Subjective and Measured Evidence for Residential Lighting Metrics in the Tropics

J. Alstan Jakubiec¹, Thanyalak Srisamranrungruang², Zhe Kong³, Geraldine Quek⁴, Riccardo Talamì⁵

¹University of Toronto, Toronto, Canada

²Meiji University, Kanagawa, Japan

³Southeast University, Nanjing, China

⁴École Polytechnique Fédérale de Lausanne, Lausanne, Switzerland

⁵Loughborough University, Loughborough, United Kingdom

Abstract

This paper presents a post-occupancy daylighting study within 17 residences in Singapore consisting of 35 participants. Each residence was visited, and a calibrated daylighting model was constructed and validated based upon 100's of individual illuminance measurements. A survey on subjective lighting quality was administered to each participant. The authors find that simulated annual climate-based daylight measures can be used to predict subjective lighting evaluations such as satisfaction with access to daylight, whether a space is perceived as dim or bright, and when overall daylighting levels are too low. Using the mean annual daylight level per sensor, at a spatial median illuminance threshold of 175 lx, more than 80% of people are predicted to be satisfied with access to daylight in kitchens; however, in bedrooms and living rooms, satisfaction with daylight was high even at low lighting levels. Kitchens can be identified as dim or bright and all residential space types can be identified as often underlit or not based upon median spatial values of annual sensor mean illuminance. Finally, the authors share reported reasons for dynamic window shading use in the residences studied—desire for privacy was found to be of similar importance to the direct sunlight, a difference from dynamic shading use in commercial spaces.

Introduction

Human factors are a huge part of recent daylighting analysis work. Renewed interest is emerging in physical reactions to light such as circadian health and alertness as well as subjective responses—visual discomfort, satisfaction with access to daylight, the relationship between contrast and emotive perception, and how the concept of 'fully daylight' is defined by users. Within this work, most of the studies based upon direct measurements and surveys are based in labs, classrooms, or offices. Labs and classrooms are the spaces most commonly available to the researcher, and offices are often open enough that polling and measurement can be widespread, minimizing effort and cost in data collection. Within the field of residential daylighting, however, there is little direct evidence for the way we assess the daylighting of residential spaces. This paper addresses this gap through a direct measurement, simulation, survey, and journaling study within residential buildings located in Singapore.

Several researchers and communities have addressed residential lighting metrics. The CIBSE Guide on

Lighting for Communal Residential Buildings (2013) suggests that residential spaces should be oriented according to the time of light exposure they would experience based upon the program and makes recommendations for window sizing but stops short of any directly measurable design metrics. The Illumination Engineering Society (IES, 2000) on the other hand makes specific recommendations for lighting levels in residential spaces—30–50 lx in corridors and stairs, 100 lx in bedrooms, bathrooms and living rooms, 500 lx for cooking and handicrafts, and 1,000 lx for tasks of even greater detail. These are based on presumed lighting and colour-rendering sufficiency rather than specific human factors. When residential daylighting is assessed with Climate-Based Daylight Metrics (CBDM's, Mardaljevic 2000), it is often through a reduced illuminance target or a varying schedule as in Singapore's Green Mark Certification system (BCA 2015) which specifies a 200 lx daylight target and an occupancy schedule of 7:00am–10:00am and 4:00pm–7:00pm. LEED version 4 for multifamily residential (USGBC 2015) specifies that 90% of spaces achieve 10 lx of daylight, and that 50% of spaces achieve 150 lx of daylight based on field measurements. 5,000 lx is a maximum not to be exceeded. Mardaljevic et al. (2012) however applied the standard Useful Daylight Illuminance (UDI) thresholds (<100 lx, fell short; 100 lx–300 lx, supplemental; 300 lx–3,000 lx, autonomous and >3,000 lx, exceeded) residential projects, noting that they were designed for office spaces. Dogan and Park (2018) proposed a new residential daylighting metric for cold and temperate climates based on a review existing literature on lighting preferences and existing design guidelines.

Direct measurement or simulation studies relate measurements to actual occupant feedback in the field. Ng (2003) found that in Hong Kong, residents had very low standards for daylight access to their windows from a survey of 1,027 participants and calculations of vertical daylight factor (VDF) on exterior windows; daylight factors inside of the spaces will be significantly lower. In bedrooms Ng found that 20% VDF was required to achieve 80% satisfaction in, but the VDF required in kitchens for an identical satisfaction level is only 4%, and 27% VDF is needed for an 80% satisfaction rate in living rooms. It is difficult to relate these values to lighting levels inside of apartments due to window glass properties, shading devices, and the size of individuals rooms being unknown. Xue, Mak, and Huang (2016) conducted a survey in 108 daylight living room spaces by

means of stuffing mailboxes. While the units were never physically measured or entered, simulation models were constructed based upon construction documents. Only illuminance uniformity and the mean Daylight Autonomy 300 lx (DA300lx) level—the percent of time where 300 lx is achieved by daylight alone—were found to significantly correlate with comfort inside of their simulated spaces. Minimum uniformity of 0.112 and DA300lx of 29.6% were recommended.

In this paper, the authors describe a new approach to post-occupancy-based daylight assessment of residential units. First, the process of measuring 17 residential units in detail and constructing calibrated daylight simulation models of each is described and validated. Then a one-time subjective survey and lighting journal system for 35 participants is described. Finally, correlations between site-measurements, annual simulations, and the collected subjective data is reported.

This article is an initial exploration of an extremely rich dataset which has been created. This initial report describes simple correlations between likely predictor variables for subjective responses where statistically-strong correlations exist. The authors aim to reduce degrees of data processing freedom and inclusion of covariates in the analysis to minimize false positives (Simmons et al. 2011).

Methodology

Space measurements and lighting model calibration

Seventeen residential units throughout Singapore are included in this study, including the following room counts by program: 17 living rooms, 22 bedrooms, 14 kitchens, 2 dining rooms, and 2 study rooms. This manuscript focuses on the living rooms, bedrooms, and kitchens as there is a larger sample of these types of program spaces. A representation of the 17 unit layouts surveyed with annual mean daytime illuminance results plotted on top are included in Figure 1.

For all 17 residential units, calibrated daylighting models were constructed. The same calibration process reported in previous works was followed (Jakubiec et al. 2018, Quek and Jakubiec 2019). 3D scan data was captured from within and exterior to each unit, reflective and transmissive material properties were measured using a reflectance spectrophotometer or illuminance ratios, and detailed 3D models were constructed in the Radiance format (Ward 1994) based on this information. Figure 2 shows the 3D scan information and the resulting daylighting model without the exterior context.

To ensure the validity of the 17 models, point-in-time illuminance data was measured along a centreline from each window at 1 m intervals into each residential space. To ensure the speed and accuracy of these measures, a tape measure was laid on the floor, and a plumb bob and level were attached to an illuminance meter. The researcher would then measure at 1 m intervals quickly while maintaining the sensor height and levelness, recording the time of measurement, spatial location, and the illuminance value.

Figure 1: Annual mean daytime illuminance without window shades in the 17 studied housing units.

Figure 2: Representative 3D scan (top) and resulting 3D model (bottom) without a depiction of the site context and surrounding buildings of unit 3.

Later, global horizontal irradiance data was extracted from nearby weather stations during the time of measurement and used to create a custom Perez all-weather sky (Perez, seals and Michalsky 1993) which is used to calculate illuminance via the Radiance engine's `rtrace` command (Ward 1994) and can be compared to the measured data. Figure 3 shows a calibration analysis with measured illuminances on the X axis and simulated illuminances on the Y axis for 236 measured points across all 17 residential units. The solid red line is the identity line ($y=x$), and the dashed lines indicate a boundary of $\pm 25\%$ accuracy in log10 space. The total root mean square error across all sensors and models is 168.2 lx, and the mean bias error is 31.6 lx, indicating a slight overprediction in the simulation models overall.

Subjective data collection

Each of the 17 housing units were visited twice. On the first visit, the physical information used in building and calibrating the 3D models illustrated in the previous section was collected. In addition, lighting journals were left with the participants. Each participant was asked to fill in lighting journal information in each studied room for at least 3 times per day for a minimum week-long duration; however, the lighting journal information is not analysed in detail in this report due to a lack of space.

A follow up second visit took place 1 week after the initial visit. During this visit, an approximately 45-minute survey was administered to each participant in the study. Lighting journals were collected, and participants were reimbursed with a S\$50 grocery voucher for their week-

long participation in the study. Table 1 illustrates a selected subset of subjective questions which will be analysed in this manuscript.

Figure 3: Measured and simulated illuminance values at 236 points in the studied residential spaces.

Results

Participant demographics

A wide range of ages were captured from young professionals to retirees. Fifty-four percent (54%, 19) of participants were female while 46% (16) were male. Only 51% (18) of participants wore corrective eyewear, either glasses or contact lenses. Eighty-three percent (29) of participants were employed, 9% (3) were retired, 6% (2) were unemployed, and 3% (1) were on compulsory military service. A histogram of participant ages is shown in Figure 4.

Figure 4: Histogram of participant ages.

Table 1: Selected questions and response options included in the subjective survey.

Question	Response Range
Demographic Questions	
1. What is your age?	≤21 years, ≤30 years, ≤40 years, ≤50 years, <65 years, or ≥65 years
2. What is your gender?	Male or Female
3. Are you wearing corrective eyewear at the time of this survey?	Glasses, Contacts, No
4. Please describe your activity status.	1. Holds a regular job, profession or internship 2. Unemployed 3. A student or pursuing education in some manner 4. Retired 5. Permanently disabled 6. In compulsory military or community service 7. Performing domestic work 8. Other
Long-term Descriptive Questions	
5. Think about the amount of daylight, not electric light, that typically reaches each room in your household. How satisfied are you with your access to daylight? Check one box per row for each room.	(Per room) Range from Very Satisfied, to Neutral, to Very Dissatisfied
7. Which adjectives typically describe the lighting in the following rooms? Check all that apply.	(Per room) Gloomy, Dim, Comfortable, Bright, Glary, and Other (free response)
10. If you have ever closed the shades in the following rooms, please give a reason or reasons why. Please check or write down all that apply.	(Per room) Privacy reasons, Excessive daylight, or Free response choice
Long-term Ranking Questions	
<i>Please rate your agreement with the following statements by checking a single box for each room in your household.</i>	
11. The total amount of light from daylight in the following rooms is often too high.	(Per room) Range from Strongly Agree to No Opinion to Strongly Disagree
12. The total amount of light from daylight in the following rooms is often too low.	

Description of collected data

One great unknown in lighting simulation is the materiality of a simulation model, which were all measured explicitly using a Konica Minolta 2600d material spectrophotometer for opaque materials and paired illuminance measurements for transparent or translucent materials. Over 400 opaque materials, shades, and glazing assemblies were measured in the 17 residential units, although roughly four-fifths of those measurements are of interior furnishings. In this manuscript, the authors have chosen to report some descriptive statistical measures—mean, median, and standard deviation from the mean—of standard material surface types: walls, floors, and glazing assemblies. Ceilings were not always explicitly measured if their visual properties were very close to those of painted walls, so they are not included here.

Table 2 lists the mean, median, and standard deviation from the mean of the material measurements. Colored walls are common inside of the residences surveyed—30 of 48 walls measured were non-white, and all walls had a mean reflectance of 72.4% but a large standard deviation of 20.8% reflectance. White walls, on the other hand, were found to be uniformly brighter than current standards (IESNA 2012) with a mean reflectance of 86.0% and a low standard deviation. Properties of glazings (23.6% standard deviation from a mean of 39.6%) and floors (22.8% standard deviation from a mean

of 47.2%) also varied wildly between residential units and between rooms with different glass and floor finish types.

Table 2: Statistical information on measured material properties inside 17 residential units. For opaque materials visible reflectance is reported while for glazings visible light transmittance is reported.

Name	Count	Mean (%)	Median (%)	Std. (%)
All walls	48	72.4	79.5	20.8
White walls	18	86.0	86.8	4.1
Glazings	38	39.6	31.8	23.6
Floors	42	47.2	53.9	22.8

In order to express the variety of lighting experienced within each program and unit, Figure 5 reports the mean spatial value of two CBDM's—mean annual daytime illuminance and DA300lx—for each space within the study using a standard 9:00am-5:00pm occupancy schedule. The authors intend this data to paint a general picture of the data collected in measuring and simulating 17 residential units.

Figure 5: Mean daytime illuminance compared against the percentage of space meeting the DA300lx_{50%} CBDM.

Figure 6: Example normal distribution and probit link function relationship.

Inferential Statistics

In view of the small number of participants ($n=35$), rather than using a grouping methodology when analysing the data as in some previous works (Wienold and Christoffersen 2006; Hirning, Isoardi and Cowling 2014;

Jakubiec, Quek and Srisamranrungruang 2018), when correlating against the survey data the authors rely on probit logistical regression. Probit regression is a type of regression where the dependent variable is binary—for example satisfied or not satisfied with daylight—and is numerically limited between 0 and 1. The resulting probit function simply reports the probability that a member of a population will satisfy the binary criteria and obviates the need to group the participants by a predictor variable. Probit results are parameterizations of the normal cumulative distribution function, $\Phi(z)$. This is illustrated in Figure 6. For example, if a regression-fit probit result is $z = 1.311442 * X - 2.085852$, then evaluating x at a value of 2.243, some measured or simulated value, will result in a z equal to ~ 0.8558 and a probability of 80.4%, the shaded area under the curve in Figure 6 (top), essentially the probability that the dependent condition will be true (1). For this reason, probit models result in an S-shaped curve (Figure 6 bottom) which is flat near a 0 or 1 probability when the z -function is at the tails of the standard normal distribution (<-3 or >3) and changing more rapidly when it is between.

Because the input data are binary, it is difficult to apply normal correlation information, such as R^2 and p -values, to logistical regression types; however, several methods in the research to generate pseudo- R^2 results have emerged. The authors use McFadden's R^2 (McFadden 1973)—defined as 1 minus the log-likelihood of the fitted model divided by the log-likelihood of a null model—to express the goodness of fit between simulations and subjective information. Evaluation of McFadden's R^2 is different from typical R^2 metrics—results as low as 0.2–0.4 represent an excellent fit. In the authors' opinion results of 0.15 represent a very good fit, 0.10 a good fit, and 0.07 a fair fit to the data.

Initially when exploring the dataset described in this manuscript, the authors correlated the responses to question 5 in Table 1 (“Think about the amount of daylight, not electric light, that typically reaches each room in your household. How satisfied are you with your access to daylight?”) with a variety of area-based CBDM's. If a participant responded that they were either “Slightly Satisfied,” “Satisfied,” or “Very Satisfied” with their access to daylight, then they are grouped in the satisfied category (1 in the probit analysis). Responses of “Neutral” satisfaction were discarded, and any dissatisfied responses were grouped under the dissatisfied category (0 in the probit analysis). CBDM's were calculated using 5-minute actual year weather data and 2 different occupancy schedules—a standard 9:00am–5:00pm occupancy period and a 7:00am–10:00am & 4:00pm–7:00pm occupancy period covering morning and evening hours presuming occupants leave their homes during the day.

Daylight Autonomy (Reinhart, Mardaljevic and Rogers 2006) results were derived using both schedules at several illuminance targets—200 lx, 300 lx, and 500 lx. Daylight Autonomy is simply the percentage of time where the illuminance target is met through daylight alone. In this paper the percentage of a space's floor area meeting a

certain time threshold, either 25% of scheduled hours or 50% of scheduled hours, is used to relate temporal information to an entire space as in IES-LM-83 (IESNA 2012) and is abbreviated as DA300lx_{50%} as an example for a 300 lx illuminance threshold and a temporal goal of meeting the illuminance criteria for 50% of scheduled hours. Useful Daylight Illuminance (UDI, Nabil and Mardaljevic 2005) is also used based on the summation of its autonomous (300 lx–3,000 lx) and supplemental (100 lx–300 lx) lighting threshold as has been used previously by Mardaljevic, UDIa+s_{50%}.

Two other measures were calculated based on the success of a previous study (Jakubiec, et al. 2018)—the mean and median spatial values of mean temporal daylight illuminance. In both cases, the mean illuminance at each sensor value over the scheduled time is calculated. In the case of median, the median sensor value of these temporal means in the space is selected. In the case of mean, the spatial mean of all temporal means is calculated. Table 3 illustrates McFadden's R^2 showing the correlation between selected calculated metrics and the answer to question 5 from Table 1. Good and very good correlations (McFadden's $R^2 > 0.10$) are colored in green while fair correlations (McFadden's $R^2 > 0.07$) are colored in blue.

From Table 3's results, several plausible metrics emerge for the prediction of satisfaction with access to daylight in residential spaces. Especially in the case of kitchen programs, simulated results correspond well with subjective data—there are 3 pseudo- R^2 correlations greater than 0.15 which indicate a very good fit. The best of these is the median of all sensor temporal mean illuminance values. On the other hand, daylight metrics predict lighting satisfaction less well in bedrooms and living rooms.

Figure 7 illustrates a graphical version of the probit relation between the median daylight sensor to reported daylight satisfaction for the three program types. The points represent participant responses for rooms with specific predicted median CBDM values, and the lines are

the probit-derived probabilities that a participant answers they are satisfied (1) or not satisfied (0) with daylight access. What emerges from this result is a program-specific response to lighting quality. Under any daylighting level, most participants were satisfied with daylight in their bedrooms. Living room spaces were also less likely to have their daylight access appraised as unsatisfactory when low levels of daylight are present. Participants assessing their kitchens, however, show a strong preference for higher daylighting levels and feel dissatisfaction with lower lighting levels. Other CBD measures such as DA200lx_{50%} and DA300lx_{25%} show these general trends as well when related to reported satisfaction.

Figure 7: Probability of being satisfied with access to daylight by room type predicted by the median sensor value of temporal mean illuminance CBD metric.

Table 3: Selected McFadden Pseudo- R^2 correlations between area-based CBD metrics and participant probabilities of being satisfied with access to daylight separated by program and occupancy schedule.

Program (Schedule)	DA200 (25%)	DA200 (50%)	DA300 (25%)	DA300 (50%)	DA500 (25%)	DA500 (50%)	UDIa+s (50%)	log10 Mean	log10 Median
Bedroom (9-5)	0.0596	0.0737	0.0691	0.0668	0.0486	0.0076	0.0863	0.0150	0.0013
Bedroom (7-10&4-7)	0.0681	0.0056	0.0391	0.0000	0.0003	0.0000	0.0143	0.0054	0.0002
Kitchen (9-5)	0.1006	0.0736	0.0792	0.0734	0.1011	0.0873	0.0896	0.0977	0.1849
Kitchen (7-10&4-7)	0.0722	0.0779	0.0754	0.0593	0.0652	0.0545	0.1620	0.0755	0.1596
Living (9-5)	0.0430	0.0249	0.0266	0.0156	0.0196	0.0243	0.0687	0.0597	0.0411
Living (7-10&4-7)	0.0243	0.0295	0.0259	0.0412	0.0455	0.0199	0.0647	0.0747	0.0577

Good and very good correlations, McFadden's $R^2 > 0.10$
Fair correlations, McFadden's $R^2 > 0.07$

In kitchens, feelings of satisfaction with access to daylight correlated strongly with many daylight metrics in kitchen spaces (see Table 3), but the most successful was the median spatial sensor value based on a mean of daytime (9:00am–5:00pm) illuminance results per sensor with a very strong McFadden's R^2 correlation of 0.1849 (see Figure 7). This means that in kitchens, it is possible to calculate the probability with which someone is satisfied with their access to daylight using the normal distribution function illustrated in Figure 6 parameterized by the probit z-function. This is shown in Equation 1 for the relationship between the median sensor value of temporal mean illuminance CBD metric and feelings of satisfaction with access to daylight in kitchens,

$$z = 1.311442 * \log_{10}(\tilde{E}) - 2.085852 \quad (1)$$

where $\tilde{E}$ is the median illuminance of all sensor temporal mean values in the space based on an annual CBD daylight simulation. At 175 lx, 80.4% of people are expected to feel satisfied with daylight levels. This is a significantly lower illuminance threshold than what a commercial standard daylight metric would use.

In bedrooms and living rooms, even at very low median illuminance levels, the majority of occupants are likely to be satisfied with their access to daylight. However, even though participants are satisfied they may still find a space “gloomy” or “dim.” They may also find a space especially “bright” or “comfortable” beyond simple satisfaction with access to daylight levels. Figures 8 and 9 continue this analysis in greater detail by investigating the subjective response feedback from question 7 in Table 1 (“Which adjectives typically describe the lighting in the following rooms?”) compared against the same median sensor value daylight metric with each sensor reporting the average value of a 9:00am–5:00pm schedule as in Figure 7. Figure 9 shows the probability of reporting a space as being typically “gloomy” or “dim” while Figure 10 shows the probability of reporting a space as being typically “comfortable” or “bright.”

As in the previous analysis, the most extreme variety of response under changing daylight levels comes in kitchen spaces. However, in this case the least varying response due to daylight is in living room spaces rather than in bedrooms. Very few living room spaces were identified as being dim or gloomy by participants, and most were seen as comfortable or bright. Few bedrooms were perceived to be dim or gloomy regardless of the daylighting level, but the perception of comfortable or bright varies strongly with daylight levels in bedrooms. Finally, Table 4 illustrates the predictive values using McFadden's R^2 in predicting “gloomy / dim” and “comfortable / bright” using the spatial median CBD metric.

Figure 8: Probability of reporting a room as typically “gloomy” or “dim” as predicted by the median sensor value of temporal mean illuminance CBDM.

Figure 9: Probability of reporting a room as typically “comfortable” or “bright” as predicted by the median sensor value of temporal mean illuminance CBDM.

Table 4: McFadden's R^2 values assessing the correlation between a space being perceived as “gloomy / dim” or “comfortable / bright” and the median sensor value of temporal mean illuminance CBDM.

Space type	Gloomy / dim prediction	Comfortable / bright prediction
Bedroom	0.0096	0.0603
Kitchen	0.1341	0.1626
Living Room	0.0097	0.0292

Dogan and Park (2018) proposed direct sunlight requirements for residential buildings in cold and temperate climates, but Singapore is a climatic context where it is constantly hot and humid and overheating risk is significant. Therefore, it is worthwhile to investigate the impact of minimal exposure on occupant residential preferences for tropical climates—questions 11 and 12 in Table 1, “The total amount of light from daylight in the following rooms is often too [high / low].” Analysis of the median sensor illuminance value related to question 11, regarding an excess of daylight, yielded poor and non-intuitive correlations; however, when assessing lighting levels being too low (question 12), there was a clear preference. This result is shown in Figure 10, where McFadden’s R^2 is 0.1236 for bedrooms, 0.1987 for kitchens, and 0.1800 for living room spaces—all good to very good correlations. In kitchens, where the largest amount of daylight is desired, a median sensor value of 300 lx, only 21.6% of participants are expected to feel that daylight levels are too low. At the same 175 lx used which rendered 80.2% of kitchen users satisfied with daylight access, 48.2% of participants are expected to feel that the daylight levels are often too low (22.3% in bedrooms and 16.5% in living rooms).

Figure 10: Probability of reporting a room’s daylight levels as typically “too low” as predicted by the median sensor value of temporal mean illuminance CBDM.

Finally, in light of the substantial amount of recent work on occupant window shade operation algorithms in commercial daylit spaces (Nezamdoost et al. 2018; Gunay et al. 2017), the authors wish to share the results of question 10 from Table 1—“If you have ever closed the shades in the following rooms, please give a reason or reasons why.” Of 78 reported reasons for closing the window shades across all room program types, 35.9% are to block direct sun, 33.3% are for privacy reasons, 17.9% are to reduce solar heat gain, and 12.8% are to block diffuse daylight.

Conclusion and discussion

The extent of analysis in this paper is limited by its format, but the authors have presented in detail a comprehensive study methodology comparing measured and simulated lighting levels in 17 residential housing units in Singapore against the subjective opinions of 35 participants who reside in the units. This manuscript represents a first look at the data and its ability to craft statistically-valid subjective models based on predictive lighting simulation data. This study is particularly novel, because it involves direct measurement and calibrated daylight modelling for the residences studied, something largely absent in the literature.

It was found that daylighting analysis in residential spaces should vary significantly from those in commercial office spaces. In bedrooms and living room spaces, high participant satisfactions with daylight access were found even at very low levels of traditional CBDM’s which form the basis of commercial daylighting metrics. This makes sense given the differences in tasks between office spaces with high light requirements for working and residential spaces where light may not be as critical. The exception to this was found to be the kitchen, a space where the task of cooking requires adequate lighting. Furthermore, it was found that CBDM’s can be used to identify when kitchens especially may be classified as typically bright / comfortable or gloomy / dim. Finally, the authors compared a CBDM with the probability of feeling that daylight levels are often too low and found that all residential program types can be assessed for this criteria.

Taking the median spatial value of all sensor mean daytime illuminance values, 175 lx was found to be a good threshold for satisfaction with access to daylight in kitchens, where a 300 lx median was necessary to cause only 21.6% of kitchen users to feel that daylight levels are too low. This ~10% median cutoff value is around 150 lx in living rooms and 200 lx in bedrooms, leading to different lighting targets depending on program. These results should have applicability for designing satisfying and well-daylit residences in the future, at least in the tropical location of Singapore.

The authors have shown that climate-based daylight metrics have direct applicability to the perception of light inside of dwellings, although not only traditional metrics can work in this regard. New ways of using climate-based daylight modelling has been explored in this study—mean and median assessments of annual mean illuminance levels do a better job of predicting subjective results than traditional CBDM’s. New means of expressing quality lighting in residential units can be achieved without relying upon electric lighting sufficiency measures typically present in codes and green building certification systems.

Limitations and future work

There are several limitations to this work. The study reported herein has been carried out in one location—Singapore. While other studies find broad acceptance from a limited sample, the authors do not wish to overstate the applicability of this work without further validation

studies. Future validation in other countries would be beneficial in finding global subjective lighting quality metrics.

The amount of analysis studies in this paper is very small compared to the number of questions in the survey and the number of potential simulation outputs, only a fraction of which were shared in the manuscript. Therefore, this work serves as an initial presentation of the methodology and early communication of results.

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