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# Calibration and Validation of Climate-Based Daylighting Models Based on One-Time Field Measurements: Office Buildings in the Tropics

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## ABSTRACT

Calibrated climate-based lighting simulation models of buildings have the capacity to perform an essential role in postoccupancy evaluations, such as annual frequency assessments of daylighting quality and visual discomfort. However, in most postoccupancy case studies the role of lighting analysis is temporally limited by instantaneous measurements or limited in scale by requiring constant monitoring with expensive sensors. It is challenging to build calibrated models based on point-in-time measurements due to the presence of electric lighting, transient use of dynamic shades, limited information on the material specifications, and short durations of accessibility to the spaces being studied. The authors propose and present a calibration process for annual daylighting and electric lighting simulation models based on one-time field measurements of large daylit and electrically lit spaces exemplified through a data set of 540 individual office desks across 10 office spaces. The calibration process includes measuring lighting, physical, and material data during a one-time visit that are used to calibrate high dynamic range images and lighting simulation models using actual weather data. The calibration accuracy is validated based on measured and simulated luminance and illuminance data. Comparing measured and simulated illuminance, relative root mean squared error (RMSE) values were 25.8% and 45.5% for horizontal and vertical measurements, respectively. When tracking errors using  $\log_{10}(\text{illuminance})$ , approximating human perceptual differences, errors of 4.3% and 6.8% were achieved. Vertical illuminance was found to vary more with measured data due to the uncertainty of monitor screen luminances. The authors aim to achieve calibrated lighting models that are reliable enough to be used in assessing the relationship of annualized lighting metrics to participants' long-term perceptions of lighting quality, thereby enabling simulation models to be used in the postoccupancy evaluation process of building lighting. This article demonstrates that measured data through one-time visits can be utilized to build reliable calibrated lighting simulation models to integrate long-term annual lighting results in postoccupancy evaluations.

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## KEYWORDS

Calibration; daylighting; model; simulation; validation

## 1. Introduction and background

Simulating daylighting and electric lighting in digital architecture models in various stages of design has become quintessential for informing design decisions to meet quantitative and qualitative lighting goals by predicting building performance prior to construction. Postoccupancy evaluations (POEs) of completed buildings and spaces close the loop by providing feedback on the end quality of a design to the building and construction industry, which can assess whether the project brief was met (Oseland 2007) as well as serve an important role by allowing researchers to generate knowledge of occupant well-being based on actual user experiences. This can well lead to new

recommendations to inform future building design. Most POEs focus on instantaneous measures of illuminance or visual comfort using high dynamic range (HDR) photography techniques within a monitoring time period. However, architects, energy consultants, engineers, lighting designers, and researchers designing for daylight today use computer daylighting simulations and annualized lighting measures (Reinhart and Fitz 2006) and, recently, are including climate-based daylighting metrics (CBDMs) and annual visual comfort analysis to assess potential designs instead of static daylighting metrics (Reinhart et al. 2006). To truly “close the loop,” these annual daylighting metrics need to be evaluated based on a comparison with

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overall user perceptions of a space and the annual lighting they experience. To this end, this article describes a process of calibrating daylight simulation models during POE field studies, which can be used to calculate annual CBDMs as a component of building POEs based on short-term visits instead of long-term monitoring. However, the proposed methodology does not aim to replace current POE methods but rather to extend and refine the capabilities of POEs by correlating actual annual daylighting metrics to the overall queried experiences of occupants. Models of 10 office buildings with 540 calibration points—participants' occupant seating locations—are calibrated and validated in this manner as a proof of concept. This study is the first large-scale calibration effort that aims to utilize long-term lighting simulation data for post-occupancy studies, enabling the comparison of CBDMs to occupant impressions in daylit spaces over a long period of time. Although the calibration and validation study is situated in the tropical climate in Singapore, the proposed workflow is applicable to any climate.

Many measurement-driven POE studies in the research literature are based on single instantaneous measurements and do not utilize long-term monitoring or annual predictive data. Bear and Bell measured illuminance, source luminances, surface reflectance, geometric factors, and subjective information for 471 participants as early as 1992. Osterhaus (2001) surveyed 86 participants in nine office spaces. Parpairi et al. (2002) measured luminance values manually and illuminance at limited points in time in three libraries from 26 typical users of the spaces. Dahlen et al. (2009) measured discomfort glare metrics using HDR photography along with illuminance and subjective information from 298 female college students over a 2-month period, categorizing overcast and clear sky conditions separately. Choi et al. (2012) measured instantaneous luminance using HDR photography and illuminance, among other Indoor Environmental Quality (IEQ) factors, at 402 occupant desks using a mobile sensor cart, although they spread their measurements out over a period of time in order to collect some level of seasonal information. Hirning et al. (2013, 2014) measured discomfort glare using HDR photography for 419 occupants not experiencing discomfort due to reflections from their monitor screen and photographs were taken from the occupant's point of view close in time to

when participants filled out a short subjective survey. Mangkuto et al. (2017) used HDR photography to measure luminance and glare metrics in an Indonesian library space over a 6-day period, collecting 86 measures paired with subjective information. Hirning et al. (2017) repeated their study in Malaysia with 341 participants in six separate office spaces. In summary, for direct measurement POE studies, it is feasible to quickly collect a large number of data from a diverse range of participants. The mean number of subjects or data points in these studies is 292. However, limitations do emerge—the vast majority of studies collect limited seasonal or temporal data, localizing the results at the specific point in time at which the measurements are taken.

Another approach employed by researchers has been to utilize long-term data monitoring in order to gather a more holistic representation of POE participants' lighting experiences. Fan et al. (2009) recorded HDR photographs and frequent subjective information using a computer application for five occupant workstations. Cameras were mounted as close to the head position of the occupant as feasible, which resulted in errors generally below 25%. Their study was later carried out for a period of 1 year (Painter et al. 2010). Konis (2013, 2014) recorded ambient environmental conditions, HDR photographs, and subjective ratings on a continuous scale for 14 participants over a 2-week period, collecting 523 data points overall. A custom sensor and polling device was created and placed upon occupant's desks; it prompted participants periodically for subjective feedback using a physical slider, at which time an HDR photograph was taken. Drosou et al. (2016) installed two high-quality HDR camera capture setups in classrooms, monitoring their lighting performance every 10 min for an entire year. Limitations included a period of data loss due to camera shutter failure and a single, fixed viewing location not from an occupant point of view. Bellia et al. (2017) continuously measured occupants in three private offices during a 3-day period while measuring luminance and illuminance. Extrapolating from the above studies, continuous measurement studies are limited by the cost and maintenance of equipment, thereby enhancing the quality of data per participant but limiting the number of participants for which data can be reasonably and affordably collected.

A third, but less utilized, approach to gathering experiential daylighting data inside of spaces has been to employ daylighting simulations, often using a validated Radiance-based engine (Ward 1994) such as Daysim (Reinhart and Walkenhorst 2001). Reinhart et al. (2014) used quasi-calibrated CBDM results paired with subjective data to identify annual lighting performance levels that correlate with perceptions of daylight. Jakubiec and Reinhart (2016) used a daylighting model based on measured material properties, exacting geometric reconstructions, and specific weather data to assess annual lighting and glare metrics for 123 participants in a POE study at 6-min time intervals, but the model's calibration was not checked with measurements and contributions from electric lighting were ignored. Bellia et al. (2017) expressed the opinion that this approach was not feasible due to the complexity and time commitments of modeling data. Mardaljevic et al. (2016) noted that CBDMs are difficult to validate in practice due to obstructions on the workplane where sensors would ordinarily be placed for long-term monitoring and that illuminance data are not ordinarily a part of building management systems. They proposed to use a continuous luminance camera to derive illuminance on vertical surfaces in order to validate CBDM illuminance calculations. Other researchers have noted the importance of appropriate material properties in simulations to achieve accurate results (Brembilla et al. 2015; Jakubiec 2016).

Though not commonly utilized in POE lighting studies, calibrating CBDM daylighting models allows researchers to refine the POE process and extend it to design processes by analyzing the same annualized lighting metrics. Instead of a long-term monitoring approach, physical and lighting measurements are collected during a short visit, and calibrated daylighting models are then built and validated before being used to simulate annual CBDM results. Time-series data from the occupant's point of view can be easily obtained for an unlimited number of participants, not limited by sensor availability or manpower. However, limitations are given by the accuracy of the models and a difficulty in evaluating their accuracy before being used to simulate annual daylighting conditions. Therefore, this article takes an approach to validate the performance of lighting simulation models for utilization in POE

lighting studies based on limited measurements. Specifically, the problem of simultaneous presence of electric lighting and daylighting is addressed. First, a methodology is presented by which detailed field measurements are taken in currently occupied buildings and used to calibrate a combined daylighting and electric lighting simulation model. Next, this method is applied to the calibration of 10 models of office spaces, and model accuracy is validated using standard root mean squared error (RMSE) and mean bias error in addition to perceived errors modified for logarithmic human vision. Finally, the discussion focuses on what the methodology proposed in this article means for future work in POE lighting analysis and research.

## 2. Methodology

Measurements at office desks of 540 occupants in 10 offices were recorded from October 2016 to August 2017. There were no specific criteria applied when choosing the office buildings—all were office buildings located in Singapore. The offices that the authors measured were a mix of public- and private-sector office buildings. Some characteristics of the 10 offices are detailed in Table 1, including the typology, types of roller blinds, glazing transmittance ( $T_{vis}$ ), window-to-wall area ratio (WWR), and whether any Green Mark (GM) award was attained. Green Mark is a green building certification system in Singapore that mirrors that of other known certification systems such as LEED, CASBEE, Green Star, etc. Calibrated climate-based daylighting models were then built according to field measurements: HDR images, illuminance and luminance measurements, material reflectance measures, space measurements, and external weather data. This section describes measurement techniques and calibration steps used to create and validate calibrated models for further climate-based daylighting analysis. Figure 1 explains the general overall workflow. Computational scripts were written to automate each process due to the large amount of data.

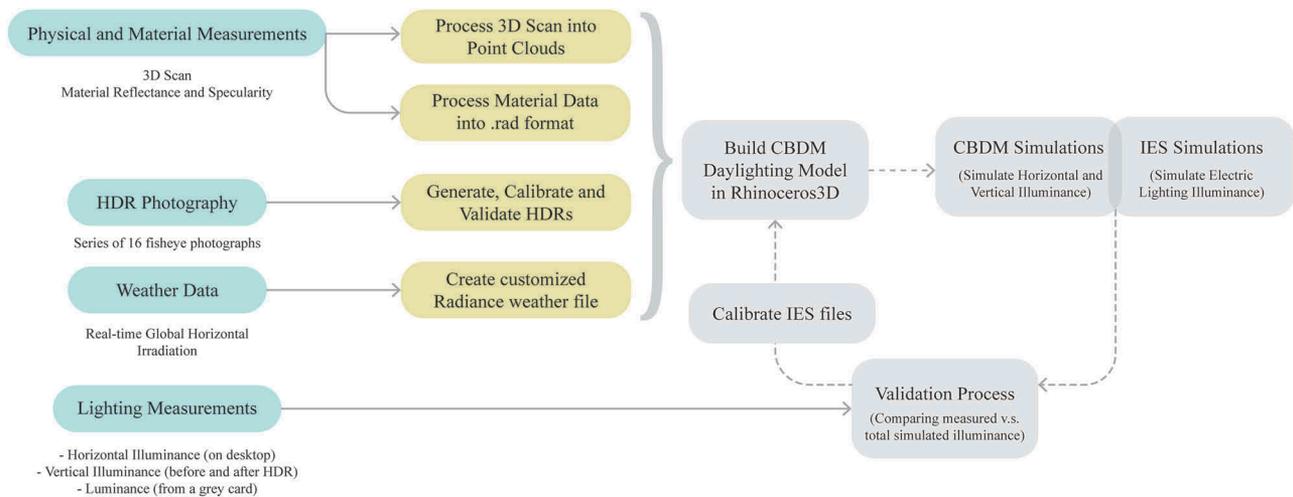
### 2.1. Field measurements

Of the 10 offices measured, some occupy multiple floors (offices 1, 8, and 10 in Table 1), and two offices are situated in the same building separated by 12

**Table 1.** Characteristics of the 10 measured office spaces.

Office building	Typology	Roller blinds	$T_{vis}$ (%)	WWR (%)	Award
1	12-Story office tower	O, T	25	62	GM Platinum
2	17-Story office tower	O, T	40	44	GM Platinum
3	20-Story office tower	T	35	64	GM Platinum
4	27-Story office tower	O, T	10	60	GM Gold
5	Office space in five-story shopping mall	T	15	25	–
6	Office space in 10-story industrial building	T	55	22	–
7	Three-story retrofitted building	T	50, 56	60	–
8	27-Story office tower	T	37	62	GM Platinum
9	17-Story office tower	O, T	32	60	GM Platinum
10	27-Story office tower	O, T	37	62	GM Platinum

Note: O = opaque; T = translucent.

**Fig. 1.** Overall workflow for calibrating climate-based daylighting models from single point-in-time measurements.

floors (offices 8 and 10 in Table 1). Beyond formal and layout differences, each office has different material finishes and luminaire selection. HDR photographs, workplane and vertical illuminance, and luminance measurements from a neutral gray card were captured and recorded at each of the 540 occupants' desks. Each set of measurements took approximately 3 to 5 min to complete. Occupants were asked immediately preceding the measurements to fill out a short subjective survey on their perceptions of instantaneous and long-term lighting quality; however, those subjective components are not the focus of this article.

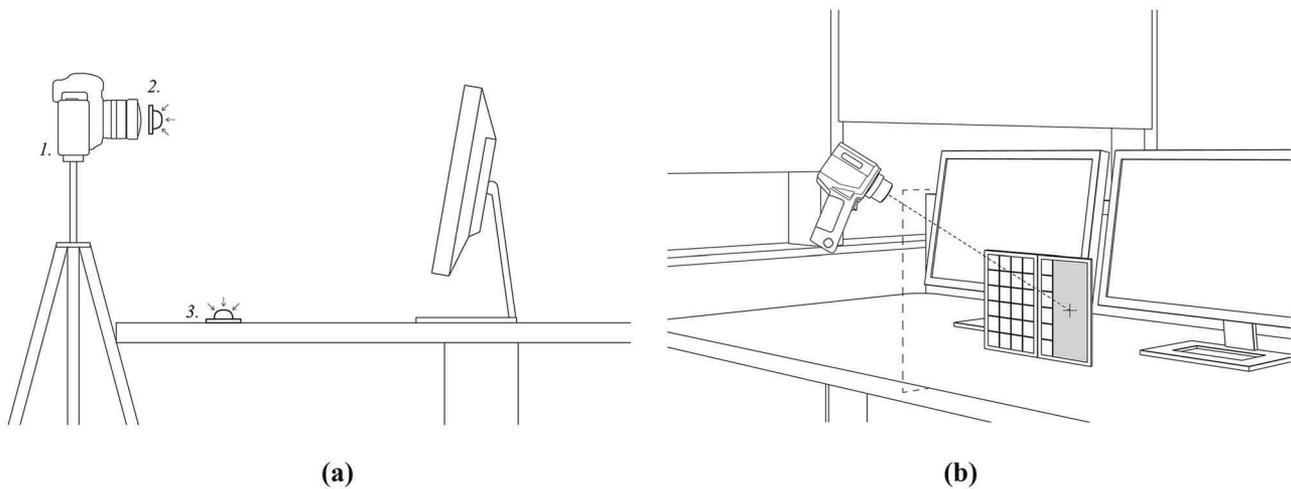
### 2.1.1. Illuminance and luminance measurements

Before measurements were taken, occupants were asked to leave their desks so that the camera and lighting sensors could be positioned freely at the eye position and on the workplane. Horizontal illuminance (lux) on the desktop surface was measured once, after the HDR photographs were

taken. Figure 2 illustrates the positioning of the illuminance and luminance meters for the respective measurements. Luminance measurements ( $\text{cd}/\text{m}^2$ ) from a gray card were recorded with a luminance meter (Konica Minolta LS-100), and vertical illuminance (lux) was recorded with an illuminance meter (Konica Minolta Illuminance Meter T-10A or Illuminance Spectrophotometer CL-500A) before the first exposure and after the last exposure of the HDR photograph were captured, in front of the fisheye lens from the occupant's viewpoint. The average value of the before and after luminance measurements were used in calibrating the images, to account for minor changes in lighting levels during the HDR capture. If illuminance or luminance values differed significantly, the image was discarded.

### 2.1.2. HDR photography

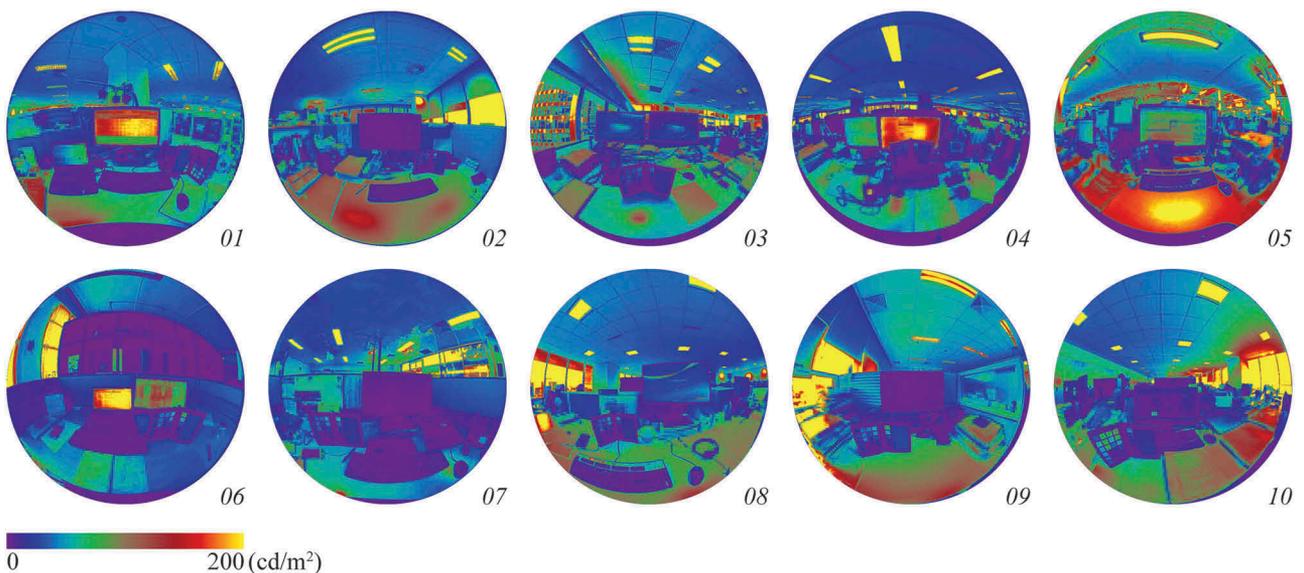
HDR fisheye photographs were taken at each occupant's desk to capture luminance values from their



**Fig. 2.** Measurements and HDR photography setup.

point of view shortly after filling out the subjective survey. The methods used are according to the recommendations proposed by Inanici (2006) and Jakubiec et al. (2016). The occupant was asked to vacate his or her desk before the measurements started—see Fig. 2a. A full-frame Digital single-lens reflex (DSLR) camera (Canon EOS 5D Mark III) with a fisheye lens (Canon EF 8–15 mm f/4L Fisheye USM or Sigma 8 mm f/3.5 EX DG Circular Fisheye Lens) was used with a stable tripod. A series of 16 photographs with exposure times at an interval of one stop from 8 s to 1/4000 s was taken. An f-stop of f/11 and ISO speed of 100 were used throughout. The white balance was set to the daylight setting.

Examples of HDR luminance maps of randomly selected participant desks from the 10 office spaces are shown in Fig. 3. The individual exposures were converted to the Radiance angular fisheye (–vta) image projection (Ward 1994) based on measurements of the lens projections taken with a panoramic tripod head. The images were then cropped to a 180° opening angle with a circular mask and resized to 800 × 800 pixels. The series of photographs was then converted into HDR images using Photosphere (Anywhere Software, Berkeley, CA). Approximately half of the HDR images captured in this study did not have a corresponding luminance measurement. These images were calibrated based on vertical



**Fig. 3.** An example of HDR image collected from each of the 10 office spaces measured.

illuminance measurements taken at the camera lens. Images with a corresponding luminance measurement were then calibrated in Photosphere manually using the luminance data measured on the gray card. Finally, vignetting correction (Jakubiec et al. 2016) was applied to the HDR photos to correct for light attenuation at the edge of the fisheye photograph.

### 2.1.3. Physical measurements

A laser scanner (FARO FOCUS 3D X330) was used to scan the interiors and exteriors of the office spaces. This acts as a geometric reference for the precise construction of a 3D model. The 3D scan data, which are in the form of a point cloud, approximates the interior layout including dimensions and positions of furniture and electric lighting—see Fig. 4 for an example. The scan files were processed and exported and imported into Rhinoceros 3D (McNeel North America, Seattle, WA) and used to build a detailed surface model. Due to the large file size of point clouds, screen captures of the relevant clipped views and measurements in 3D space using a point cloud analysis software were used to calibrate the geometry of the model, instead of the actual point cloud. However, laser scanning is an optional step and may be replaced by hand measurements or using as-built Building Information Modeling (BIM) models after verifying their measurements. The surface geometry created in this step is converted to polygonal meshes and exported to the Radiance .rad format (Ward 1994) using the DIVA plugin (Jakubiec and Reinhart 2011).

### 2.1.4. Measurement of material reflectance data and translation to Radiance material definitions

Material reflectance data of surfaces were measured using a spectrophotometer (Konica Minolta CM-2600d Spectrophotometer) based on an average

value of three-point measurements across each surface material type. Each material finish had two types of reflectance recorded, specular component included (SCI) and specular component excluded, respectively, which are both full-spectrum colorimetric measurements. The difference between specular component included and specular component excluded is used to derive the specular versus diffuse components of reflectance. A photo is also taken for reference, and roughness values are estimated based on the visual appearance of the images (Jones and Reinhart 2017). The material data were converted to Radiance material definitions as described by Jakubiec (2016). Where the glazing transmittance information was not obtainable, it was either measured if the windows were operable or estimated from initial visualization simulations. Where the glazing transmittance was known, it was converted to transmissivity by multiplying by 1.09 (Jacobs 2012). A generic monitor model was used for all of the desks, modeled according to Jones and Reinhart (2017) but with modifications to match the average observed screen luminances in Singapore with a high-state pixel luminance of  $125 \text{ cd/m}^2$  and low-state pixel luminance of  $33 \text{ cd/m}^2$ . A generic roller blind with a direct normal transmittance of 0.01, front reflectance of 0.37, back reflectance of 0.56, diffuse transmittance of 0.2, and transmittance that drops to zero at  $84^\circ$  was used. It can be accordingly calibrated for specific roller shade types in different offices. A typical set of Radiance material definitions measured and produced for one of the office spaces is shown in Table 2. Alternatively, cheaper and substantially accurate methods to measure material reflectance are also available, such as the illuminance method, using the Chartered Institution of Building Services Engineers (CIBSE) color chart or RAL color fan, according to Gradillas's comparisons (Gradillas

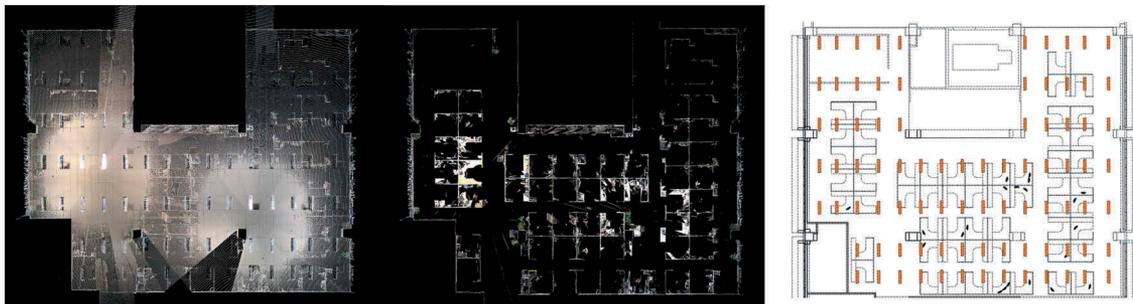


Fig. 4. Example of 3D scan point cloud and screen captures of furniture plan and luminaires (orange rectangles) from office 1.

**Table 2.** Example list of Radiance material definitions from office 5.

	Material	Radiance definition
Interior	Wood laminate table top	Void plastic TableTop 0 0 5 0.6112 0.4779 0.3081 0.0141 0.15
	Beige partition fabric	Void plastic PartitionFabric 0 0 5 0.6249 0.5803 0.4762 0.0097 0.10
	Gray carpet	Void plastic GreyCarpet 5 0.0731 0.0708 0.0654 0.0000 0.40
	Gray mullions	Void plastic GreyMullions 5 0.4618 0.4716 0.4765 0.0374 0.05
	White wall	Void plastic WhiteWall 5 0.8911 0.8933 0.8495 0.0107 0.30
	White column	Void plastic WhiteColumn 5 0.8884 0.8896 0.8423 0.0113 0.30
	Acoustic ceiling panels	Void plastic AcousticCeilingPanels 5 0.8752 0.8717 0.8471 0.0079 0.40
	Light shelf (bottom)	Void plastic LightShelfBottom 5 0.4851 0.4963 0.4958 0.0552 0.05
	Light shelf (top)	Void plastic LightShelfTop 5 0.4929 0.5007 0.4951 0.0515 0.05
	Opaque roller shade	Void plastic OpaqueShade 5 0.5812 0.5560 0.4676 0.0059 0.20
	Glazing	Void glass Glazing 3 0.3815 0.3815 0.3815
	Roller blinds	Void BRTDfunc RollerBlinds 10 0 0 0 tspec tspec tspec 0 0 0 mechoshade.cal 0 9 0.37 0.37 0.37 0.56 0.56 0.56 0.2 0.2 0.2
	Exterior	White painted wall
External mullions		Void plastic ExternalMullions 0 0 5 0.4732 0.5545 0.5009 0.0252 0.15
Decorative floor tiles		Void plastic DecorativeExternalFloorTiles 0 0 5 0.1545 0.1628 0.1390 0.0089 0.2
Specular steel handrail		Void plastic SpecularSteelHandrail 0 0 5 0.2247 0.2896 0.2991 0.3287 0.05
Asphalt		Void plastic Asphalt 0 0 5 0.1086 0.0998 0.0850 0.0004 0.4
Wood plank walkway		Void plastic WoodPlankWalkway 0 0 5 0.1162 0.0958 0.0841 0.0011 0.4
Monitor	Screen	Void trans MonitorScreen 0 0 7 0.575 0.575 0.575 0.033 0.01 0.88 1
	High-state pixel	Void glow MonitorHigh 0 0 4 1.396 1.396 1.396 0
	Low-state pixel	Void glow MonitorLow 0 0 4 0.3352 0.3352 0.3352 0
	Dark plastic	Void plastic MonitorPlasticBlack 0 0 5 0.054 0.054 0.062 0.013 0.1
	Light plastic	Void plastic MonitorPlasticSilver 5 0.464 0.470 0.452 0.078 0.1

2015). Another possible technique is one developed by Mardeljevic et al. (2015) using HDR imaging to derive surface reflectance maps through an interpolated illuminance map and an HDR luminance map.

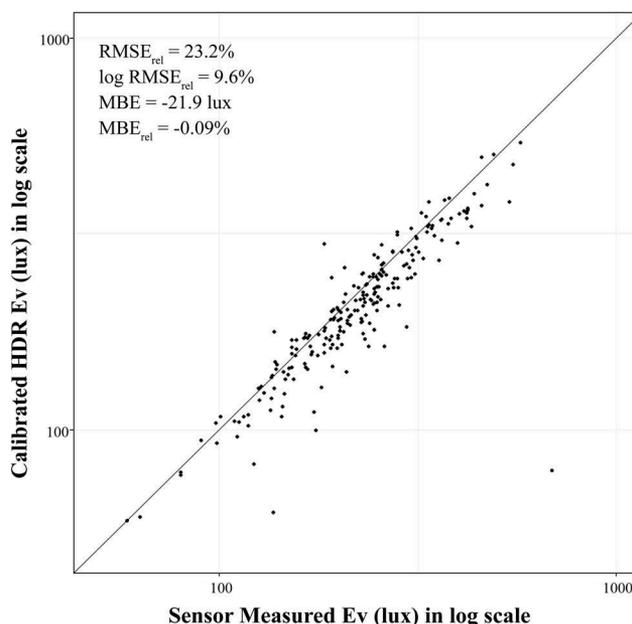
## 2.2. External measurements

Real-time weather data were collected from an existing weather station located at the rooftop of the authors' university campus at 36 m above ground level with no urban obstructions. Global horizontal solar irradiation ( $W/m^2$ ) was measured from a silicon pyranometer and recorded every 5 min by a data logger. Global horizontal solar irradiation was split using Reindl et al.'s (1990) method into direct-horizontal and diffuse-horizontal irradiance. A customized Radiance .wea weather file (Reinhart and Walkenhorst 2001) was then created for each office space back-dated 1 year from the date of visit. For example, if the date of the visit was May 16, 2017, a custom weather file was created between May 16, 2016, and May 17, 2017.

## 2.3. Validation of HDR images

To validate the accuracy of the HDR images, which were used for glare analysis and point-in-time calibration of the daylighting model, measured vertical illuminance,  $E_{mea}$ , was compared to the total pixel

illuminance contribution from the equi-angular HDR images  $E_v$ , as calculated in (1). Because the HDR images with illuminance measurements were calibrated to the measured illuminances, only the HDR images that were calibrated through the luminance measurements are included in this validation, shown in Fig. 5. The gray line illustrates the ideal



**Fig. 5.** Total pixel illuminance contribution vs. measured vertical illuminance for luminance-calibrated HDR images.

calibration of HDR images, and it is notable that the total pixel illuminance contribution fell slightly below the sensor-measured vertical illuminance for luminance-calibrated images.

$$IE_v = \sum_{\theta_p < 90^\circ} L_p \omega_p \cos \theta_p, \quad (1)$$

where  $L_p$  is the luminance ( $\text{cd}/\text{m}^2$ ) of the individual pixel,  $p$ ;  $\omega_p$  is the solid angle (str) of that pixel; and  $\theta_p$  is the incident angle from the pixel to the center of the photograph. The authors then calculated the RMSE between the HDR illuminance and sensor-measured illuminance with (2) as follows:

$$RMSE = \sqrt{\frac{\sum (E_v - E_{mea})^2}{n}}, \quad (2)$$

where  $E_v$  is the total pixel illumination contribution derived from  $n$  HDR images, and  $E_{mea}$  is the measured vertical illuminance. The relative RMSE,  $RMSE_{rel}$ , refers to the percentage deviation from the mean and relative mean bias error  $MBE_{rel}$  is the mean bias error relative to the mean. Both were calculated according to (3)–(5):

$$RMSE_{rel} = \frac{RMSE}{E_{mea}} \quad (3)$$

$$MBE = \frac{\sum (E_v - E_{mea})}{n} \quad (4)$$

$$MBE_{rel} = \frac{MBE}{E_{mea}}, \quad (5)$$

where  $\bar{E}_{mea}$  is the mean of the measured vertical illuminances. RMSE on the logarithmic scale was also calculated, because the photopic sensitivity response of the human eye to lighting intensity is on a logarithmic scale rather than on a linear basis (Reinhart and Andersen 2006). Hence,  $\log RMSE_{rel}$  was also calculated as per (6) and (7):

$$\log RMSE = \sqrt{\frac{\sum (\log_{10} E_v - \log_{10} E_{mea})^2}{n}} \quad (6)$$

$$\log RMSE_{rel} = \frac{\log RMSE}{\log_{10} \bar{E}_{mea}}. \quad (7)$$

The results showed an  $RMSE_{rel}$  of 23.24% in linear space,  $\log RMSE_{rel}$  of 9.60% in logarithmic visual space, and a slight negative bias of  $-9.91\%$   $MBE_{rel}$ , where  $MBE$  in linear space is  $-21.9$  lux, as illustrated in Fig. 5.

## 2.4. Calibration of electric lighting

Because the exact model and lamp selection of the luminaires were not available, an appropriate IES file (IES 1991) was selected to be used in the simulation models, based on luminaire dimensions and photometric distributions observed in the captured HDR images. After loading the IES file into the lighting simulation model, the luminaires were located as per the 3D scan data. An occupant's viewpoint was simulated using high-quality ambient Radiance parameters (see Table 3), and the global horizontal irradiance value recorded by the weather station nearest to the time of field measurement was used as the input for the Perez all-weather sky model (Perez et al. 1993) during a calculation. To keep daylight contribution to a minimum, a viewpoint further away from the facade was chosen when calibrating the photometric distribution and intensity of electric lighting data. A scale factor was approximated and *ies2rad* (Ward 1994) was run to multiply the brightness output of the luminaires. This process was repeated until an appropriate scaling factor was reached as shown in Fig. 6. Although a desk further away from the facade was selected to reduce errors due to the high variability of daylight, which may skew the calibration process of electric lighting, daylight was still included as ambient lighting in the scene.

## 2.5. CBDM simulation data and IES simulation data

Grid-based annual lighting simulations without roller blinds and electric lighting were run for all 10 office spaces indicating the various daylighting conditions

**Table 3.** Typical Radiance parameters used for visualizations and validation simulations.

Radiance parameters	Visualizations	Climate-based simulations
Ambient bounces (ab)	4	6
Ambient divisions (ad)	1000	2000
Ambient supersamples (as)	500	1000
Ambient resolution (ar)	500	1000
Ambient accuracy (aa)	0.1	0.1

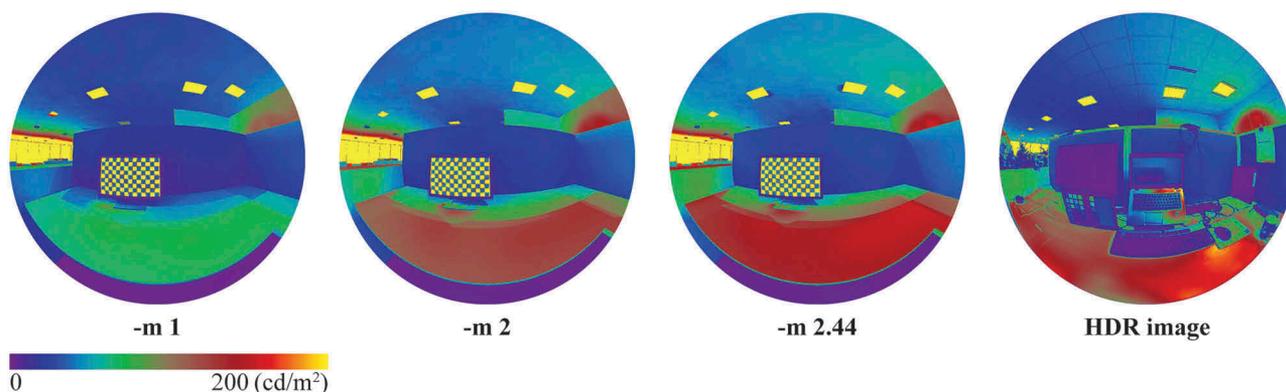


Fig. 6. Calibration of electric lighting.

due to the diverse building typologies, materials, floor plans, and building depths. Figure 7 illustrates the variation in daylight experienced by the participants in the 10 surveyed office spaces represented by annual mean illuminance. A red line illustrates a daylight autonomy value of [75%] at an illuminance threshold of 300 lux. For validation purposes, climate-based daylighting simulations were run using Daysim (Reinhart and Walkenhorst 2001) for each office space, with roller blinds, at 5-min time steps using the custom weather data file generated for each office space. The Radiance parameters used for the climate-based simulations are as shown in Table 3 with six ambient bounces. Because light is additive, the simulated daylight and electric light illuminances were simulated separately and were summed up to calculate total simulated horizontal or vertical illuminance from electric lighting and daylighting. Electric lighting simulations included only light from luminaires and monitor screens and were simulated at four ambient bounces instead of six. These simulated values at the nearest simulated time step to the field HDR and illuminance measurements were validated against the measured lighting data, which are detailed further in the next section.

### 3. Results

After the iterative process of calibrating the electric and daylighting portions of the lighting simulation models (see Fig. 1), the authors compared the accuracy of the results with measurements by extracting the point-in-time simulation data nearest to the time of measurement for each of the 540 occupant desks

measured during the 13-month period of this study.  $RMSE_{rel}$  values of 25.8% and 45.5% were achieved between sensor-measured illuminance and simulated point-in-time illuminances horizontally and vertically as illustrated in Fig. 8. The gray line is a  $y = x$  identity line representing the ideal calibration situation. Vertical illuminance deviates from the measured illuminance more than horizontal illuminance. Vertical  $RMSE_{rel}$  values were higher due to the variety of monitor types and configurations measured at various workstations where on-off status, brightness setting, monitor type, monitor size, and monitor number vary widely between participants; all of these have an impact on measured vertical illuminance. Logarithmic differences are known to express perceived lighting differences by the human eye better than actual absolute differences in different lighting situations (Reinhart and Andersen 2006). Hence, we used  $logRMSE_{rel}$  as a paired validation measure of the CBDM daylighting models indicating how close calculations come to human perceptual differences in addition to standard linear lighting unit errors. In the base-10 logarithmic visual space, the models had 4.3% and 6.8%  $logRMSE_{rel}$  for horizontal and vertical illuminances, respectively. The overall  $MBE$  was 0.3 lux (0.0006%) and 61.8 lux (23.3%) for horizontal and vertical simulated illuminance, respectively.

Figure 10 compares two selected calibrated HDR images to simulated visualizations using false color luminance images scaled between 0 and 300  $cd/m^2$ . Overall these images are representative of those simulated during the calibration process. Differences specifically in the monitor brightnesses can be observed based on discrete

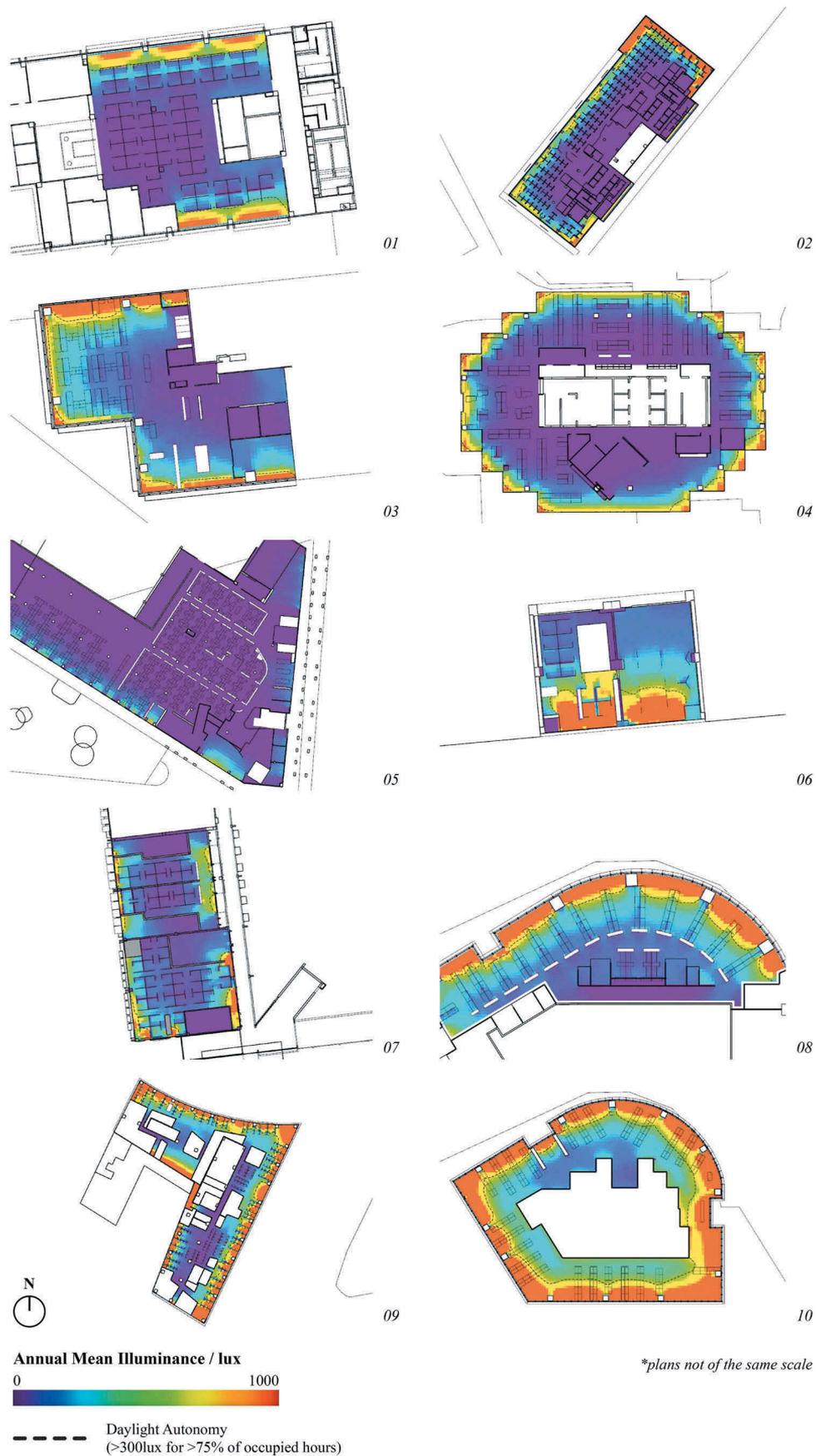


Fig. 7. Annual mean illuminance and daylight autonomy for all 10 offices simulated (without roller blinds and electric lighting).

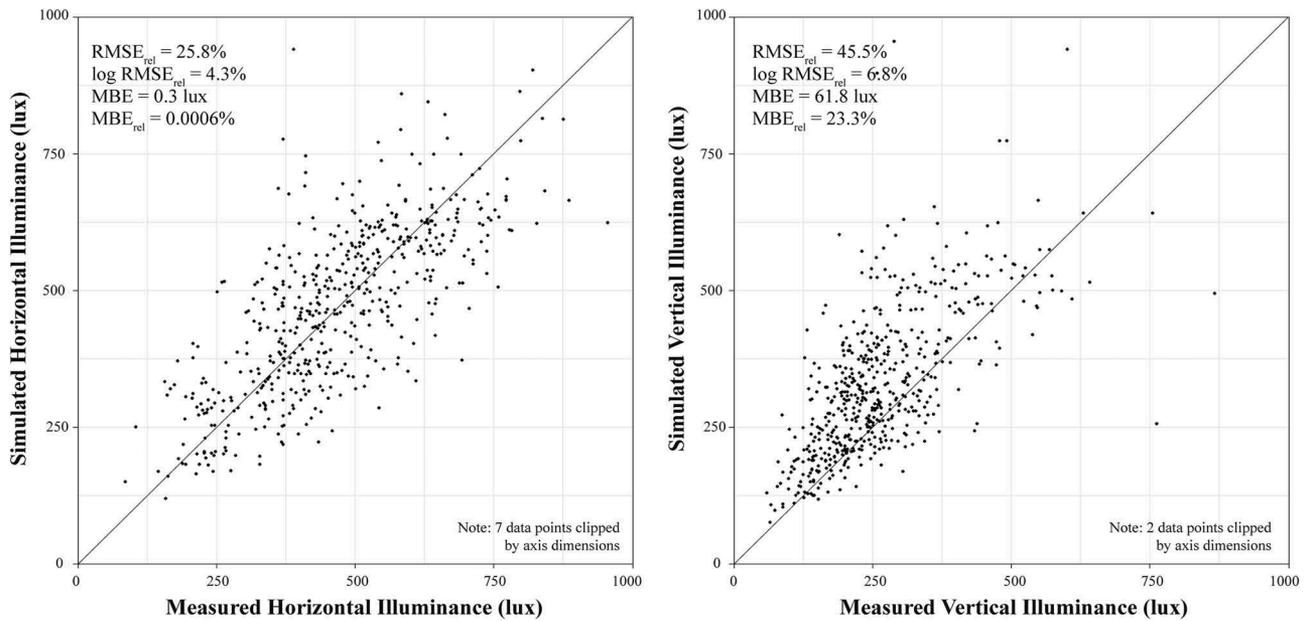


Fig. 8. Scatter plots of measured vs. simulated horizontal and vertical illuminance.

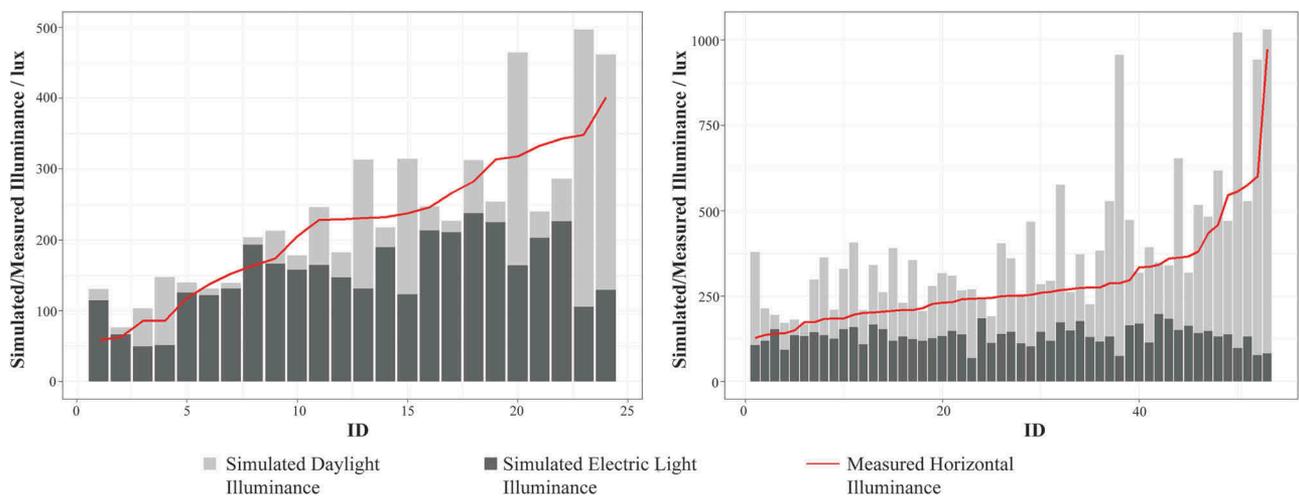


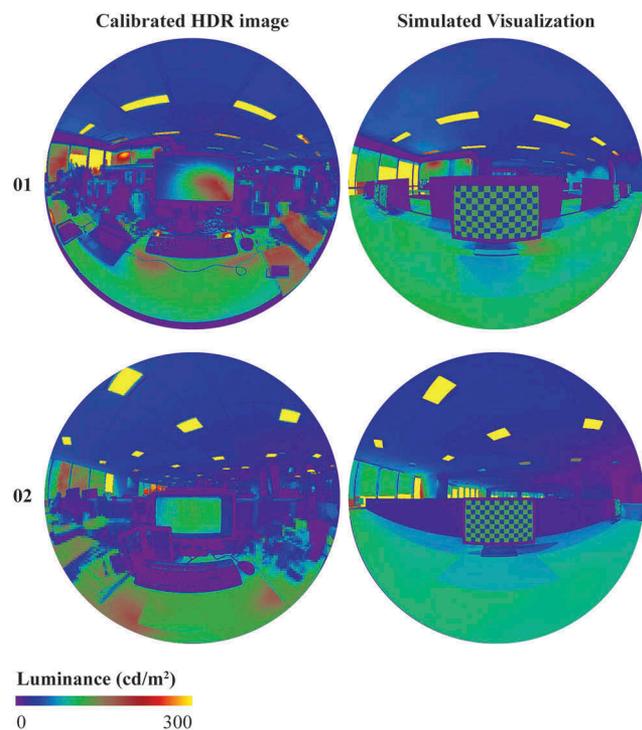
Fig. 9. Simulated daylight and electric light illuminances of offices 7 and 10 as stacked column plots and field-measured horizontal illuminance as a red line.

user factors as mentioned as a cause of high vertical errors. Figure 11 compares the accuracy of the simulation models per office space (as shown in Fig. 6) by their horizontal (yellow) and vertical (blue)  $RMSE_{rel}$  values. Office 4 is an example of a well-calibrated model with both horizontal and vertical  $RMSE_{rel}$  values of approximately 25%. Figure 9 depicts individual horizontal illuminance simulation results (stacked bars) compared to measured values (red lines) for buildings 7 and 10. Results are split between the electric lighting and daylighting simulation contributions.

Simulated illuminances follow the overall trend of field-measured horizontal illuminance, and daylighting components of the calculated illuminance tend to be more volatile than electric lighting calculations as might be expected considering desired even workplane illuminances from electric lighting in most office spaces.

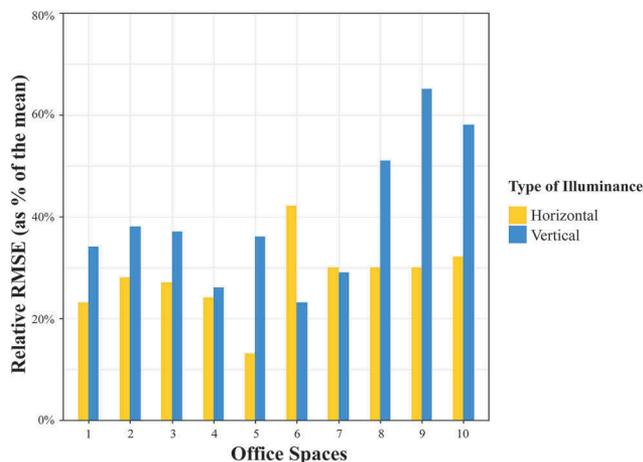
#### 4. Discussion

The authors believe that sharing their experience with the field measurement and calibration



**Fig. 10.** Comparison of calibrated HDR images and simulated visualizations from the same viewpoint.

process of the 10 models in this article would be beneficial to the reader. To achieve more accurate simulation results from the lighting models, the authors suggest identifying problematic data points—illuminance calculations at participant desks with large discrete errors—and resolving modeling issues for those desks by comparing their HDR images to simulated model views using measured solar data and a Perez sky model



**Fig. 11.** Horizontal and vertical  $RMSE_{rel}$  values between measured and simulated point-in-time values.

(Perez et al. 1993). Large discrete errors found in this study during the early calibration process were mostly attributed to modeling errors that influenced daylighting and electric lighting issues or both. For electric lighting discrepancies, typical corrections include identifying missing luminaire fixtures, making sure that they were not coplanar with ceiling surfaces, and adjusting their luminous power (see Fig. 6). Calibration of electric lighting may prove difficult but is important to capture in simulations to describe the occupants' experiences. The proposed method can also be used by measuring the building with electric lights turned off; however, that was not an option in this study. On the other hand, for daylighting discrepancies, adjustments in roller blind position and missing roller blinds were common modeling errors. In some cases, the transmission and angular properties of roller blinds had to be adjusted based on measured values. Roller blind statuses may be uncertain throughout the year, but the authors' focus is validating the instantaneous condition by simulating the horizontal and vertical illuminance values, at the same time step as measurement, to be validated against actual measurement values. In addition, reproducing actual user behavior is impossible without long-term monitoring, so a first possibility is to apply the methodology to a design-type model without active shades. Secondly, some researchers have suggested using blind control algorithms, and this may also be applied to the CBDM daylighting models with ease, if desired. For example, Gunay et al. (2017) have suggested outputting ranges of results based on different plausible models, though others are mostly prescriptive (Nezamdoost et al. 2014; Reinhart 2004). A third method is to monitor the blind usage with a drawstring potentiometer to capture actual blind behavior over a period of time (McNeil 2018). Future work on field measurement of roller blinds would be beneficial, because diffuse and specular transmission data were rarely available in the authors' experience and are difficult to measure in the field. There were often difficulties in discerning the sources of predictive errors between simulation and reality due to the presence of both daylight and electric lighting in the HDR images used to compare with the simulated visualizations. In most cases,

building-level biases (increased horizontal illuminance levels at each desk) were able to identify when the electric lighting was the cause of a significant error.

In addition, field calibrations of lighting models have many difficulties in practice that have not been found in other calibration studies, which are often based upon unoccupied spaces. The issues arising from monitor variety, screen image, user-specific brightness settings, and the choice to turn a monitor off before a measurement have already been described. Initially, the authors noticed a higher  $MBE_{overall}$  of around 100 lux for vertical illuminance ultimately caused by monitor screens. Based on the HDR measurements, the authors attributed the main cause to the effective peak luminance of monitor screens being too high at  $250 \text{ cd/m}^2$ , and the peak luminance was reduced to  $125 \text{ cd/m}^2$ , which reduced the relative and bias errors. Each individual participant also had a variety of desk layout differences and personal or work items or clutter present that influenced the lighting results. Observation of Fig. 3 illustrates placement differences in keyboards and monitors as well as a wealth of objects that are impractical to model individually and likely change from day to day. These are real limitations that must be accepted as error sources when field calibrating lighting models. Other error sources which are difficult to surmount are the difficulty in selecting IES data sets with accurate photometric distributions, unknown maintenance and cleaning cycles, a variety of lamps with varied lumen outputs installed throughout buildings, and proxy geometry of the simulated electric lights not reflecting the direct view of the light source from the actual luminaire geometry in reality even though the overall photometric distribution is accurate.

The proposed field calibration method presented in this article has several limitations. It is sometimes difficult to obtain information on actual glazing transmittances for fixed glazing, because they cannot be measured easily in the field. Modeling directional and diffusing properties of complex glazing and roller blinds also presents challenges where no detailed goniophotometer measurements exist. Where possible, the authors have tried to obtain accurate information from the individual building developers to increase the accuracy of the models. In addition, the location of the weather station may cause

discrepancies in the custom sky models used to simulate the instantaneous lighting data used in calibrations because global horizontal irradiance is recorded from a different location on the island up to 25 km away in the case of this study. In the future, portable irradiance data loggers should be utilized at least during the field measurement period. Although the authors used Reindl et al.'s (1990) splitting model to derive direct and diffuse components from the global horizontal irradiance, it is possible to derive diffuse fractions from global measures, time, and location. Based on previous research (Chandrasekaran and Kumar 1994), researchers compared measured diffuse fractions and a computed model for a tropical location to the one preferred by Reindl et al. (1990). It was found that clear sky conditions under humid tropical conditions had a higher diffuse fraction than the model of Reindl et al. (1990) but that the relative standard deviation only improved from 32.2% to 29.4% using a tropically derived splitting model. Although the International Weather for Energy Calculation weather data are also mostly derived from global horizontal irradiance methods using splitting algorithms and sometimes observed cloud cover, further improvements can be achieved with seasonally specific splitting models.

Six participant data points were removed during data analysis due to horizontal and vertical illuminance errors of more than 1000 lux, which may be attributed to weather data inaccuracies likely due to disparate cloud cover patterns at specific times. These discrepancies are typical and expected of field measurements, unlike precise laboratory measurements, which can be controlled to a higher level of accuracy. Dynamic shading devices are included in the calibration models, but their operation will obviously vary across the year. The authors suggest that simulating a calibrated model without dynamic shades represents the base design case, which is useful to compare with subjective participant opinions. Behavioral and automated dynamic shading models may also be applied to resultant annual simulations.

## 5. Conclusion

The proposed process to build calibrated climate-based models for POEs based on one-time field measurements at each building is validated through comparing measured and simulated illuminance data, and

the results are sufficiently positive, with  $\log RMSE_{rel}$  values of 4.3% and 6.8% and  $RMSE_{rel}$  values of 25.8% and 45.5% for horizontal and vertical illuminances. Though 20% is often seen as a best-case validation result in the lighting community, the authors suggest that the additional horizontal error observed in this study is acceptable given the complex field conditions and the fact that the errors only make up a small logarithmic perceived difference in lighting. Vertically with regards to occupant monitors, errors begin to grow unacceptably large, and it may be beneficial to specifically measure monitor screen brightnesses or to turn them off in future field measurement and calibration studies. Because occupied spaces are usually of limited access to researchers, the noninvasive method presented here can allow reliable annual lighting information to be used for POEs through short visits instead of relying on long-term and invasive direct monitoring data using illuminance sensors or HDR photographs. Because the proposed workflow does not require constant monitoring and is noninvasive, this could also increase willingness of participants to engage in lighting POE studies.

The authors find that the proposed workflow of building calibrated models of existing spaces opens up possibilities of assessing long-term quantitative lighting results after a short visit for measurements that can be analyzed in correlation to subjective occupant responses that are collected in the same visit. This provides a reasonably reliable set of instantaneous and long-term lighting results and subjective responses from occupants for in-depth analysis, of which initial results have been reported elsewhere (Jakubiec et al. 2018). The authors acknowledge that the proposed methodology may be more complex than a simpler point-in-time measurement (which is also included in the proposed process as well), but building calibrated CBDM daylighting models enables researchers to simulate annual daylighting metrics based on measured annual weather data. At the same time, it is significantly cheaper than long-term monitoring techniques due to lower manpower and equipment requirements because measurements can be collected from multiple users using a single set of instruments during a short visit. Predicted lighting results from the design or construction phase of the building may also be analyzed with the postoccupancy results later, for an additional feedback loop to architects and lighting

designers and policymakers for lighting requirements in sustainable building assessment criteria.

Although the accuracy of field-calibrated models is not expected to surpass that of those in controlled laboratory setups, it is still a sufficiently reliable method to determine and detect lighting variations in a POE study. Problematic data points with large discrete errors have to be identified and rectified while calibrating the simulation models, as well as correcting for global errors due to electric lighting. In addition, some limitations in practice such as individual user differences in monitor screens, items in the workspace, and shade use must be accepted. The authors believe that the validation process presented in this article is important to accurately drive POE results based on calibrated annual lighting simulations by nearly eliminating bias errors and minimizing relative errors.

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