Reality bites: measuring actual daylighting performance in classrooms

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Reality Bites: Measuring Actual Daylighting Performance in Classrooms

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ABSTRACT: Climate-based daylight modelling (CBDM) is providing the basis for yearlong indoor daylighting performance predictions. However, evidence of long-term actual daylighting performance of indoor spaces in use is limited. Since 2013, CBDM has been a mandatory requirement for the approval of school designs that fall under the UK’s £6 billion Priority Schools Building Programme. Specifying daylight compliance of schools with CBDM metrics increases the urgency for evidence of actual performance of classrooms. This paper describes a method for long-term monitoring of classrooms in use. It also identifies the key confounding factors that make the validation of CBDM metrics in practice a daunting task. Two UK classrooms are used as case studies and are monitored daily for six months with a 10-minute resolution. Using a robust method, based on High Dynamic Range (HDR) imaging, this work makes a case for the significance of real world daylighting performance measurements. Moreover it provides an overview of the first steps toward the evaluation of the practical application of CBDM prediction methods and metrics.

Keywords: daylight, schools, monitoring, HDR imaging, CBDM simulation

INTRODUCTION

Findings from the areas of biology and medicine increasingly point to the importance of daylight exposure to human physiology and wellbeing (Silvester and Konstantinou, 2010). At the same time, efforts to reduce energy consumption in buildings, where people spend about 90% of their time, often pose limitations to the quantity and quality of daylight indoors (Reinhart et al., 2006). This competing relationship gives rise to an on-going debate over metrics appropriate for the specification and evaluation of daylighting performance (Mardaljevic, 2015).

In 2013, the UK Education Funding Agency (EFA) changed the metrics used to specify daylight compliance of school designs funded by the government’s £6 billion Priority Schools Building Programme (PSBP) (EFA, 2014). Under the new mandatory requirements the widely used Daylight Factor (DF) was replaced by climate-based daylight modelling (CBDM) metrics. This effectively made daylighting simulation tools mandatory because, unlike daylight factors, CBDM metrics cannot be determined by analytical, graphical or tabular means. On the one hand, this bold move urges a skills upgrade for school building designers that will most likely incur a cost. On the other hand, it produces designs that should take into account climate and orientation conditions leading to more realistic predictions of year-round daylighting performance. At any rate, it questions the widespread and persistent reliance on the prediction of relative measures of daylight illuminance, which is largely without validation, and it spurs increased interest in evidence from real world performance.

Existing work on actual daylighting performance of any building type calls for additional field studies (Konis, 2014; Parpairi, 2002) and notes that indoor illumination data is rarely recorded by building management systems (Mardaljevic et al., 2015). Particularly in educational environments, field studies on actual performance are sporadic (Bellia et al., 2011; Winterbottom and Wilkins, 2009), more so in the case of those which focus on in-use classrooms and include users’ subjective responses (Axarli and Meresi, 2008; Wu, 2005). The spatially and temporally limited resolution of existing actual performance data acts as a constricting factor in the in-depth exploration of parameters that affect the agreement between measured and simulated performance. Moreover, meeting the increased sophistication of CBDM predictive models poses a further challenge to the resolution and duration of monitoring data which could serve to validate the predictions.

This paper presents a methodology for the nonintrusive long-term (6 months) monitoring of actual daylighting performance in two occupied classrooms. The aim is to record and investigate real world performance in order to identify the key confounding factors that make the validation of climate-based
daylight metrics in practice a daunting task. An overview of how real world performance data can contribute toward the potential validation of CBDM metrics is also presented.

The two classrooms used for the case studies are shown in Figure 1. The data included in this paper cover approximately six months. Monitoring physical parameters of the visual environment was achieved by means of High Dynamic Range (HDR) imaging, a technique that produces accurate per-pixel measures of luminance from images captured using consumer digital cameras (Reinhart et al., 2005) and has previously been used in daylight assessment studies (Mardaljevic et al., 2015; Konis, 2014; Bellia et al., 2011). HDR images were taken every 10 minutes by a DSLR camera tethered to a Mac Mini (resulting in approximately 1TB of data) and were supplemented by external solar radiation data: direct normal and diffuse horizontal illuminance and irradiance.

**CASE STUDY DESCRIPTION**

The research setting comprised two secondary school classrooms in the East Midlands region of the UK (Loughborough coordinates: 52°46’ N and 1°12’ W) referred to in this study as L3 and L7. While both are part of the same education establishment, L3 is in a building completed in 2014 and L7 in a 1960’s building (Fig. 1). Classroom selection was such as to include variation in age, floor and glazing area, class layout, orientation, aspect, view obstructions and shading controls (Table 1). In terms of use, classrooms with identical function were selected, i.e. where sit-down weekly rotating classes were held (studio, laboratory and workshop spaces were excluded).

**Table 1: Building characteristics of the case study classrooms**

<table>
<thead>
<tr>
<th>BUILDING CHARACTERISTICS</th>
<th>L3</th>
<th>L7</th>
</tr>
</thead>
<tbody>
<tr>
<td>Floor area (m²)</td>
<td>88.15</td>
<td>42.40</td>
</tr>
<tr>
<td>Glazing area total (m²)</td>
<td>24.23</td>
<td>16.07</td>
</tr>
<tr>
<td>Effective glazing area (m²)</td>
<td>24.23</td>
<td>10.18</td>
</tr>
<tr>
<td>Orientation</td>
<td>NW</td>
<td>NE &amp; SE</td>
</tr>
<tr>
<td>Aspect</td>
<td>Single</td>
<td>Double adjacent</td>
</tr>
<tr>
<td>View obstructions</td>
<td>Trees</td>
<td>Trees</td>
</tr>
<tr>
<td>Level (floor)</td>
<td>1st</td>
<td>1st</td>
</tr>
<tr>
<td>Smartboard orientation (facing)</td>
<td>WS</td>
<td>SW</td>
</tr>
<tr>
<td>External shading</td>
<td>Manual vertical blinds</td>
<td>Manual vertical blinds</td>
</tr>
<tr>
<td>Shading &amp; controls</td>
<td>Manual horizontal</td>
<td>Manual horizontal</td>
</tr>
</tbody>
</table>

Figure 1: Section and plan views of two UK classrooms (L3 top, L7 bottom) used as case studies, with images of the actual exteriors, interiors, as well as their respective simulation models (left to right).
The monitoring period covered July 22 to December 31, 2015. During this period classes were held from September 7 until December 18 with the exception of a week in October. Classroom L3 had a Northwest facing fully glazed wall with thick black panel framing and no blinds. Classroom L7 was double aspect with windows on two adjacent walls facing Northeast and Southeast. Vertical blinds were fitted on the NE wall-to-wall windows and a window panel on the SE wall, while horizontal blinds shaded the remaining SE windows positioned above head height. Both spaces used smartboards. Before commencement of the study, ethics considerations were addressed and approval was granted by school stakeholders and the authors’ university.

MONITORING METHODOLOGY
This section describes how HDR imaging was deployed to monitor a classroom environment, overcoming the main challenges encountered in previous studies in schools (Drosou et al., 2015). The main advantage of the method is that it facilitates the nonintrusive investigation of both the quantitative and qualitative aspects of daylighting. Concerning the former, the simultaneous collection of luminance values for multiple points in a space was carried out, while concerning the latter the observation of user electric light and blinds behaviour over extended periods of time was determined from the images.

![Figure 2: HDR Monitoring installation showing the setup components (left) and positioning (right) in classroom L7.](image)

The HDR capture setup comprised a mains-powered Canon EOS 600D Digital SLR camera fitted with an ultra wide-angle Canon EF-S 10-18mm f/4.5-5.6 IS STM lens used at its maximum angle (98°). The automated capture and storage of the images required the camera to be connected to a computer. For this purpose a Mac Mini (2.6GHz, dual-core Intel Core i5, 8GB memory, 1TB storage) was used. To reduce any acoustic disturbance to on-going teaching, the camera and lens were encased in a sound blimp (Fig. 2); a modified Pelican briefcase used by film stills photographers to reduce the sound of the clicking shutter. Locking and chaining the casing to a bookshelf fixed the camera in place and deterred equipment vandalism and theft. The setup was positioned on a high shelf at the rear corner of the classrooms so as to capture the smartboard, ceiling lights, blinds, desk layout and to follow the prevalent gaze direction of the students.

The software used to control the camera image sequence capture was gphoto2 (1), which is freely available, operates across all computer platforms and supports over 1700 camera models. The Unix crontab command was configured to automate the capture of the image sequence from 8:00 up to 17:50 daily at an interval of 10 minutes. Table 2 shows the settings that were used for aperture, shutter speed, whitebalance, ISO, number of conventional (jpeg) images. Following each capture sequence, the conventional jpeg images were compiled into a HDR image using hdrgen – the same ‘engine’ used by the Photosphere software (2). Luminance data from the images were analysed with the IDL® programming code. HDR captures were automatically synchronised with a cloud storage account to provide an additional level of data security, e.g. to protect against data loss due to failure or theft of the hardware. Daily checking of the cloud storage data also allowed for remote monitoring of the capture process. And so the few occasions where the process did stall were quickly noticed and the data loss minimised.

### Table 2: Camera settings for HDR image capture

<table>
<thead>
<tr>
<th>SETTING</th>
<th>VALUES</th>
</tr>
</thead>
<tbody>
<tr>
<td>Conventional photo format</td>
<td>JPG</td>
</tr>
<tr>
<td>Number of conventional photos (time steps)</td>
<td>7</td>
</tr>
<tr>
<td>JPG exposure</td>
<td></td>
</tr>
<tr>
<td>Aperture</td>
<td>f/8.0</td>
</tr>
<tr>
<td>Shutter speed</td>
<td>1/2000 - 2 second</td>
</tr>
<tr>
<td>ISO</td>
<td>100</td>
</tr>
<tr>
<td>Whitebalance</td>
<td>Daylight</td>
</tr>
<tr>
<td>HDR photo schedule</td>
<td>Daily</td>
</tr>
<tr>
<td>Start</td>
<td>08:00</td>
</tr>
<tr>
<td>End</td>
<td>17:50</td>
</tr>
<tr>
<td>Interval</td>
<td>10min</td>
</tr>
</tbody>
</table>

Calibration of the HDR images followed the procedure described by Jacobs (2007) and Inanici (2006). It included determining the response curve of the specific camera; calibrating the luminance of the HDR images against physical measurements with a Konica Minolta LS-100 luminance meter; post-processing the HDR images by applying a vignetting correction. The final calibrated HDR image was a data map containing a measurement of luminance at every pixel of the image.
Lastly, for secondary calibration of the HDR images, a Hanwell ML4000 (4701) illuminance meter was placed in the captured scene for approximately one month.

Further parameters recorded were the reflectance of main classroom surfaces and external solar data. Reflectance of the walls, ceiling, carpet and smartboard was measured using the luminance meter and a white card of known reflectance as reference. Reflectance was also estimated by identifying the closest match between each surface’s colour to standard colour samples of known reflectance. External solar radiation data were collected by means of a BF5 Sunshine Sensor by Delta-T, which was placed on the roof of a nearby building. The output of this device is in lux, rendering it suitable for illumination studies.

CBDM: ASSUMPTIONS AND REALITY
Building simulation is usually employed during the design stage of a building project, e.g. to evaluate and compare the expected performance of multiple design solutions. However, to be used effectively, validation procedures have to ensure that reality is simulated as closely as possible. These are typically conducted in test rooms under controlled conditions, so that every aspect of reality is reproduced in the simulation and the remaining uncertainty corresponds to the uncertainty of the model itself. Confounding factors (i.e. variable and unpredictable), abundant in any real situation, have to be met with assumptions, which depend highly on the expertise and knowledge of the modeller.

The first decision made before performing a CBDM evaluation concerns the climate data used for the specific location. For the current work, both the EnergyPlus weather file (EPW) for Birmingham and the CIBSE weather file for Nottingham were deemed suitable sources of prevailing climatic conditions for the simulation of CBDM metrics.

The construction of the 3D model introduces different ranges of uncertainty, depending on the complexity of the real scene. Even after reaching a high level of geometrical accuracy, the position of movable elements, such as furniture, can potentially alter the predicted outcomes, i.e. the CBDM metrics. The impact on the model is especially pronounced when these elements are part of, or directly affect the fenestration system e.g. curtains, blinds, shades, etc. Another factor affecting lighting simulation studies is the precision in modelling the exterior environment, as it can lead to various degrees of daylight obstruction or additional ingress of daylight via reflections.

An additional source of uncertainty is the assignment of reflectance values for each material within and in the vicinity of the room. Uncertainties may arise from measuring instrument errors and the presence of complex materials or patterns that cannot be easily sampled. Standard reflectance values or material properties retrieved from databases are used instead.

Arguably, the biggest assumptions that need to be introduced are the ones related to the presence of people and the prediction of their behaviour. The use of electric light, of blinds and other shading devices is not dictated exclusively by the presence (or absence) of daylight. However, some user behavioural models are available for insertion in the simulation process; they usually set a certain threshold in terms of illuminance levels, luminance levels or DGP (Daylight Glare Probability) that triggers a user’s response, coupled with the set occupancy schedule (Jakubiec, 2012; Reinhart, 2004).

MONITORED DATA
An inventory of the monitored luminance values from processing HDR images for each classroom is compiled and presented in the form of a temporal map (Fig. 3). Each small shaded square shows the average pixel luminance across a single HDR image using false colour. This compact form of presentation provides a high-level overview of a vast amount of data, and reveals the temporal dynamics of the (spatially averaged) luminous environment on a 10 minute basis – note the use of a logarithmic colour scale.

In the case of L3, with the unobstructed NW glazed wall, high average luminance values tend to gradually occur less frequently and closer to midday as daylight hours progressively decrease (Fig. 3 left). In contrast, the NE orientated L7 openings, which face deciduous trees, exhibit variability during and between days, more so in winter than in the summer months, when high average luminance values tend to occur in the mornings (Fig. 3 right). This manner of presenting data also reveals gaps in the dataset – the break in October is due to a camera shutter failure, after over 6 months of continuous use (April-October). Fortunately, this coincided with the autumn term break, so not much occupied period data was lost.

HDR images that covered the months when classes were held (September 7 to December 18) were processed manually by viewing each of the HDR images. This involved viewing 4980 images for L7 and 5655 images for L3. The discrepancy corresponds to about 11 days of monitoring and was due mostly to the shutter failure. Systematic manual data extraction from each of the images resulted in the compilation of a
showing the space being occupied (by 59 images in controls were in place) showing we wa for daily matrix showed that L7 was used for teaching (and brief checks).

The error found was 4.84% (3 data recording errors in am and one at pm) images of L3 for each of 31 days. The process, matrix compilation, human error in the simultaneous image viewing and visual display technologies (i.e. smartboard projector (i.e. on tabular matrix comprising information on: occupancy (i.e. on-going lesson or maintenance cleaning); use of visual display technologies (i.e. smartboard projector on/off); the state of electric lights/blinds (i.e. vertical blinds 75% pulled open with slats rotated perpendicular to the plane of the window glass).

This matrix enabled the quantification of the users’ visual interventions and behaviour. The degree of human error in the simultaneous image viewing and matrix compilation, a time consuming and repetitive process, was calculated by checking two random (one at am and one at pm) images of L3 for each of 31 days. The error found was 4.84% (3 data recording errors in 62 checks).

In regard to classroom function, analysis of the matrix showed that L7 was used for teaching (and brief daily cleaning) in 23.74% of the monitoring time, while for L3 it was 25%. During these periods, the smartboard was used 68.19% and 58.91% of the time, while laptops were used 11.00% and 48.09% respectively. Images showing the electric lights switched on (only manual controls were in place) exceeded in number those showing the space being occupied (by 59 images in L7 and 69 in L3) meaning that lights were left on when the space was not being used. This was found to cumulatively represent about 10hrs and 11hrs respectively in the span of the occupied period.

Moreover, it was revealed that in L7 the pair of light fixtures closest to the windows was used less frequently than those in the middle and rear of the classroom (1060 vs 1105 vs 1114), there being separate switches per pair of fixtures. Similar behaviour was observed in L3 (949 vs 1434 vs 1474), where the controls configuration included a switch for lights directly above the teacher’s desk, in place of mid-room lights.

Observation of blinds use in L7 (L3 had no shading system) confirms information that was sourced during a walkthrough of the site with a teacher; the horizontal blinds of the southeast wall always remained shut. During the school’s operation and for the window closest to the smartboard and teacher’s desk, 63.13% of images showed the blinds covering 0-25% of the window area. For the same sized window further away on the same Northeast wall, this number was 13.47%. Blinds were completely shut in 15.58% and 77.63% of the images respectively. The discrepancy between the
numbers of the same window represented the duration of recorded intermediate blinds states.

DISCUSSION

CBDM metric validation in relation to daylighting performance of real world spaces requires, ideally, continuous datasets over a period of one year. Standardised files are usually compiled from individual months taken from several years of monitored data. Accordingly, it would be a pointless exercise to compare, say, a week or a month of predicted illuminance values (derived from standardised climate data using CBDM) with measurements taken during the same time period in an actual year. However, one would expect annual summaries for overall performance measures to be broadly similar from one year to the next since the effects of unique patterns in the data become much less significant when a full year is considered.

Where model geometry is concerned, although the 3D simulation models were based on detailed measurements of dimensions and architectural features, in reality desks were often rearranged, even weekly in L7. The same classroom was also affected by external modelling features, as the large deciduous trees obstructing the operable windows contributed to substantial daylight performance variations between the summer and winter months.

Regarding occupancy schedules, measurements and simulation agreed that in L3 there was ingress of direct sunlight onto the smartboard wall from 4pm onward in the summer months, when the sun sets at a higher North point. In calculating for CBDM metrics as specified by the PSBP recommendations, the hours of direct sun exposure were excluded from the calculation since the schedule considered for simulation is ‘8:30am until 4pm (full year data including weekends and holiday periods)’ (EFA, 2014). However, the actual use of L3 for teaching was until 5pm.

The monitoring method presented facilitates the assessment of not only actual but operational daylighting performance, by providing data at a fine time interval and enabling the observation of actions users take to meet their visual needs. The authors are undertaking further study to associate daylighting performance in classrooms with subjective views of students. This could lead to an enhanced understanding of current visual needs and the reasoning behind electric light and blinds use; potentially informing the development of more realistic user models for daylighting simulation, specific to the particular environment of classrooms.

In actual classrooms, walls are used for the display of numerous teaching materials of varying reflective properties. There is no established method to estimate and apply realistic reflectance values in a simulation model. A related HDR technique can be used to both measure arbitrarily complex patterns of diffuse surface reflectance and also infer (from interpolation) illuminance fields across surfaces (Mardaljevic et al., 2015). It is largely impractical, if at all possible in occupied classrooms, to reliably monitor illuminance levels across desks. However, CBDM compliance targets are specified based on them. Work is in progress (Mardaljevic et al., 2016) whereby vertical wall illuminance is used as a proxy to infer horizontal illuminance. An evaluation of measured and simulated profiles of wall illuminance over long periods can, in principle, provide reliable inference data for illumination on the horizontal, consequently producing evidence for whether or not the design-intended illumination levels have been achieved.

![Figure 4: Derived illumination field across L7 wall section: HDR image of wall with white cards of known reflectance (top) and resulting illumination field in false colour (bottom).](image)

The relation between incident illumination, diffuse reflectance and resulting surface luminance is commonly used to determine material reflectivity from paired measurements of luminance and illuminance. The same relation can be used with HDR images to determine the illuminance field across, say, walls provided that the reflectance at locations distributed across the image is known. For the HDR image of the classroom wall shown in Figure 4 (top), a number of white cards (reflectance 0.88) were distributed across the wall above desk height. From the HDR luminance the illuminance (in lux) at each of the cards was derived. The illumination field across that area of the wall –
CONCLUSION

Direct evidence for assessing the impact of the UK’s post-2013 daylight policy for school building design will not be available until compliant schools are built and occupied. However, this paper presents a robust methodology for monitoring long-term actual daylighting performance in any building type. The method is particularly suited for monitoring occupied educational environments because it overcomes constraints faced by previous classroom field studies, such as causing class and teaching disruption.

A further advantage is that it allows the observation of the actions building users take to meet their visual needs and improve their visual comfort. In this research, this included use of specific electric lights and partial and full use of blinds, as well as times when the lights were left on in unoccupied classrooms. Such information is valuable for informing the development of realistic user models that will subsequently contribute to the better agreement between real and simulated daylighting performance. Quantifying the influence that key confounding factors, such as occupancy, climate, geometry and reflectance, have on this agreement requires not only the rigorous measurement of luminous environment parameters in actual spaces in use, but also an investigation into the current visual needs of the occupants and the drivers behind their behaviour. This paper highlights the case for the significance of actual daylighting performance measurements with an overview of the first steps taken toward the assessment of the practical application of CBDM metrics.

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