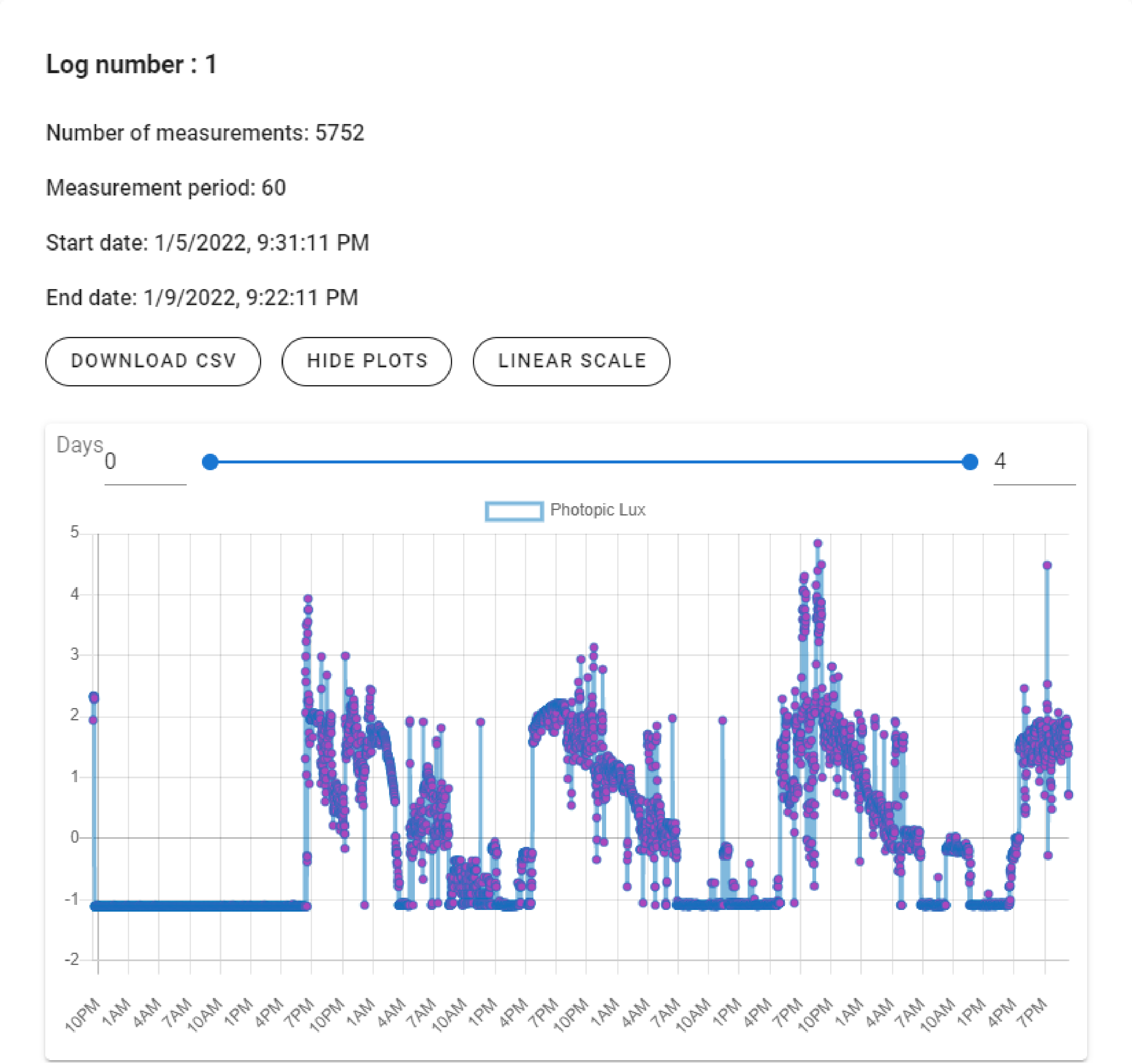
The Process

- Participant Registration and data acquisition
  - Participant completes registration process
    - Fills in relevant questionnaires and required information via the web interface
  - Wears the sensors for a set time
  - Researchers upload the data via web interface
- Data
  - Data is available to Users who are part of the organization and study
  - Can be made accessible to a wider community if subscribed to the schema



Data Analytics

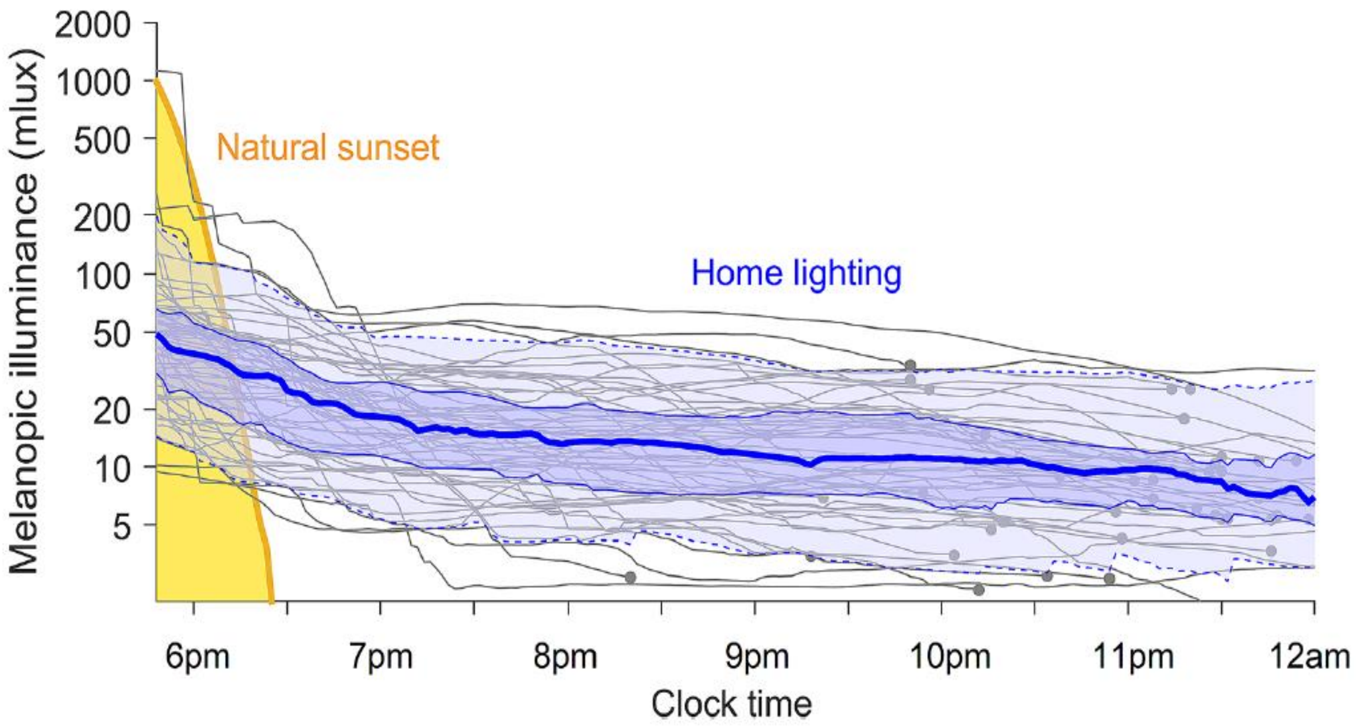
- The web interface is used for data visualization and analytics
  - Data visualization
    - Plots
  - Data analysis
    - Sleep parameters
    - Alpha-opic illuminances
  - Data Download
    - Download data over specified time frames



Data Visualisation

The database linked to a data analytics and visualization platform (example, Grafana) to provide an interactive data dashboard that allows easy analysis and visualisation of information.

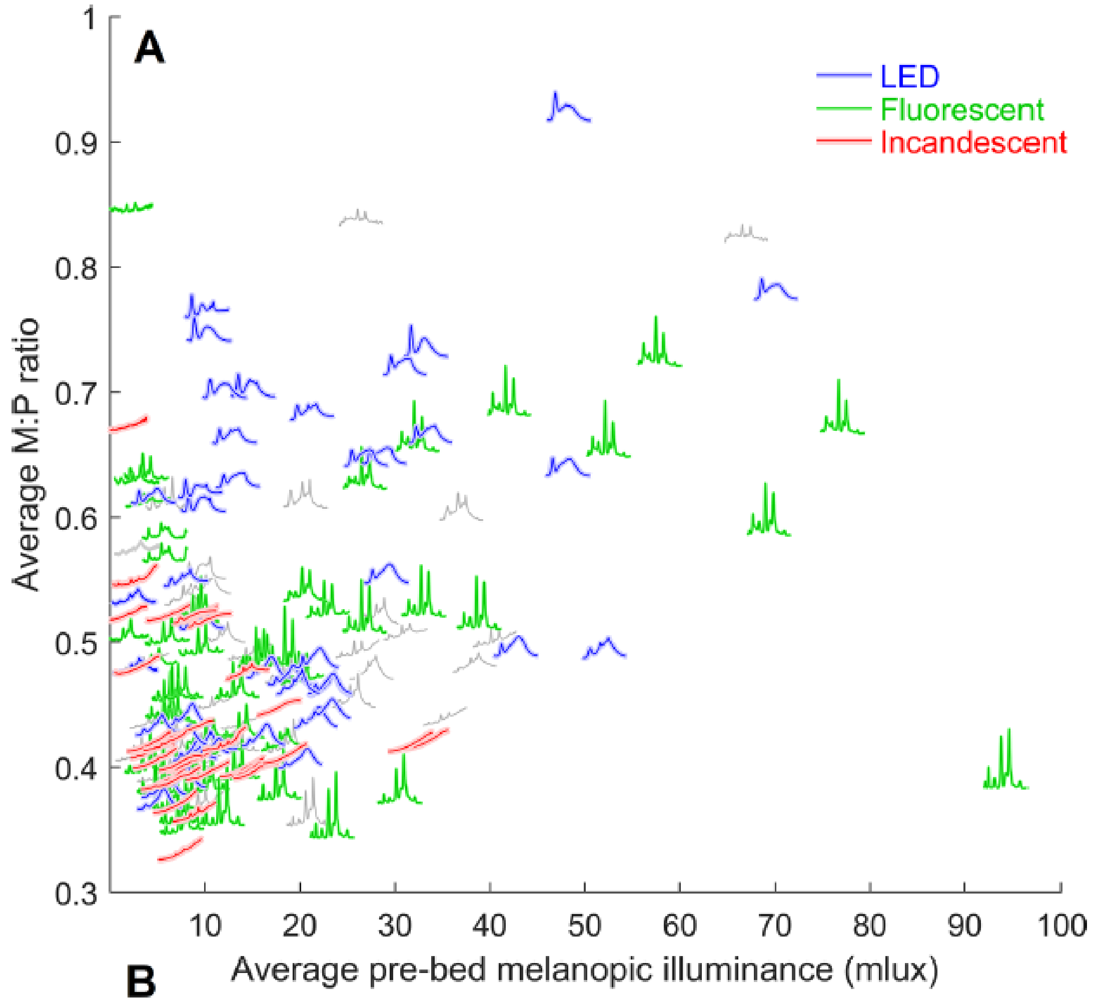
Case study: Measurement of home lighting

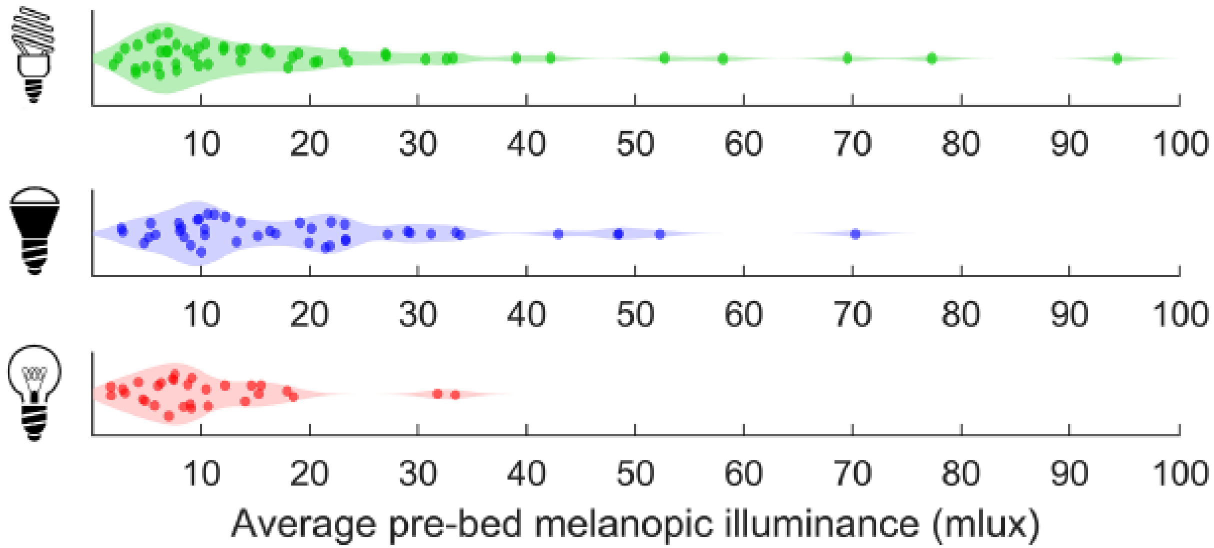


Home lighting and natural sunset spectra were measured using our wearable light spectral sensor. It was found that home lighting persisted at biologically impactful levels throughout the evening.

S. W. Cain *et al.*, "Evening home lighting adversely impacts the circadian system and sleep," *Scientific reports,* vol. 10, no. 1, pp. 1-10, 2020.

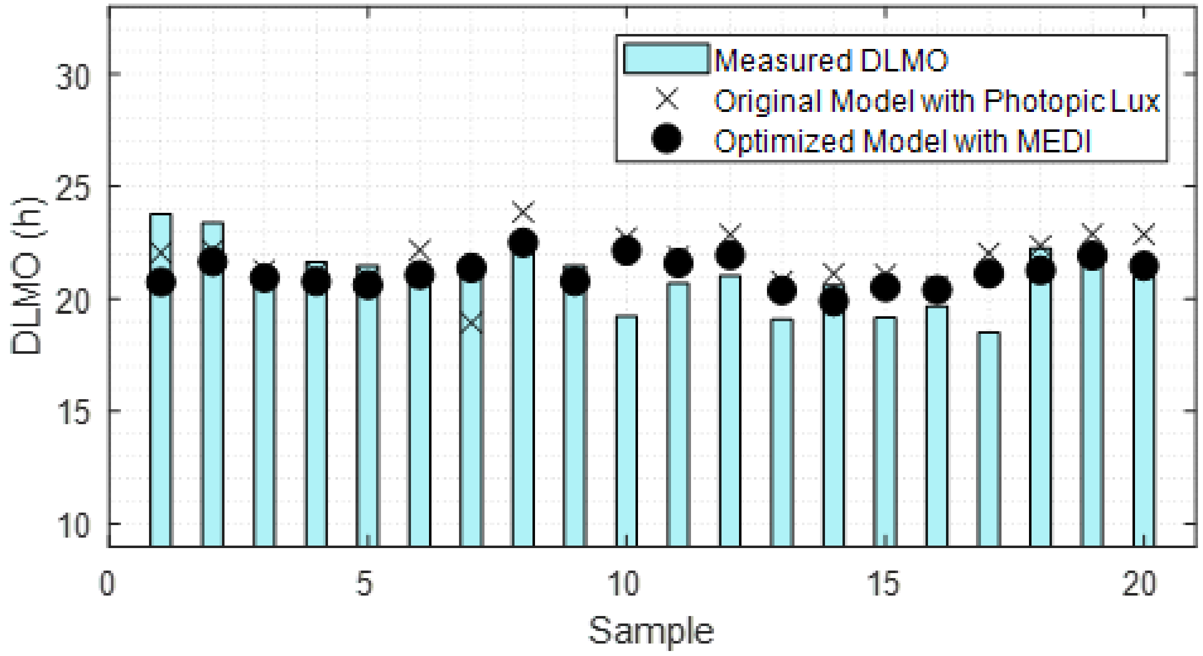
Case study: Measurement of home lighting

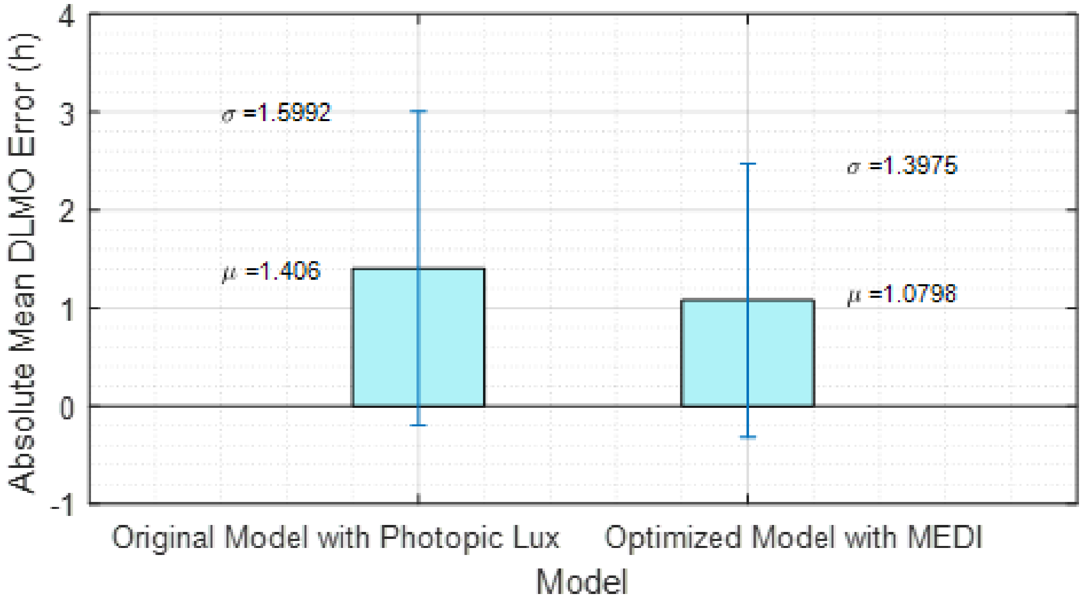




It could be established that the light spectrum is highly variable between homes, with a 20-fold range in average melanopic illuminance in the 3hrs leading up to bedtime.

Case Study: Improving the accuracy of DLMO prediction via mathematical modelling (unpublished)





An optimized pace maker model for Dim Light Melatonin Onset (DLMO) with Melanopic Equivalent Daylight Illuminance (MEDI) performs 23.21% better than the original model with photopic illuminance input.

Conclusion

Daily personal light exposure if

measured accurately, conforming to standards, using validated sensors and adhering to a meta-data schema

can result in a powerful database that can unravel many unknown pathways between light and humans

Thank you