

Evaluating Human Visual Preference and Performance
in an Office Environment Using Luminance-based Metrics

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Abstract

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There are not adequate human factors research studies available that examine luminance-based measures as they relate to human visual preference and acceptance in spaces with daylight. The objective of this research is to study several luminance-based metrics to support improved integrated lighting design recommendations, computational analysis methods and control technologies. Therefore, this dissertation executed a two-day pilot study (n=18) and a six-month repeated-measures experiment (n=45) in mock office spaces under naturally occurring daylight conditions in Boise, Idaho. Recent developments in High Dynamic Range digital photography permit investigation of high-resolution luminance-based metrics. Once these metrics and associated recommended criteria are established, they can support computational daylighting design analysis and integrated luminous environmental control systems to improve occupant

satisfaction and increase energy savings over traditional illuminance-based methods. This dissertation also examined human visual performance differences in scenes rated as visually comfortable and those having “just uncomfortable glare.” This was done to determine if, and to what extent, visual performance decrements exist under uncomfortable conditions.

Luminance-based metrics proved more capable than illuminance-based metrics at fitting the range of subjective responses on visual comfort items. Standard deviation of window luminance produced the highest adjusted squared correlation coefficient of any single metric with subjective responses ($_{adj}r^2=0.38$, $F_{1,860}=536$, $p\text{-value}<0.01$). Additionally, metrics based upon luminance within the 40° horizontal band of vision performed strongly. A bounded-borderline between comfort and discomfort is proposed as preliminary criteria for several of the highest-ranked metrics. Illuminance-based metrics, traditional luminance ratios and the recently proposed Daylight Glare Probability were less able to fit subjective responses. The strongest multiple regression model was for the “too dim–too bright” rating of the window wall ($_{adj}R^2=0.49$, $F_{3,688}=222$, $p\text{-value} < 0.01$) and was built upon three variables: standard deviation of window luminance, 50th percentile luminance value from the view window and the percent of the 40° horizontal band $> 2000 \text{ cd/m}^2$.

Additionally, a significant decrement (0.51-1.65%) in visual performance was found for one of three objective performance tests in glaring scenes. A significant “seasonal” effect was found for measured sensitivity to brightness between summer and fall using a controlled repeated-measures test. Finally, several human acceptance-based approaches to improve luminous environmental control systems are proposed.

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DEDICATION

To Kim, my only Love.

1 Introduction

1.1 Background

A daylit space can be described as comprising several key attributes: 1) it uses daylight as the primary source of daytime illumination to accommodate the occupants' visual demands, 2) it is experienced as a visually and thermally comfortable place, 3) it is connected to outdoor phenomena and 4) it persistently maximizes electric lighting energy savings while minimizing peak energy demand (Van Den Wymelenberg 2008). It is generally accepted that daylight and views help to create healthy, comfortable and productive work environments for users, and therefore should be included in contemporary office spaces. However, there is inadequate research to support design recommendations with regard to daylight sufficiency or excessiveness. Historically, the Illuminating Engineering Society (IES) provides very little guidance to designers seeking to provide functionally daylit spaces that also minimize visual discomfort. The 10th edition of the Lighting Handbook (DiLaura et al. 2011) and annualized simulation-based daylight sufficiency recommended criteria (IESNA-Daylight Metrics Committee 2012) provide encouraging progress. As beneficial as these documents may prove to be, they still rely primarily on horizontal illuminance-based criteria rather than luminance-based criteria. This is in large part due to the complexity and variability of daylight and the general lack of research available for luminance-based metrics and criteria derived from spaces with daylight. It is understood that it is the physical measure of luminance, rather than illuminance, that corresponds best to human perception of brightness (Cuttle 2004). Moreover, contemporary office occupants spend a significant amount of time working on vertical tasks (computer

monitors) rather than paper-based horizontal tasks. Therefore, it is hypothesized that occupant preferences in office settings are better predicted by patterns of luminance in the vertical visual field than horizontal illuminance.

While daylight in buildings holds tremendous potential to save energy, it must be provided in a manner that is acceptable to occupants for the potential energy savings to be realized. Current daylight-sensing lighting control systems do not adequately consider occupant visual preferences, and are therefore often disabled by building occupants. In fact, occupant intervention accounts for over 70% of non-functional daylight-sensing lighting control systems (Heschong, Howlett, McHugh, & Pande, 2005). Window blinds are typically operated manually to prevent occasional excessive brightness or sunlight penetration, undesirable computer screen reflections, or discomfort glare. However, blinds are closed far longer than necessary, reducing the use of available daylight and negating much of the associated energy and human benefits. These human comfort driven factors can result in intentionally-daylit spaces that perform poorly, not only from a comfort perspective but also from an energy perspective.

At the same time, building energy codes are becoming increasingly more stringent. Organizations such as the American Institute of Architects (AIA) and the American Society of Heating Refrigerating and Air-conditioning Engineers (ASHRAE) have committed to constructing “net-zero energy buildings” by the year 2030 with successive interim milestones. Recent energy code proposals by ASHRAE and the International Code Council committees target increased restrictions on the amount of window area and further reductions of electric lighting in office buildings. These aggressive energy targets, combined with sometimes poorly performing intentionally daylit buildings, have some energy efficiency advocates pushing for performance-based codes as the only pathway for delivering well daylit buildings. Seen this

way, the pursuit of aggressive energy codes could have a negative consequence with regard to human health and well-being if not balanced with an equal set of priorities based upon sound visual comfort research.

Without a doubt, designers who intend to provide functionally daylit spaces meeting all four of the attributes listed above will benefit from improved metrics and corresponding criteria. These criteria can be used to guide design analysis as well as to control integrated lighting environments during operation. Current illuminance-based electric lighting design recommendations are not adequate to address the present demands placed upon architects, engineers and lighting designers to deliver visually comfortable and energy efficient workplaces that use daylight as the primary source of illumination.

1.2 Aims

There are not adequate human factors research studies available that examine luminance-based measures as they relate to human visual preference and acceptance in spaces with daylight. The objective of this study is to address this critical barrier in the field of lighting and daylighting design. Recognizing the potential shortcomings of existing illuminance-based lighting quality guidelines, lighting control technologies and simulation methods, and given the recent development of more sophisticated luminance-based data collection, this dissertation aims to advance the foundational human factors research to support improved integrated lighting design recommendations, computational analysis methods and control technologies. To achieve this goal, 45 subjects were examined in a repeated-measures design in a mock office space under naturally occurring (and systematically categorized) daylight conditions.

The specific aims are:

Aim 1) To determine which lighting metrics (luminance-based and illuminance-based) are more strongly associated with *subjective measures* of human visual preference and acceptance (using Likert-type and semantic differential questionnaire items) in an office space with daylight only, and with both daylight and electric light (integrated lighting), and to identify recommended design criteria.

Aim 2) To determine whether, and to what extent, *objective measures* of human visual performance (proof-reading on paper and computer screens, manuscript typing, visual search and numerical verification) and creativity are significantly better in an office space with environmental lighting rated as “most preferred” (MP) as compared to the same space with environmental lighting conditions rated as “just uncomfortable” (JU).

Aim 3) To provide guidance for the application of the lighting metrics (luminance-based and illuminance-based) identified as most representative of human visual acceptance and preference in the context of integrated luminous (electric lighting and solar shading) environmental control systems.

1.3 Overview of the dissertation

Section 2 provides the necessary context of, and need for, this dissertation. Section 2.1 reviews existing human visual performance literature. Section 2.2 reviews the best practices in daylight-sensing electric lighting control, motorized blind control and human behavioral interactions with, and energy use implications of, these practices. Section 2.3 provides a review of existing lighting metrics and recommended criteria. Section 2.4 summarizes a two-day pilot study that was used to guide the research plan executed in the six-month laboratory study.

Sections 3.1 through 3.4 describe the experimental design, research setting, participant recruitment, the study day procedures and conditions. Sections 3.5 describes the location and frequency of the measured data and Section 3.6 describes the data processing, cleaning and statistical analysis methods. Section 4 documents the results of the dissertation, Section 5 discusses the results in depth and Section 6 summarizes the major contributions and suggested future research that emerged from this dissertation. Finally, Section 7 documents the references and Section 8 provides a range of appendices.

2 Literature Review

The first section of the literature review (2.1) provides the necessary context to support several research questions examined in this dissertation related to human visual performance in scenes with daylight. Section 2.2 reviews environmental control systems including applications of, and user interaction with, electric lighting controls and blinds, and highlights recent proof of concept research regarding luminance-based luminous environmental controls. Section 2.3 details relevant historic and current human visual preference and acceptance metrics based upon illuminance measurement and luminance measurement. It also describes the use of High Dynamic Range (HDR) photography in luminance measurement. Finally, section 2.4 documents the major findings of a pilot study executed to support the development of the research and analysis methodology employed in this dissertation.

2.1 Lighting and human visual performance

Human health and productivity benefits and energy savings may be associated with using natural daylight (Boyce 2003; Boyce, Hunter, et al. 2003). If executed appropriately, a high quality daylight design that makes provisions to reduce glare, provide useful diffuse daylight and incorporate a high quality view is likely to have beneficial effects on worker satisfaction, mood and productivity. However, simply including abundant daylight in a building is not enough. If daylight is accompanied with glare and thermal stress or the design significantly reduces visual or acoustical privacy, the inclusion of daylight can reduce worker satisfaction, mood and productivity.

Some researchers argue that the topic of daylighting and its effect on human productivity has been exhausted and additional research is not warranted. For example, Boyce et al. (2003) state that research “...examining the effect of daylight on visual performance... [is] unnecessary as knowledge in that area is already sufficient to predict the results.” The authors continue, stating, “...examining the effect of daylighting on mood and hence productivity, could be undertaken but given the amount of work that has already been done in this area and the confusing pattern of results obtained, the probability of success is low.” Furthermore, a literature survey on determinants of lighting quality (Veitch & Newsham 1996) indicates that illuminance is important for visual performance only at extremely low levels; and it does not significantly affect the task performance over a wide range of illuminance levels and varieties of tasks.

Conversely, some researchers suggest that more work should be done to examine the effects of daylight on productivity (Goodman et al. 2006). Furthermore, visual performance studies (R. Blackwell 1959; Boyce 1973; Rea & Ouellette 1991) and daylighting glare metrics (Chauvel et al. 1982; Hopkinson 1972; Wienold & Christoffersen 2006) establish a relationship between luminance, comfort, visibility and performance. While acknowledging Boyce’s caution, this section builds a case for human productivity research to be conducted under a wide range of daylighting conditions including the extremes of discomfort and disability glare. The effect of lighting and daylighting on human productivity can occur through three distinct physiological human systems: the visual system, the perceptual system and the circadian system (Boyce, Hunter, et al. 2003). This dissertation examines the visual and perceptual system but does not address the circadian system in a direct manner.

2.1.1 The human visual system and performance

The visual system comprises the eye and brain working together to generate an image of the scene upon the retina and preparing it for interpretation by the brain (Boyce 2003). In this context, visual performance depends upon the characteristics of the task being viewed in combination with the physiological characteristics of the visual system. “The perceptual system takes over once the retinal image has been processed by the visual system” (Boyce 2003).

Five factors affect visibility, and subsequently visual task performance: visual size, luminance contrast, color difference, retinal image quality and retinal illuminance (Boyce 2003). Visual size is the angle subtended at the eye by the visual stimulus. Luminance contrast is the difference between the task and background luminance divided by the background luminance. Color difference can be measured with various color space values and is important in tasks including visual search and when luminance contrast is low. Retinal image quality is sharpness and increases as luminance increases. It relates to the stimulus itself, the amount of light scatter in the space and the ability of the visual system to focus the image on the retina. The visual system degrades with age beyond 30 years. Retinal illuminance is a measure of illuminance falling upon the retina and dictates the adaptation of the visual system (Boyce 2003). “Another complication is that eye performance changes with light-level ([retinal] illuminance), age, contrast, target eccentricity, etc., all of which affect the ability to perform tasks and can compromise experimental findings from task performance studies” (Goodman et al. 2006).

2.1.1.1 Relative visual performance models

Many of the factors affecting visibility can be easily measured and therefore a model of visual task performance is possible. Rea and his associates developed the Relative Visual

Performance (RVP) models giving consideration to task size, background luminance (eventually retinal illuminance measured in trolands) and luminance contrast, with modifications suggested for age differences (Rea 1981; Rea 1986; Rea & Ouellette 1988; Rea & Ouellette 1991; Rea et al. 1990). This work developed a precise methodology to predict visual performance given variables of luminance contrast and background luminance.

The RVP models are useful for predicting task performance for highly visual tasks in electrically illuminated settings and have not been studied in settings with daylight. Specifically, a total of 64 different visual stimulus conditions were tested (16 contrasts ranging from 0.09-0.9 and four background luminances ranging between 12-169 cd/m^2). The studies were conducted on young adults with excellent vision. Age translations were suggested (but not directly tested) based upon previously documented changes in the optics of the eye with age (reductions in retinal illuminance and retinal contrast).

Rea's findings are summarized in a three-dimensional representation of the visual performance model with RVP plotted linearly on the vertical axis and background luminance and contrast plotted logarithmically on the x-y axes (Figure 1). It was found that RVP differs little from medium (0.5) to high (1) contrast; in fact, it changes very little with contrast above 0.3. RVP changes very little over a wide range of contrast values and background luminances and the model only begins to identify a performance difference at very low values for either factor. The shape of this model has come to be known as the “plateau and escarpment” of visual performance. Given this model, with young workers and assuming a contrast of 0.7 for text and a reflectance of 0.8 for paper, a reduction from 650 lux to 400 lux would result in a 0.3% reduction in RVP for a young worker (1% for an older worker). A further reduction to 150 lux would result in a total of 2% reduction in RVP for a young worker (Rea 1986). It can also be

said that it is not possible to achieve the same level of performance for a difficult task compared to a simple visual task just by increasing illuminance. Similarly, increasing task size has a larger effect on improving performance than does increasing illuminance.

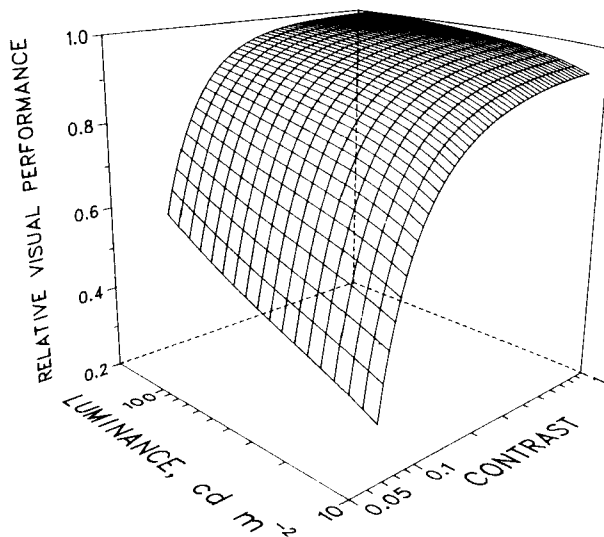


Figure 1 - Three-dimensional representation of the visual performance model developed by Rea (1986).

It is important to emphasize that these models are useful for the measurement of visual performance only and may not adequately translate to overall task performance depending on task type. The models are useful in settings with luminance conditions typical of electrically illuminated office spaces, not spaces with daylight, and are applicable to text-based tasks with relatively high visual demands such as transcription from paper. No studies have examined RVP under daylight conditions and there is presently no construct by which to consider the effects of increased daylight on long-term visual performance or excessive daylight on short-term visual performance.

2.1.1.2 Disability glare and performance

Daylight does not always increase productivity, and in some settings with glare it may result in reduced productivity. There are two main types of glare: discomfort glare and disability glare. Discomfort glare pertains more directly to the perceptual system and is discussed further in section 2.1.2 and section 2.3.2.2, whereas disability glare pertains more directly to the visual system. Disability glare is caused by light scatter in the eye (Vos 1984), which forms a luminous veil over an extended portion of the retinal image. Several disability glare calculations have been developed to estimate the effect of the equivalent veiling luminance on the luminance contrast of the object and modifications to the equations for age and iris color have also been determined (Vos 2003).

Disability glare plays a role in visual performance and therefore potentially impacts measures of productivity, although disability glare studies have focused more on safety, such as in nighttime roadway lighting and in aviation settings, than on testing human productivity. It may be feasible to study the effects of disability glare on visual performance in offices with view windows. A very bright sky or the direct sun located in close proximity to the visual axis can cause disability glare and may result in measurable visual performance effects in office environments, although no studies were found to support this hypothesis.

2.1.2 The human perceptual system and performance

According to Goodman et al. (2006) "...only changes in lighting conditions that directly affect task visibility have a definite impact on task performance." The operative word is "definite." The impact that task visibility, via the visual system, has on performance is the most direct and well defined. It is possible that the perceptual system also influences human performance, but the current research has provided answers that are less concrete and less

consistent than for effects of the visual system. “These studies frequently give inconclusive and conflicting results: changes in the lighting that affect the perception of the space but not visibility may, or may not, affect task performance, depending on the strength of the impact of the lighting on mood and motivation relative to other factors that may also have an influence, such as boredom, ambient noise and time of day” (Goodman et al. 2006).

The level of visual comfort is one aspect of the perceptual system that may affect performance, even though it does not directly reduce visibility. Visual comfort research has focused primarily on human preference and acceptance ratings as they relate to objective lighting measures rather than objective measures pertaining to human performance and is therefore reviewed more thoroughly in section 2.3.2.2. However, similar to disability glare, discomfort glare may result in measurable visual performance effects in office environments, although no studies were found to support this hypothesis.

2.1.3 A proposed model for visual performance research in settings with daylight

While Rea's work in RVP models adequately addresses the visual aspects of tasks, the models should not be extended directly as a measure of overall task performance, especially with tasks that are not highly visually based. Furthermore, the RVP models are only applicable to electrically illuminated spaces with background luminances between 12-169 cd/m². In fact, most of the performance research related to the visual and perceptual systems has been executed under electric lighting only, thus making it difficult to draw conclusions from these data or be confident in their methods as they relate to research considering daylighting effects. Further complicating matters is the fact that tests of performance are prone to “learning effects” or “practice effects” over even a short period of time (Newsham et al. 2004; Veitch & Newsham 2000a).

Boyce et al. (2006a) conducted an extensive and well-executed study investigating recessed lighting, indirect-direct pendant lighting and levels of user control and the resulting effects upon users' satisfaction and performance. Satisfaction was high for both types of lighting, 70% for recessed direct lighting with no user control and 91% for indirect-direct electric lighting with user controls. The study showed a rather substantial increase in satisfaction but little effect on performance. On this point, the authors suggest that researchers should no longer attempt to quantify individuals' performance improvements due to various lighting conditions, instead promoting long-term field studies and organizational performance research. While this study does not pertain directly to effects of daylight on performance, it does indicate that with generally high lighting satisfaction levels (greater than 70%) office task performance does not appear to improve even as satisfaction increases (to 91%). This could be explained in a similar fashion to the findings of the RVP models as a "plateau and escarpment" phenomenon.

Generally, as satisfaction surpasses a threshold value, performance does not increase. Therefore, it might be expected that performance will generally not change so long as task visibility is adequate, regardless of the light source. This line of reasoning would suggest that future studies under daylight settings focus attention on reduced performance at lower satisfaction thresholds, such as those that may be associated with glare, rather than trying to establish that performance improves with increased satisfaction or higher light levels. This is especially true with self-illuminated visual tasks as is the case with most computer-based office work.

Could the RVP models be adapted to explore upper thresholds for visual distraction or disability glare in settings with daylight? While disability glare research is extensive, experiments examining visual performance relative to disability glare are rare. Could models

similar to RVP be found to define thresholds of disability glare? Indeed, Boyce et al. (2003) offer several recommendations regarding visual performance research in daylight settings. “Benefits in visual performance are more likely to be found when the task involves fine color discrimination and the daylight is delivered at high levels without glare or any reduction in task visibility caused by veiling reflections or shadows. Benefits in visual performance are unlikely to be found where the task is achromatic and visually easy. Decrements in visual performance are likely when the daylight is delivered in such a way that task visibility is reduced, either because the amount of light on the task is inadequate, or glare, or veiling reflections, or strong shadows are present.”

In addition to disability glare effects via the visual system, the perceptual system effects associated with discomfort glare are also important factors to consider when studying human productivity in settings with daylight. Little research has investigated the performance-related aspects of discomfort glare.

Hopkinson suggests that, “The disabling effects of glare can be investigated by studying the changes which occur in visual ability of visual performance with and without the presence of the glaring light source”(Hopkinson 1972). However, he also stated that “Much time and trouble has been spent in seeking objective correlates with glare discomfort, such as the activity of the frontalis muscles [in the face] or the diameter of the pupil, and although these may be useful pointers to the presence of discomfort, they do not correlate directly and linearly with the magnitude of discomfort” (Hopkinson 1972). Essentially, Hopkinson stated that while physiological measures might be somewhat useful for assessing disability glare, they are not useful for assessing discomfort glare (Hopkinson & J. B. Collins 1970). These authors go on to state that “No successful studies have been made using specific visual tasks and the performance

of them as the basis for evaluation. Attempts have indeed been made to evaluate glare in this way (Bartlett & Pollock 1935; P. T. Stone & Groves 1968) but all the investigators who have attempted such “behaviorist” investigations have found that acute subjective discomfort arises from situations which give rise to little or no decrement in visual performance....” They continue, “If such decrement does exist, it probably only results from very long exposures, that is, over days, weeks or months to a glaring situation. Glare is essentially a matter of annoyance and distress rather than direct reduction in visual performance.” This does not provide encouragement to this line of investigation; however, other studies show some evidence that performance tests using paper-based tasks are warranted when examining differing levels of glare conditions (Linhart & Scartezzini 2011; Osterhaus & Bailey 1992).

2.2 Environmental control systems

2.2.1 Electric lighting use and control

There are several strategies currently in use for the control of electric lighting in commercial buildings including manual, scheduled clock, occupancy or vacancy sensing, daylight-sensing and, recently, peak electricity demand response controls. Depending on the application, these controls may be operated as on/off, step-switching, step-dimming or continuous dimming systems. In some cases these technologies are deployed in sophisticated arrangements with multiple combined strategies and detailed zonal configurations. These technologies have been evolving for decades and, in a sense, are quite mature. However, significant problems persist in real world applications.

Of all the lighting control systems outlined above, automated daylight-sensing controls are the most complicated and require the most attention to ensure successful implementation. There are several critical aspects regarding system design and implementation that must be handled carefully to ensure that the system saves energy. However, electric lighting comprises almost 25% of the total electricity used in buildings in the United States (US-DOE, 2006) and buildings comprise over 75% of the total electricity used nationwide (US-EIA, 2008), thus pursuing a way to improve the performance of lighting control systems is a worthwhile endeavor. This section outlines the current best practices in luminous environment controls and the benefits and limitations associated with them.

2.2.1.1 Predicted and realized lighting energy savings

Daylight-sensing lighting control systems have been in use for decades but have been slow to penetrate the market. However, new energy codes are causing a dramatic increase in their application¹, thus increasing the urgency to improve their effectiveness to deliver energy savings while minimizing occupant dissatisfaction.

In office settings, daylight-sensing systems typically dim electric lights in response to illumination signals at ceiling-mounted photocells. This is known as a closed-loop proportional configuration and the photocell is ideally pointed toward the main work surface. The photocell receives illumination from both daylight and electric light sources and is sometimes equipped with shielding to avoid registering brightness extremes from windows (Rubinstein, G. Ward, & Verderber, 1989). It is reasonable to argue that these systems are not intended to improve user

¹ Dimming ballasts are expected to see a 3% compound annual growth rate (CAGR) in North America (Frost & Sullivan 2009) and energy efficient lighting in general is expected to see 8.2% CAGR in Europe through 2014 (Frost & Sullivan 2008).

satisfaction, rather simply to save energy, and can at best go unnoticed by building inhabitants. The aim of the system is to achieve constant desktop illumination in the presence of variable daylight levels by adding the appropriate amount of electric light. While a direct measure of illumination on the desktop would be most logical for this purpose, due to desk clutter, shadowing, and other occupant interruptions, ceiling illuminance (E_{ceiling}) has been used as a surrogate. This requires various calibration procedures during the commissioning process since the workplane and the ceiling can have drastically different illuminance values at a given time. Several studies have been conducted to improve calibration procedures for various daylighting conditions, control configurations and architectural settings (A. Choi & R. G. Mistrick 2001; S. Y. Kim & J. J. Kim 2007; Littlefair & Motin 2001; F. Rubinstein et al. 1989); however, problems persist.

The theoretical annual energy savings potential of daylight-sensing controls is fundamentally based upon the amount of daylight available in a control zone throughout the year and the ability of the photocell(s) to accurately sense the daylight and relay the appropriate signals to dimming ballasts. Any number of modifying factors can result in more or less energy savings than predicted including the actual amount of daylight that enters the space (weather patterns, blind positions), the functionality of the system (design, installation, calibration) and occupant interactions (disabling, overriding).

Laboratory settings provide a reasonable upper bound for energy savings potential since they control for many confounding factors but incorporate several real world factors. A review of laboratory studies in sidelighting applications indicates that, under controlled conditions without the influence of user behavior, lighting savings due to daylight have a very wide (between 20-60% savings) range of potential. Littlefair (2001) reported 45-55 % potential

lighting savings from three years worth of illumination data, Roche (2002) reported 60% lighting savings for a dimming system with automated blinds and Lee and Selkowitz (2006) reported 20-23% lighting savings from an open-loop (photocell senses daylight illumination only) system with windows from one side and 52-59% with windows on two sides. The next logical question is - how much energy is actually being saved in real world applications?

Field studies also produce a wide range of findings, from <0% (due to increased voltage of dimming ballasts, or lights inadvertently being left on after hours due to daylight control) to 156% of predicted savings (Galasiu et al. 2007; Heschong et al. 2005; Jennings et al. 1999; McHugh et al. 2004; Moore et al. 2003; Pigg et al. 1996; Reinhart & Voss 2003). Savings from toplit spaces were more predictable than sidelit spaces (Heschong et al. 2005; McHugh et al. 2004). In these studies, blind use was found to be a substantial factor that reduced predictability from sidelit spaces, as were intentionally disabled control systems as outlined in Table 1, suggesting that users were not satisfied with operation. The accumulation of these studies, especially Pigg et al. (1996) and Heschong et al. (2005) suggests that the current state of daylight-sensing controls is not performing adequately, especially in sidelit architectural applications. However, recent studies show some improvement, likely due to improved calibration instructions provided by manufacturers and increased attention to detail by utility incentive programs (Acker & Van Den Wymelenberg 2010).

Table 1 - Reasons for poor daylight-sensing control functionality [following (Heschong et al. 2005)]

Reason	Count	Percent
<i>Intentionally disabled</i>	35	71.5%
Set point intentionally set too high	17	34.5%
Photocell taped over	7	14.5%
Entire system intentionally deactivated	7	14.5%
Photocell wires intentionally disconnected	4	8%
<i>Unintentionally non-functioning</i>	14	28.5%
System had never worked	5	10.5%
System had never been initiated	4	8%
Daylight levels were too low	4	8%
Photocell not compatible with EMS	1	2%

2.2.1.2 User attitudes and lighting control

As suggested by Table 1, building inhabitants have a great deal to do with the overall success of daylight-sensing lighting control systems. A few studies have investigated this explicitly. Vine et al. (1998) reported that as people gain more control over their visual environment (subsequently, less automation) comfort scores improve. To the contrary, Escuyer and Fontoynt (2001) reported that automatic daylight-sensing dimming was not annoying to survey participants (n=41). However, similar to Vine et al., they also found that manually-controlled dimming produced conscious satisfaction among users. These conflicting data can be partly explained by Moore et al. (2002b), through results of a field study (410 participants) that suggested people are not happy with daylight-sensing lighting controls if insufficient illumination was provided when daylight illuminance was low. In other words, people find it a problem if they notice that daylighting and electric lighting (integrated lighting) is insufficient. This matches intuition; however, other problems have also been cited. Littlefair (2001) reported anecdotally, “one problem with this control type is frequent switching, annoying occupants.” Boardass et al. (1994) suggest a very broad set of complicating factors including “...poor window design; complex furniture layouts; VDU screen visibility; limited understanding of occupant and

management requirements and behavior; poor implementation and commissioning; misplaced sophistication and poor ergonomics.” Finally, a growing body of research suggests that the most fundamental premise of daylight-sensing lighting controls, maintaining constant desktop illumination, may in fact be flawed. As stated by Newsham et al. (2008), “...several studies have shown that, given a free choice, people in daylit spaces do not use manual controls to maintain constant desktop illuminance (E_{desktop}). This has led to suggestions that occupant preferences are not driven by E_{desktop} , but by a desire to balance luminance or illuminance ratios [(Halonen & Lehtovaara 1995)], or by time-of-day effects [(Tenner et al. 1997)].” Therefore, it is not simply the limits of current technology or the manner in which the current technology is applied that is called into question. If these points are valid, then in order to improve performance of any type of daylight-sensing lighting control system additional human factors research is necessary, especially daylong research focused on luminance measures.

2.2.2 Blind use and control

[Text in this section reprinted with permission, (Van Den Wymelenberg 2012) © Energy and Buildings, 2012.] Window coverings (hereafter blinds) are used by people for many reasons, come in a wide variety of types and shapes and can be located inside, outside or within the envelope of a building. The position and operational patterns of blinds affect the energy consumption of buildings as well as human visual comfort. There is no comprehensive consensus about the way people operate blinds or the motivating factors that influence their decisions. However, there is a substantial body of research that offers guidance and this section aims to solidify current knowledge, identify knowledge gaps and document future research needs.

Accurate knowledge of blind use is needed in order to improve the accuracy of predictive energy and daylighting simulation, and can serve to inform new automated control algorithms.

Blind position and operation affect the amount and distribution of daylight entering a building as well as all forms of thermal transfer through windows. As detailed in section 2.2.1.1, daylight-sensing lighting controls hold the potential to save significant energy; however, realized savings are reduced if window blinds are closed. Blinds have the potential to reduce cooling energy and peak cooling demand, especially if located outside of the thermal envelope. Effective daylight-sensing lighting controls can also reduce cooling loads by minimizing waste heat from lights. Not accounting for blind use in simulation practice may provide misleading information used in decision-making during design stages and slow the refinement of algorithms for automated façade control.

Intuition suggests that blind use by occupants is dictated by demands of visual and thermal comfort; however, occupant concerns for privacy, the quality of the view or social dynamics are other possible factors. Rea (1984) detailed several factors that affect occupants' use of blinds including the orientation of the window, time of day, time of year, weather conditions, latitude, workstation position within the room, occupant activities, occupant habits and electric lighting characteristics. Inkarojrit (2005) organized these and other factors into four categories that influence use of blinds. Most of the factors offered by Rea fall into 1) physical factors, but Inkarojrit also identified 2) physiological factors (such as individual sensitivity to brightness), 3) psychological factors (such as a desire for privacy or access to view) and 4) social factors (such as a sense of blind ownership or organizational policy). These factors illustrate the complexity associated with research of blind use patterns and user motivations. This dissertation examines physical factors and physiological factors only.

2.2.2.1 Energy implications of blind use

Substantially less daylight enters a building when blinds are down and therefore daylight-sensing control systems do not save as much energy. In a simulation of total building energy use Newsham (Newsham 1994) studied four blind control strategies: always closed, always open, always closed from April-October and “manually” controlled to close at 233 W/m^2 falling onto an occupant. Assuming daylight harvesting, the increased blind use carried a penalty of 66% for lighting energy and 33% total energy. Reinhart (2004) conducted a simulation-based study and used a stochastic method for lighting and blind control. Three blind control types were studied (automated, dynamic manual user and static manual user), and lighting energy savings ranged from 0-60% depending on the lighting and blind control type. Munudhane and Reinhart (2010) updated existing nomographs (Selkowitz & Gabel 1984) for estimating lighting energy savings due to daylight by adding effects of various lighting control and blind use assumptions. In a building in Boston, MA, with 40% window-wall ratio, 65% visible light transmission and a space targeting 30 foot-candles, a building with daylight harvesting and no blinds saves 65% lighting energy and only 40% with a mix of passive and active blind users. Few studies report results for interactive effects between automated blinds, integrated daylight-sensing lighting controls and whole building energy use. No studies examining energy saved from external automated blinds were identified. A few studies have examined the benefit of internal automated blinds in lab or field settings (J. H. Kim et al. 2009; Lee et al. 1998; Roche 2002) and reported savings in peak cooling load (5-30%), cooling and ventilation energy savings (10-30%), lighting energy savings (20-45% compared to systems with photocell dimming and static blinds) and total energy savings (25%) for all systems.

2.2.2.2 *Blind occlusion from field studies*

A total of 24 office buildings have been studied and detailed results provided for blind occlusion² values. Included are six in Maryland (Rubin et al. 1978), one in Ottawa, Canada (Rea 1984), one academic office building in Wisconsin (Pigg et al. 1996), six in small English cities (Lindsay & Littlefair 1992; Littlefair 2002), three in London (Foster & Oreszczyn 2001), two in California (Inkarojrit 2005), one in France (Sutter et al. 2006), one in Korea (J. H. Kim et al. 2009), two in Austria (Mahdavi 2009), and one academic office building in Washington (Day et al. 2012). Additionally, 26 buildings across five European countries provide basic summary data for blind occlusion.

It is difficult to make generalizations about typical blind occlusion values since data collection methods have not been applied consistently. From the 50 buildings included in the occlusion field studies listed above, orientation, sky condition, season, time of day, view type, and cooling system type have all been reported to statistically affect blind occlusion. The most consistent findings are that orientation and sky condition are important factors. However, view type and cooling system type have only been considered in one study each, and only a few studies have examined seasonal effects. The strongest effect, not surprisingly, appears to be for north facades having less occlusion, typically just 15-25% across studies (Rubin et al. 1978; Pigg et al. 1996; Mahdavi 2009; Day et al. 2012) spanning a variety of climates. South façade occlusion was most commonly 40-70% (Rea 1984; Inkarojrit 2005; Rubin et al. 1978; Pigg et al. 1996; Littlefair 2002; Day et al. 2012) and these data also span multiple climate zones. Not as many studies have data for east and west facades but the results tend to be in the 20-50% occlusion range (Rea 1984; Mahdavi 2009; Day et al. 2012). After orientation, the next strongest

² Occlusion is the amount of the window covered by blinds and should consider both blind height and slat tilt if appropriate.

factor appears to be season, although only as reported by Nicol et al. from 26 European countries. Most notably, Nicol et al. reported 15-20% occlusion for winter, as compared to 30-35% for autumn and 35-40% for both spring and summer. The next strongest factor appears to be sky condition. It is somewhat surprising that sky condition has not been shown to have a stronger effect. The most substantial effects are from two buildings that show 10-20% less occlusion on overcast days for select facades, specifically east (Rea 1984) and south (J. H. Kim et al. 2009). The most substantial study to investigate this was by Nicol et al. and they showed an even smaller effect with only 7% less occlusion on overcast days as compared to clear days. On the whole, these results support the notion suggested by Rubin et al. that people formulate their decisions about blind position over a period of weeks or months, and not days or hours. However, there are two notable exceptions that reported a relationship between blind occlusion and time of day following logical sunlight patterns (Inoue et al. 1988; Lindsay & Littlefair 1992).

2.2.2.3 Rate of change from field studies

One important aspect of understanding patterns of blind use is simply to know typical blind adjustment frequency or “rate of change.” This review identified four papers that have attempted to quantify manual blind rate of change from a total of 42 buildings in field studies (Rubin et al. 1978; Lindsay & Littlefair 1992; Inoue et al. 1988; Nicol et al. 2006). Only two studies were identified that examined motorized blind rate of change (Sutter et al. 2006; J. H. Kim et al. 2009) and just one study that examined rate of change for a fully automated system (Reinhart & Voss 2003).

There is not enough literature to suggest blind use frequencies in a detailed manner; however, some preliminary conclusions can be drawn. Most importantly, manual blinds

examined in field studies have a very low daily rate of change. The simple average of 42³ buildings studied in the field reveals just a 15% daily rate of change. It has also been shown that 35% of blinds are not changed over a period as long as four months (Pigg et al. 1996) and 30% are self-reported as never being adjusted (Sze 2009). There is some evidence to support the notion of an “active” blind user profile, meaning that if manual blinds are adjusted on a given day they are more likely to be adjusted again (Lindsay & Littlefair 1992; Nicol et al. 2006). However, it has also been shown that only 5% of blinds are adjusted more than once per day (J. H. Kim et al. 2009). Season (Nicol et al. 2006), orientation (Lindsay & Littlefair 1992; J. H. Kim et al. 2009) floor (lower versus upper) (Lindsay & Littlefair 1992) and sky condition (J. H. Kim et al. 2009) have been shown to affect blind rate of change but too few studies are available to predict patterns of operation using these factors. Motorized blinds have a higher rate of operation per day than manual blinds (Sutter et al. 2006; J. H. Kim et al. 2009) but too few studies are available to provide detailed guidance for use in simulations. However, this underpins the importance of access to functional blind control as was also suggested by Sze and Day et al. Not surprisingly, automated blinds have a much higher rate of operation than either manual or motorized blinds (Reinhart & Voss 2003). Finally, some studies have overstated blind rate of change by broadly applying results of field studies that were only representative of the portion of blinds that moved on a given day to represent all blinds in a building.

Blind rate of change tends to be described as a percentage of blinds that move per day. However, in the case of motorized or automated systems it has been reported as the number of movements per day per window or per private office. Future research should present both the

³ Note that it was not explicitly stated that the 6.8% rate of change reported by Nicol et al. (Nicol et al. 2006) was representative of all 26 buildings in their database.

percentage of blinds that move on a given day and, for those that move, the number of times they move per day.

2.2.2.4 Illuminance, luminance, irradiance and blind use

Following up on general reasons for blind use and in addition to blind rate of change, it is important to understand how specific quantitative measures correlate with, and can be used to, predict user-requested blind movements. Understanding these relationships could inform future blind control algorithms as well as simulation with blind use.

Several types of quantitative measures have been explored and are categorized by measures of visible light and irradiance. Despite the fact that there is a substantial body of research in this area, there are still no generally agreed upon threshold values for triggering manual blind movement. Too few studies are available that report either illuminance or luminance data in relation to blind closures or opening. Two studies (Sutter et al. 2006; Reinhart & Voss 2003) suggest that exterior vertical illuminance (vertical illuminance; hereafter E_v) of 41,000 and 50,000 lux were the most common values for manually closing motorized blinds and 13,000 and 25,000 lux were the most common values for manually opening motorized blinds, thus suggesting a phenomenon known as “blind hysteresis.” Initial studies into luminance values and blind use suggest further research is warranted. Sutter et al. showed that only 25% of people accepted average window luminance values greater than 3,200 cd/m^2 and Van Den Wymelenberg et al. (2010) found that blinds were drawn in users’ preferred scenes to ensure that no more than 10% of the scene (HDR luminance pixels) exceeded 2,000 cd/m^2 .

While there is general evidence for a solar irradiance-based blind control predictor, there is lack of consensus about whether an absolute threshold is sufficient, what that threshold should

be, where it should be measured and whether it needs to be combined with solar penetration depth. The irradiance values reported in Van Den Wymelenberg (2012) suggest wide disparity among the irradiance values for the determination of the threshold between sunlight and diffuse light, and even less agreement about human response to sunlight. This is not surprising given that discerning a threshold between sunlight and shadow can be imprecise and due to the well documented variability of human sensitivity to brightness. Furthermore, the documented differences in measurement location and reductions to values recorded inside the envelope make it more difficult to interpret these results.

Several factors are affected by solar penetration depth. Deeper penetration could result in increased heat gain, potentially more people in direct sun, higher likelihood of a direct line of sight to the disc of the sun and, very often, higher contrast in the room. Nonetheless, combining the presence of direct sun with penetration depth seems useful. Future field research should consider measuring irradiance horizontally at the work surface, thus combining irradiance data with occupant position at a known distance from the window, and resolving both solar intensity and distance from façade measurement in a single value. Additionally, vertical irradiance on the façade should be recorded to inform future control systems integration and predictive energy modeling research, and future studies should investigate whether there is a correlation between vertical irradiance and depth of sunlight penetration.

Only three studies were found that measured irradiance data for closures of normal manual blinds: one has unknown measurement location (Oscar Faber Associates 1992), one was measured vertically inside the envelope with unknown glass properties (Inoue et al. 1988) and one was measured horizontally on the roof (Sukru Tokel 2006). One study was found with vertical exterior irradiance data for manually-controlled motorized closures (Mahdavi 2009) and

a second reported E_v values for blind closures roughly equivalent to 370 W/m^2 (Sutter et al. 2006). Finally, one study of an automated system (Reinhart & Voss 2003) reported exterior E_v for user overrides roughly equivalent to 450 W/m^2 . While additional research is needed to determine absolute value ranges, available data suggest that future research should consider a sunlight threshold in addition to the depth of penetration of sunlight when monitoring user blind control or suggesting automated blind control algorithms.

2.2.2.5 User attitudes toward automated blinds

In a survey conducted by Inkarojrit (2005) of 113 office workers, 44.5% of the subjects indicated that they “preferred” to have automated louver blinds. A more favorable figure was presented as a result of a small laboratory study ($n=14$) in which almost 60% of the subjects indicated they would suggest a system like the one used in the study (motorized blinds and daylight-sensing dimming) for use in their own office building (Vine et al., 1998). From a survey conducted in conjunction with a large field study of offices with automatic louver blinds, the most significant negative response was that the blinds closed even when people felt it was not required, followed shortly thereafter by blinds opening when people thought they should stay closed (Inoue et al., 1988). Similarly, Reinhart and Voss (Reinhart & Voss 2003) reported that 88% of user overrides of automated blinds were to reopen the blinds after an automated closure. Lee and others (Lee, Hughes, et al. 2007; Lee, Clear, et al. 2007) documented the control algorithm for the New York Times Headquarters building. The motorized roller fabric blinds are controlled to block direct sun to a specified horizontal distance from the window. There are three types of overrides: manual override dictated by users, “sky brightness” overrides dictated by photocells mounted vertically inside the glass, and neighboring building shadow overrides

dictated by sun position and a 3D geometry model of the surroundings. The sky brightness overrides, regardless of sky condition, limit average window luminance to approximately 2,000 cd/m² based upon illuminance values carefully calibrated to serve as a proxy for luminance measurement. It is noteworthy that user overrides are infrequent and that the automated system dictates 98% of all blind movements. Similar to Inoue et al. and Reinhart and Voss, almost all (97%) of the user overrides are requests to re-open blinds and very few (3%) are to close the blinds (Ashmore 2011) suggesting that more lenient blind closure threshold may be warranted.

2.2.3 Luminance-based control systems

As has been demonstrated in sections 2.2.1 and 2.2.2 current best practices of automated lighting and blind controls leave something to be desired in terms of realized energy savings and user satisfaction. One application of the investigation in this dissertation is the potential of luminance-based measures as an alternative or addition to illuminance as control input for lighting and blind systems. This section describes the rationale and supporting evidence for luminance-based lighting and blind controls. Specifically, it argues that luminance is a better measure of human perception of brightness than illuminance; it outlines recent proof of concept research regarding luminance-based lighting and blind controls; and it documents some known concerns and limitations of this control approach.

2.2.3.1 Light and human sensation

Luminance is the physical measure most closely associated with human visual perception of the brightness sensation. However, given that luminance is a physical measure of a human sensation, some inconsistency is to be expected. For example, consider the fact that adaptation mediates human perception of brightness. A simple example of this is to consider the perception

of brightness of automobile headlights that are turned on during the day as compared to the perception of the same headlights at night. The same light source, having the same luminance, is perceived as brighter at night when the eye is adapted to lower nighttime light levels. Pupillary adaptation, color, illuminance, reflectance and scene characteristics all play a role in brightness perception. Despite these conditions, luminance is still the best physical measure of human brightness sensation.

As noted by Kambich and Rea (1987), “Although not perfectly correlated, luminance is the physical quality which corresponds best to brightness. Therefore, to evaluate lighting one can measure luminance.” But what is meant by “...not perfectly correlated...”? Cuttle (2004) disputes the notion of using luminance as a measure of brightness stating, “brightness, as it is generally understood, does not provide a valid basis for designing interior lighting.” Cuttle argues that “brightness” is actually the perception of *illumination* and that “lightness” is the perception of *reflectance*. He argues that luminance is broken into the perception of illumination and reflectance, and that these perceptions are separate and have distinct scales. In application, Cuttle’s argument might be best supported by the fact that two surfaces of equal luminance may indeed have different components of reflectance and illuminance, and in some cases it would be possible to differentiate the brightness of the two surfaces. Indeed Cuttle effectively demonstrated this in a laboratory setting. However, in the discussion section of Cuttle’s paper, Loe asserts “that for design purposes we accept the fundamental differences between brightness and luminance but that we look to luminance and luminance ratios as a simple way forward for the design of the lit appearance of a space.” While these distinctions are valuable, as Loe (Cuttle 2004) and Kambich and Rea (1987) suggest, luminance can be used as a physical measure closely correlating to brightness.

2.2.3.2 Recent proof of concept research

Contemporary office occupants spend a significant amount of time working on vertical tasks (computer monitors) rather than paper-based horizontal tasks, and it therefore stands to reason that occupant preferences in office settings might be better predicted by patterns of luminance in the vertical visual field than horizontal illuminance. Current best practices in lighting and blind control typically rely on a single illuminance value to explain a complex luminous scene, whereas luminance maps collected with validated HDR photographic techniques (Debevec & Malik 1997; Inanici 2006; Reinhard et al. 2005) provide millions of pixel values that can be used to describe the variability in the luminous environment. The HDR photography technique is discussed in more depth in section 2.3.2.3. Some argue that E_v is an adequate indicator of occupant visual comfort (Wienold 2007), and while it may be an improvement over horizontal illuminance (Van Den Wymelenberg et al. 2010) and is easier to calculate in both real and simulated environments, it can not describe the luminous variability of a scene.

Research into camera-based lighting controls is not new and dates back at least to Glennie et al. (1992). The hope for camera-based lighting and blind controls has always been to improve user satisfaction or at least increase user acceptance of automatic control of the luminous environment while also saving energy. However, Glennie et al. did not include rigorous human factors testing, rather their research focused on assembling the technical components used to construct a camera-based system to control electric lights relative to user-requested luminance values. The camera was positioned on the ceiling and required extensive recalibration if bumped or if the regions of interest within the room changed. Surprisingly, no research in this area was found between 1992 and 2006 when Sarkar and Mistrick (2006) carried the idea forward using HDR imaging with a complementary metal–oxide–semiconductor

(CMOS) image sensor as found in most contemporary digital cameras. A similar arrangement of equipment as that of Glennie et al. was deployed; however, Sarkar and Mistrick used the luminance data in conjunction with reflectance data from key horizontal surfaces in the field of view (FOV) to calculate horizontal illumination on these surfaces and used the approximate illuminance values to control the electric lights. This demanded careful site calibration that required all surfaces of interest (classroom desks in this case) and the camera itself to remain perfectly stationary. Sarkar et al. (2008) carried this work forward using a CMOS video camera to measure scene luminance, estimate horizontal illuminance and dim or switch off electric lighting accordingly. The authors report that the prototype system maintained desired illuminance thresholds despite complex luminance patterns in the space, including spots of direct sunlight. Furthermore, they suggest that the occupancy sensor application is viable and can detect very small movements; however, it showed limitations at low light levels. A recent study illustrated that less than 20% error is possible when calculating illuminance values from HDR images (Bellia et al. 2011).

These efforts further demonstrated the viability of using cameras as lighting control sensors; however, several additional limitations should be noted. Similar to Glennie et al, Sarkar reports on the need to keep specular reflections from the sun out of the line of sight of the camera and suggest the camera should be placed near the window wall but pointed in the opposite direction. This raises concerns about the viability of the system to be extended to control blinds in order to mitigate glare, support occupant preference, or maximize daylight potential for energy savings. Also, simplifying the richness of luminance distribution data to a small number of horizontal illumination values in order to control electric lighting obfuscates the greatest benefit of camera-based control systems.

The first study that moved the camera near to the occupant's point of view for luminous control was reported by Newsham et al. (2008). In an office laboratory setting with low daylight levels (typically < 500 lux measured horizontally and 20% visible light transmitting glazing) and no glare (maximum sky luminance from seated position < 2500 cd/m²), temporary office workers (n=40) spent one day performing typical office activities. Subjects were prompted to use manual dimming controls of electric lighting every 30 minutes. Illuminance and luminance data were collected in an adjacent identical (electric lighting within ~ 3% error) office laboratory room just before and just after each user adjustment. Blinds were removed from the experiment to avoid confounding lighting control with blind control. Luminance maps were recorded in the identical office laboratory from the equivalent eye position of the subject in the adjacent room using a HDR photography technique. Regarding the ability of luminance measures to predict electric lighting dimming choice it was reported that the best luminance-based predictor was the ratio of the 75th and 25th percentiles of scene luminance. This metric explained 0.31 of the variance of personal dimmer choice while, somewhat surprisingly, total E_{desktop} explained 0.36. However, ceiling illuminance, as is commonly used with daylight-sensing lighting controls, was a worse predictor, explaining just 0.19 of the variance.

2.2.3.3 Known concerns

There are potential privacy concerns with using cameras as a lighting control mechanism; however, these data might be useful for security purposes as suggested by Newsham and Arsenault (2009). In their paper, Inanici commented that using low-resolution pixilated data might minimize privacy concerns. The general acceptance of computers with built in cameras may also provide justification. The camera should be as close to the observers' eyes as possible

and should remain relatively stable during the multiple exposure capture, both of which provide challenges in practice. Preliminary research (Newsham & Arsenault 2009; Sarkar et al. 2008) has demonstrated the potential for a camera to provide occupancy detection but there are limitations in settings with daylight due to variability, low light, and because of the time delay, where true occupancy sensing rather than vacancy sensing is needed. Finally, deploying luminance-based control in open-plan offices will likely produce conflicting signals due to the distinct FOV for multiple cameras. It is plausible that a decision set could be programmed to address this; however, it would require constant modulation between acceptance and preference thresholds for multiple users. Galasiu and Veitch (2006) completed a thorough literature review and concluded, “we do not yet know what control system features would be most acceptable, nor what range of luminous conditions the system should permit.” They note the potential of “behaviorally-derived algorithms and semi-automated systems” for controlling lights and blinds. However, it is clear that more human factors research at the individual level in a laboratory environment is required before new blind and lighting control algorithms should be implemented in open office field settings.

2.3 Human visual preference and acceptance lighting metrics

2.3.1 Illuminance-based metrics

Due to its ease of use and low cost to measure, horizontal illumination is the most widely applied architectural lighting design metric. However, even under electric light sources only, illuminance preference varies greatly, from 100-800 lux (Boyce et al. 2006b; Newsham & Veitch 2001; Veitch & Newsham 2000b) and has a mean value between 400-500 lux. It has been reported that the choice of any fixed illumination value will only be preferred by at most 55% of

the users (Boyce et al. 2006b). Few studies have reported user preference for illumination under daylight conditions alone. One found that 300 lux of daylight was preferred (n=20) (Laurentin et al. 2000) while another study found a wide range of preferred desktop daylight illuminance and a preferred mean of 3,623 lux(n=18) (Van Den Wymelenberg et al. 2010).

There is a lack of consensus regarding illumination preference under combined daylight and electric lighting conditions. Not surprisingly, the range for preferred conditions with the inclusion of daylight extend much higher than under electric lighting only, but the low extremity is just as low under daylight as under electric lighting conditions alone and several of the mean values reported are similar. The vast majority of research suggests that users select lower electric light levels as daylight increases if they are given access to controls (Bülow-Hübe 2000; Escuyer & Fontoynt 2001; Halonen & Lehtovaara 1995; Love 1998; Newsham, Aries, et al. 2008). The preferred horizontal illumination ranges and means reported for combined lighting scenes are summarized here:

- 230-1,000 lux with a mean of 510 (Halonen & Lehtovaara 1995)
- 790-2146 lux (Vine et al. 1998)
- Mean in winter (287 lux), spring (343 lux), summer (419 lux) (Moore et al. 2002a)
- 91-770 lux with a mean 288 lux ((Moore et al. 2003)
- 100-600 lux, 100-300 lux for computer users (Escuyer & Fontoynt 2001)
- Mean of 551 lux (Newsham, Aries, et al. 2008)

In scenes with daylight, the daylight factor has been the most widely used metric of evaluation until very recently with the prevalence of the current U.S. Green Building Council's (USGBC) Leadership in Energy and Environmental Design (LEED) rating system which now promotes a minimum of 10 foot-candle (108 lux) and maximum of 500 foot-candles (5381 lux) daylight threshold at specified times. Daylight factor is the ratio of daylight illumination measured at any given horizontal indoor analysis point to the unobstructed outdoor illumination

available at the same time, technically under a CIE overcast sky (Moon & Spencer 1942; Waldram 1909). Daylight factor is a useful metric for the measurement and prediction of daylight in buildings but it is limited to use under overcast skies and is criticized for promoting too much heat gain and glare in sunny climates (Mardaljevic et al. 2009).

With the advent of advanced computational daylight simulation in conjunction with annualized typical weather files, there has been a wide array of new dynamic climate-based daylighting metrics. Daylight Autonomy (DA) was the first of these and is represented as a percentage of annual daytime (or specified operating) hours that a given point in a space is above a specified illumination threshold. It was originally proposed by the Association Suisse des Electriciens in 1989 and updated by Reinhart and Walkenhorst (2001). It can relate to electric lighting energy savings if the user-defined threshold is set based upon electric lighting criteria. Several dynamic daylight metrics are reported elsewhere (Mardaljevic et al. 2009; Reinhart et al. 2006; Collaborative for High Performance Schools 2009). Until recently, there has been no guidance with regard to daylight sufficiency or daylight excessiveness in terms of annual daylight illumination performance. However, the Illuminating Engineering Society's (IES) Daylight Metrics Committee (DMC) recently proposed a Lighting Measurement document (LM-83) that defines analysis methods and preliminary performance criteria for a metric of daylight sufficiency using a form of daylight autonomy as it related to human subjective preference ratings in 61 spaces (IESNA-Daylight Metrics Committee 2012). The DMC termed the daylight sufficiency metric *spatial* Daylight Autonomy (sDA) and it is defined as the percent of a given analysis area (e.g. a given space) that meets a daylight illuminance indicator value for a specified fraction of the operating hours per year. For specific analyses within a range of defined use types, the DMC states that a 300 lux indicator value shall be used and that 50% of the analysis

hours from 8:00-18:00 be used ($sDA_{300,50\%}$) and suggests “nominally acceptable” daylight sufficiency as 55% $sDA_{300,50\%}$ and “preferred” daylight sufficiency as 75% $sDA_{300,50\%}$. The sDA metric as defined by LM-83 was corroborated by Reinhart and Weissman (2012) as the best metric for differentiating between student assessments of the “daylit” and “non-daylit” areas of a single sidelit space. The DMC also recommended a measurement technique and preliminary criteria for a daylight excessiveness metric they called Annual Sunlight Exposure (ASE) which uses illuminance as a proxy for discerning the extent of sunlight penetration on an annual basis considering cloud cover and architectural obstructions.

2.3.2 Luminance-based metrics

As reported in section 2.3.1, human acceptance and preference vary widely under primarily electrically illuminated spaces. Due to the complexities related to daylight in buildings (e.g. variability with time of day, time of year, sky condition, view quantity, view quality, extremes of brightness values, discomfort glare, etc.) the bounds of human preference are wider in spaces with daylight. Several attributes provide moderating effects to subjective preference assessments in daylit spaces. For example, recent research (Tuaycharoen & Tregenza 2005; Tuaycharoen & Tregenza 2007) has identified and begun to quantify the moderating effects that the quality of a view has on human assessment of glare from daylight (brightness accompanied by a better view is rated as less glaring). While it is unlikely that any single measurement type (illuminance, luminance, view quality) will adequately describe the bounds of human acceptance and preference in spaces with daylight, as was noted in section 2.2.3, it stands to reason that luminance-based metrics will more closely correlate with subjective acceptance and preference measures than illuminance because luminance more closely relates to human perception of brightness. This section reviews luminance ratios, absolute luminance values and glare indices

that have been used to characterize visual preference and acceptance of the luminous environment.

2.3.2.1 Luminance ratios and absolute values

As noted by Osterhaus (2006), Luckiesh (1944) was one of the first to propose the use of “brightness (luminance) ratios as a basis for ensuring lighting quality...” stating “one may conclude that, for prolonged critical seeing,

1. Brightness ratios smaller than **1:5** are desirable.
2. Brightness ratios greater than **1:10** should be avoided if reasonably possible.
3. Brightness ratios of greater than **1:100** should not be tolerated.”

These criteria did not differentiate between daylight and electric light sources. Egan (1983) provided a more nuanced set of luminance ratio recommendations to guide comfort assessment as shown below [from Osterhaus (2006)].

1. **2:1** Perceptible brightness difference for focus
2. **3:1** Between task and adjacent darker surroundings
3. **10:1** Between task and remote darker surfaces; clearly noticeable brightness difference for focus and transition between adjoining spaces
4. **20:1** Between lighting fixtures (or windows) and sizable adjacent surfaces
5. **40:1** Should not be exceeded anywhere within normal FOV (exceptions would include crystal chandeliers)
6. **50:1** Will highlight objects to exclusion of everything else in the FOV

Current recommendations by the IESNA (DiLaura et al. 2011) list the maximum luminance ratios as shown below (*note, no specific references are offered for this recommendation, and other ratios cite the previous Handbook (Rea 2000)).

1. **1:3** Between task and adjacent light surrounds
2. **3:1** Between task and adjacent dark surrounds
3. **1:10** Between task and remote light surfaces
4. **10:1** Between task and remote dark surfaces
5. ***20:1** Between daylight-media and daylight-media-adjacent-surfaces

Other studies have been conducted and provide recommended luminance ratios in a similar range as those above (Govén et al. 2002) as well as absolute luminance recommendations (Berrutto et al. 1997). The results from studies discussed thus address environments with electric light. One early study that was conducted both with and without daylight could only provide luminance ratio and absolute luminance recommendations for spaces without daylight due to wide variability in the results of spaces with daylight (van Ooyen et al. 1987).

Loe, Carter and colleagues (Carter et al. 1994; Loe et al. 1994) conducted human preference research (n=16, 12) examining luminance distribution in an open office environment. While these studies were conducted in a windowless space and the specific results are not applicable to spaces with daylight, some of the luminance analysis methods are useful to review. “The experiment showed that people preferred the office to be lit so that it appeared ‘bright’ and ‘interesting.’ The ‘bright’ installations were those that contained lit surfaces within the normal FOV and the most ‘interesting’ installations were those that contained areas of light and shade” (Loe et al. 1994). Two luminance calculations were introduced, “visual interest” and “visual lightness.” The first measure, “visual interest,” was assessed by the non-uniformity of the

lighting design. This value was determined as the ratio of 90th percentile to 10th percentile luminance within the 40° horizontal band. It was recommended that commercial spaces (without daylight) might consider ratios between 1:10 and 1:50 as a working guide. The second measure, “visual lightness,” was assessed by the overall brightness of the space. This value was determined to be the average luminance of the 40° horizontal band. It was recommended that for commercial applications (without daylight) that the average luminance of the 40° horizontal band should not be less than 30 cd/m² while an upper threshold was not determined. While a detailed discussion as to how the 40° horizontal band was determined was not offered, the authors stated, “...the situation involving the horizontal band of width 40° was considered the most logical and influential because it encompasses the main area viewed when a person looks around a space” (Loe et al. 1994). However, other areas of interest (entire scene, ceiling, etc.) also showed high coefficients of determination for the visual interest and visual lightness measures. In a follow-up study some of the same authors suggested that areas outside of the 40° horizontal band also appear to influence users’ subjective assessments as well (Carter et al. 1994). A larger study (n=94) was conducted by Veitch and Newsham (2000b) and reported some support and modifications for the visual interest and visual lightness findings by Loe et. al and Carter et. al; however, it too was limited to electrically illuminated spaces.

In a small (4.5m x 6.5m) open-plan mock-up office with an east facing window, participants (n=20) controlled dimmable electric lighting fixtures in response to daylight availability (Halonen & Lehtovaara 1995). It was reported that under low daylight conditions (with blinds down and rotated closed early and late in the day) the preferred average luminance ratios from a white paper-based task to a light colored back wall opposite the window ranged from 1:1.7-5.6 with an average ratio of 1:3.3. It was also reported that under a wide range of

daylight conditions, the preferred average luminance ratios of a white paper-based task and a light colored back wall opposite the window ranged from approximately 1:2.25-10 with an average of approximately 1:5. The preferred luminance ratios with daylight present were about twice as extreme as those under the reference condition with blinds closed. Window luminance values were not reported.

Sutter et. al (2006) found that a space with daylight was comfortable for users with luminance ratios of 1:6:20 (task:adjacent:remote), twice as extreme as those traditionally recommend by IESNA (1:3:10), but in line with the new recommendation for daylight media (1:20). The authors also found that users tolerated up to 1:50 as long as it was restricted to relatively small areas, comprising less than 5% of the FOV. Sutter et. al also found that users maintained average window luminance values of less than 1,800 cd/m^2 in 75% of cases studied. Fisekis et al. (2003) determined the borderline between comfort and discomfort (BCD) to be 2,500 cd/m^2 . Interestingly, Chauvel et al. (1982) found that the most substantial parameter affecting glare through windows was the luminance of the sky, and that it needed to be below 2,000 cd/m^2 to meaningfully improve the situation. In accumulation, these results lend some support to the choice of 2,000 cd/m^2 as the blind control threshold for the unobstructed portion of the window at the New York Times Headquarters (Lee, Clear, et al. 2007).

2.3.2.2 Glare indices

In addition to absolute luminance values and luminance ratios, glare indices have been used to evaluate the luminous environment. As found in Hopkinson et. al (1966) glare was defined by the CIE in 1957 as “a condition of vision in which there is discomfort or a reduction in the ability to see significant objects, or both, due to an unsuitable distribution or range of

luminance or to extreme contrasts in space or time.” Another definition is offered by the IESNA; glare is “the sensation produced by luminance within the visual field that is sufficiently greater than the luminance to which the eyes are adapted to cause annoyance, discomfort or loss in visual performance and visibility” (Rea 2000). These definitions highlight two types of glare: discomfort glare and disability glare. Discomfort glare is “glare which causes discomfort without necessarily impairing the vision of objects;” and disability glare is “glare which impairs the vision of objects without necessarily causing discomfort” (Hopkinson et al. 1966). There are two commonly accepted discomfort glare indices for use with electric lighting and they are Visual Comfort Probability (VCP) (2001) which is used in North America, and the Uniform Glare Ratio (UGR) (Commission Internationale de l’Eclairage 1995; Sørensen 1987), which is used elsewhere. There is moderate agreement about the use of these indices for electric lighting applications but there is no consensus regarding glare indices for daylight applications. Two recent literature reviews provide excellent historical overviews of the multitude of glare indices (Eble-Hankins & Waters 2004; Osterhaus 2005).

Research about the effects of glare on humans can be categorized as either physiological or psychophysical. Physiological glare research refers to the measure of the physical response of the human being, namely the eye. Research of physiological effects of glare has been slow in part because early findings (Hopkinson 1963) indicated a clear, though insignificant, connection between discomfort glare and the physiological measure of pupillary action. Nonetheless, researchers have pursued additional physiological understanding of glare including more research on pupil size (Berman et al. 1995; Ferwerda 1998), activity of the fascial orbicularis oculi muscles (Berman et al. 1995), blink rate (Helland et al. 2008), mapping brain functions (Raynham et al. 2006) and eye-tracking (Sarey Khanie et al. 2011) in glaring environments with

moderate success. Osterhaus et. al (2005) stressed the need for continued physiological investigation as physiological detection technologies progress.

Psychophysical experiments are measurements of a combination of human physiological and psychological response to stimulus and can be used to quantify otherwise subjective human reactions or sensations such as is the case with human perception of glare from daylight sources. Hopkinson’s (1940) borderline criteria is an example of a psychophysical experimentation scale, where a viewer describes his or her visual environment and refers to glare as “just imperceptible,” “just acceptable,” “just uncomfortable” or “just intolerable” (see Table 2). Most psychophysical experiments present participants with a glare scenario, record their subjective response to using some type of multiple criteria scale and develop a calculation (see Equation 1) that includes the following variables (Boyce 2003):

1. luminance of glare source (measured in cd/m^2)
2. size and location of the glare source (solid angle, measured in steradian)
3. number of glare sources (including subsets of large sources)
4. angular displacement of glare source relative to observer’s line of sight
5. luminance of background (measured in cd/m^2 , attempting to account for observer’s eye adaptation)

$$\text{Glare sensation} = \frac{(\text{luminance of glare source})^x * (\text{angular subtense of glare source at the eye})^x}{(\text{luminance of background})^y * (\text{deviation [position] of glare source from line of sight})^z}$$

Where: x, y, and z are exponential weighting factors

Equation 1 - Fundamental glare equation components

2.3.2.2.1 Daylight glare index (DGI)

Hopkinson and his colleagues developed Daylight Glare Index (DGI) in the 1950’s-1970’s (R. G. Hopkinson, 1963, 1972; R. G. Hopkinson & Collins, 1963; R.G. Hopkinson et al.,

1966) relying on large area electric light glare sources. This was primarily due to the technological difficulty of capturing the necessary numerical inputs for the glare equation from a real window since it is a non-uniform and highly variable light source. Chauvel et al. (1982) updated DGI using data from a space with daylight through real windows but excluding direct sunlight or reflected sunlight. They found that glare from a window is independent of window size and distance from the observer so long as the window size is greater than 1-2% of the floor area. They reported that factors of glare source size, surface reflectance, distance from window and viewing position “produced only marginal variations in the predicted glare index,” whereas they found the luminance of the glare sources to be the most telling with regard to subjective assessments “but it is necessary to reach a very low level – 2,000 cd/m² – to improve the situation.” Not surprisingly, the authors stated that discomfort ratings varied substantially by participant and that perceptions of glare were influenced by the activity ongoing in the room. They also noted that glare from windows was not rated as severely as glare from electric lighting sources. Tuaycharoen and Tregenza (2007) have subsequently corroborated this last point.

Since 1982, there have been a large number of modifications to DGI, each adjusting the variables in the original algorithm to better fit the variance of discrete small participant samples. An overview of recent proposed DGI modifications and the limitations found by each research team is available elsewhere (Osterhaus 2005). None of the modifications have gained wide acceptance.

Table 2 - Daylight Glare Index scale, follows (Chauvel et al. 1982)

Glare criterion	Daylight Glare Index (DGI)
<i>just perceptible</i>	16
<i>just acceptable</i>	20
<i>just uncomfortable</i>	26
<i>just intolerable</i>	28

2.3.2.2.2 *Daylight Glare Probability (DGP)*

This daylight glare evaluation method was developed by Wienold and Christoffersen (2006) as an attempt to improve upon limitations of previous indices. This method tries to define “the probability that a person is disturbed instead of the glare magnitude....” In this manner it is similar to thermal comfort metrics such as percent of people dissatisfied (PPD) and differs from previous glare indices that focused on describing the level of glare severity. Participants (n=70) conducted multiple psychophysical experiments (349 unique data sets) in a small office space with three window configurations and two participant viewpoints under stable clear skies only. The studies were conducted in nearly identical spaces in Denmark and in Germany. Factors of orientation, window size and configuration, shading devices, glass type and interior surface color and reflectivity were nearly identical. Multiple horizontal and vertical (eye) illuminance measurements were recorded several times per minute. HDR photographs were recorded and used as the primary data set. Outdoor illuminance measures of global horizontal, horizontal diffuse and vertical on the façade were also recorded.

Participants spent time engaged in various activities such as reading and working on a computer with a LCD screen and rated the general daylighting condition as either comfortable or uncomfortable. The absolute window luminance method resulted in a squared correlation coefficient of only 0.12. The DGI (presumably the version offered by Chauvel et. al, 1982) resulted in a squared correlation coefficient of 0.56. The squared correlation coefficient for DGP was 0.94. While the result is encouraging, this must be tempered for several reasons. First, the DGP equation was created to provide the best fit with the given data set whereas DGI was developed to fit a different data set. Second, a higher degree of correlation is expected inherently by using a binary measure (comfortable or uncomfortable) rather than a four-point linear scale

(such as is the case with DGI) for the basis of glare evaluation. Third, DGP was developed using only clear stable skies. Fourth, this fit was conducted on mean data from several bins along the range of DGP, and anytime means are used in regression the value increases. And fifth, other research (Painter et al. 2009; Van Den Wymelenberg et al. 2010) has demonstrated limitations to the DGP model in other spaces.

2.3.2.3 HDR Imaging, image subtraction, and computational techniques

Using HDR photography techniques (Debevec & Malik 1997; Reinhard et al. 2005; Inanici 2006), it is possible to collect and analyze complex datasets and correlate luminance distribution patterns with user preference and acceptance thresholds relatively quickly and with high accuracy. Single quantities, whether they are luminance or illuminance measures, are not very informative about the quantitative and qualitative dynamics of lighting across an entire space. High-resolution luminance mapping techniques provide much more information about a luminous environment than a limited number of illuminance or luminance measurements. The flexibility of per-pixel HDR images in conjunction with image processing functions is extremely valuable. Specific regions of interest such as vertical and horizontal task areas, windows, the ceiling, individual walls and other key surfaces can be analyzed individually by defining various masks (Figure 2).

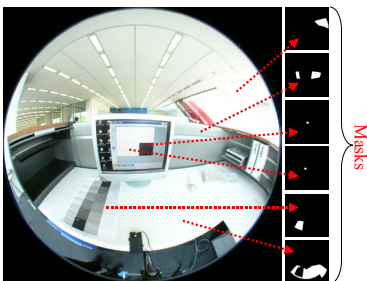


Figure 2 – Example of image subtraction and separation, source: (Inanici 2005)

Human vision comprises foveal, binocular and peripheral vision. “The human visual system can be quite insensitive to large luminance differences in the total FOV, but it is very sensitive to small luminance differences in the foveal region” (Inanici 2005). Figure 3 and Figure 4 show two potential mask definitions that can be used to determine other luminance-based metrics. Figure 3 represents the zones of human vision on a fisheye photograph and Figure 4 represents successive 60° concentric bands.

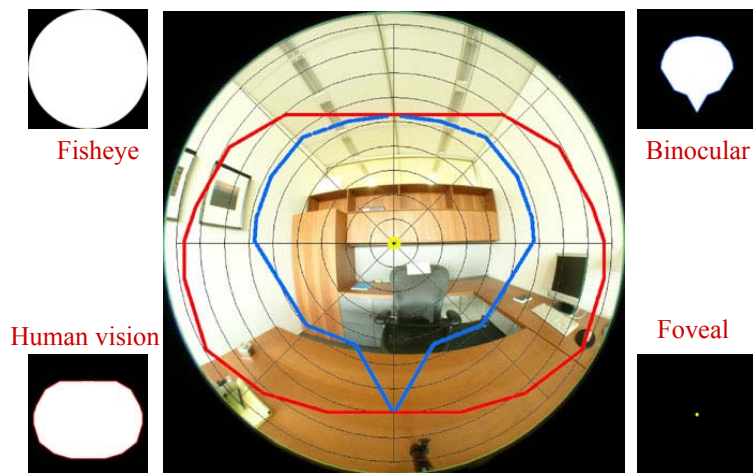


Figure 3 - Human visual zones, foveal, binocular, peripheral, source: (Inanici 2005)

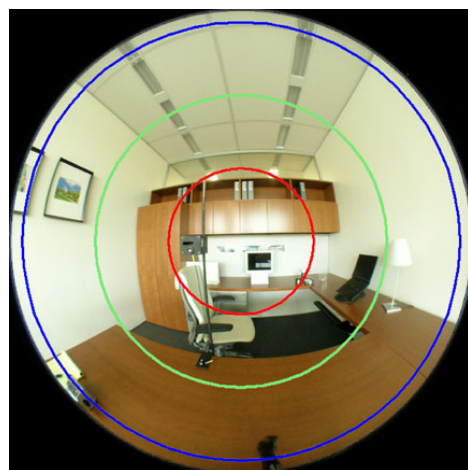


Figure 4 - Successive 30-degree cones of vision, source: (Inanici 2005)

Glare analysis software is available and can be used in combination with the image masking techniques to identify glare sources and perform glare calculations. In RADIANCE, the *findglare* program is used to determine the number, location and intensity of glare sources. This function uses a luminance ratio of 7:1 as a default threshold between potential glare sources and the average luminance of the visual field, but this ratio can be modified by the user (Ward 1993). A follow-on function called *glarendx* can then be used to determine the value of the identified glare source using various indices such as DGI.

Evalglare (Wienold 2008; Wienold & Christoffersen 2006) offers a few improvements over *findglare* and *glarendx*. It combines glare source identification and scene glare evaluation into a single function. Evalglare can be used to determine DGI and several other glare indices but was developed to perform the calculation of DGP. For calculation of DGP, Evalglare uses a 1:5 luminance ratio between task and background (recommended default) to identify glare sources. In this case, the user defines the size and position of the task area and the remainder of the scene is then determined to be the background luminance. Wienold (2009) has applied Evalglare to annual hourly simulation by simplifying the equation to rely either on E_v only or a combination of E_v and a simplified Radiance image⁴ to capture peak glare sources.

Others have used HDR photography to evaluate spaces with daylight beyond just testing glare metrics. In a pilot study, Howlett et al. (2007) reported stability over time and reliability for various luminance-based daylight metrics including:

1. Normalized Unified Glare Rating* – this was described as the UGR given by Photolux software assuming a normalized exterior horizontal illuminance of 2000 foot-candles
2. Luminance (room) variation* – the standard deviation/average luminance

⁴ The simplified Radiance image sets ambient bounces to zero or one (-ab = 0, -ab = 1)

3. Ceiling variation – the standard deviation of the ceiling luminance/average ceiling luminance
4. Back wall brightness – average back wall luminance/average luminance
5. Window contrast – average luminance of the window/average luminance of the window surround
6. Directionality* – using a small Lambertian pyramid and gnomon and measuring the ratio of luminance on opposite sides of the pyramid
7. Luminance daylight factor* – average scene luminance/exterior illuminance

The metrics noted with asterisks (*) were suggested as the most useful for future investigations. This study also explored the notion of variability over time and between spaces and used the statistic “coefficient of variation” (standard deviation/mean) and proposed the notion of coefficient of variation ratio (COV ratio) that was determined to be the COV between space/COV over time.

Newsham et al. (Newsham, Aries, et al. 2008) studied a glare-free (max sky luminance < 2500 cd/m²) office laboratory setting with low daylight levels (typically < 500 lux) and low visible light transmission glazing (20% vlt) where participants (n=40) spent one day performing typical office activities. Subjects were prompted to use dimming controls of electric lighting every 30 minutes. It was found that the best luminance-based predictor was the ratio of the 75th:25th percentile (proportion of variance explained = 0.31). The luminance measures investigated included:

1. Average desk
2. Average window
3. Average wall
4. Ratios of the above
5. % pixels above and below various absolute thresholds
6. Luminance of the 2nd, 10th, 25th, 75th, and 95th percentiles pixel (and ratios of each)

Painter et al. (2009) conducted a 12-month longitudinal study of six workstations in an academic office building in the UK. In addition to established glare metrics, the authors reported

the coefficients of determination for subjective glare ratings as they relate to several measures including:

1. DGP
2. Average scene luminance
3. Average background luminance
4. Vertical eye illuminance
5. Maximum luminance of glare sources

There are other studies not previously reviewed that have deployed HDR luminance-mapping techniques to conduct glare evaluations in example settings (Bellia et al. 2009; Coyne et al. 2008), to evaluate lighting or daylight design alternatives in real settings (Borisuit et al. 2010) or in simulated environments (Gagne & Andersen 2011; Gagne & Andersen 2011; Gagne et al. 2011).

2.4 Moving forward with human visual preference and acceptance lighting metrics

This literature review provided necessary context in areas of human visual performance research (section 2.1), environmental control systems including the use of both electric lighting controls and blinds (section 2.2), and human preference and acceptance lighting metrics (section 2.3). The momentum associated with HDR imaging is substantial and the diversity of application is noteworthy. This literature review has highlighted the use of HDR imaging to support visual comfort research (section 2.3.2), in the control of the luminous environment (section 2.2.3), and in the evaluation of design alternatives in both real world and simulated environments.

The use of HDR imaging is most prevalent in glare research. An improved understanding of glare is certainly worth exploring with advanced luminance mapping techniques; however, this area of inquiry is not enough. This only establishes the acceptance threshold, whereas it is also important to understand more about preferred luminance distribution

in daylit spaces in order to help improve the overall quality of daylighting design, inform future daylighting design standards, and support improved control of electric lighting and blind control systems. As suggested by Newsham and Veitch (2001) the difference between an individual's preferred scene and the actual scene impacts mood and satisfaction, and therefore may influence productivity. Newsham and Arsenault (2009) suggested that additional research should be conducted over a wide range of luminance values under multiple sky conditions. Additionally, other building orientations, architectural daylighting configurations and office layouts should also be examined. While this dissertation does not address each of these suggestions, it does pursue an additional environment over multiple sky conditions spanning a six-month period.

The research conducted to date definitely provides useful guiding information. However, each study has employed different data collection methods for securing HDR images, thus limiting the ability to make comparisons between studies. Inanici (2006) reported on a highly accurate HDR capture process producing less than 10% error over a wide range of luminances. This method also discussed detailed correction procedures including exposure correction, lens vignetting correction and absolute value calibration. Human factors experiments related to luminance preference using HDR photography should adhere to these best practice procedures to ensure consistent and accurate data. If these methods are not deployed consistently, it will be very difficult to know if disagreements between research samples are due to shortcomings of the candidate luminance metrics, variability from the samples or scenes studied, or simply due to error in data collection. While field studies implementing HDR photography for luminance mapping are underway, and will likely be informative, there is still a need for more human factors research in a more controlled environment before field research will attain its greatest utility.

2.4.1 Pilot study

This dissertation comprises a six-month within-subjects repeated-measures experiment and a two-day pilot study. The two-day pilot study (Van Den Wymelenberg et al. 2010) was executed to provide an opportunity to test the hardware and improve the data collection, processing and analysis methodology for use in the six-month experiment. It also served to prioritize candidate luminance metrics for evaluating participant preference ratings and acceptance thresholds. The pilot used a private office measuring 3.5m x 4.5m (~16 m²) with a large southwest-facing window (33° from true South) exposure in Boise, Idaho (43° N and 116° W), participants (n=18) from the University of Idaho architecture program completed basic computer tasks for a period of about 20 minutes. This was a repeated-measures design whereby each participant manipulated louver blind height and tilt to create scenes they determined to be the “most preferable” (“P”) and “just disturbing” (“JD”) lighting condition from their seated position for the primary purposes of computer work (Figure 5). Participants completed a six-item Likert-type questionnaire for each condition (Table 3).

The experiment was conducted on December 16th–17th between 11:30-16:00. Three types of luminance threshold methods were explored: scene-based luminance threshold, absolute luminance threshold and task-based luminance threshold as shown in Figure 6. Candidate luminance metrics were tested for their ability to discern between “P” and “JD” scenes and correlate with Likert scale responses. A thorough examination of the results is available elsewhere (Van Den Wymelenberg et al. 2010).

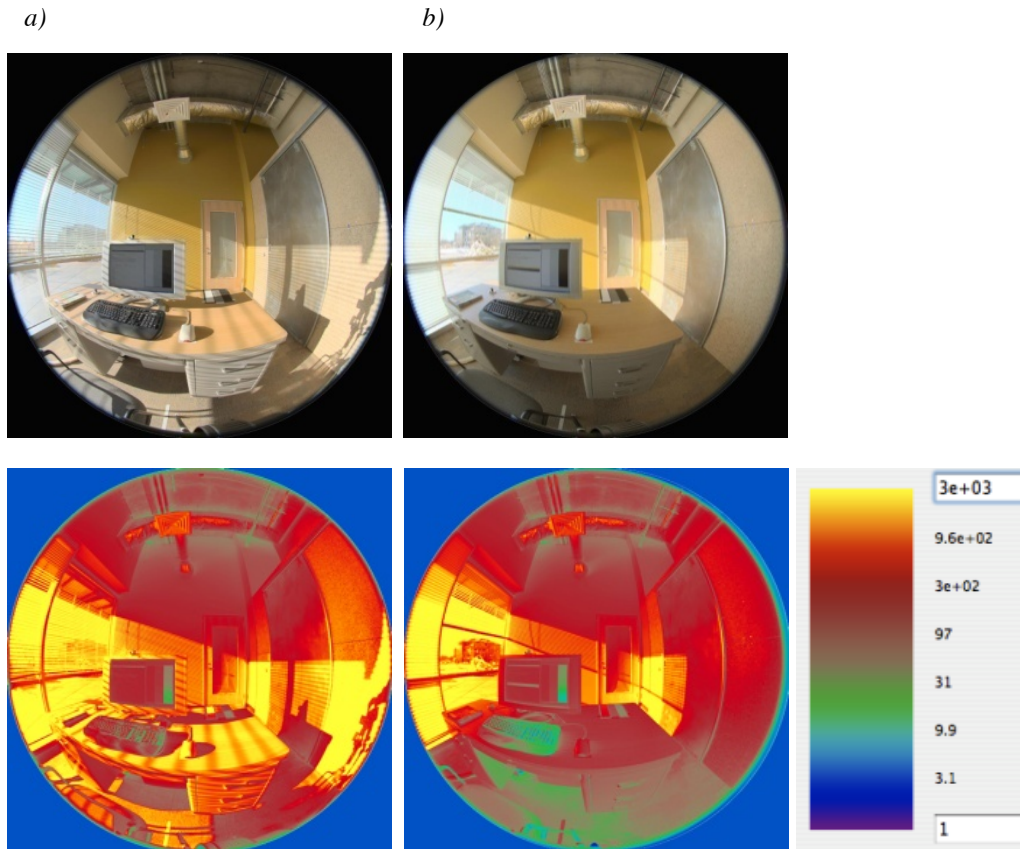


Figure 5 - Example JD (a) and P (b) scene by a participant

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Table 3 - Pilot study Likert subjective comfort questionnaire, following (Van Den Wymelenberg et al. 2010)

Pilot-Q01 - I am pleased with the visual appearance of the office
Pilot-Q02 - I like the vertical surface brightness
Pilot-Q03 - I am satisfied with the amount of light for computer work
Pilot-Q04 - I am satisfied with the amount of light for paper-based reading work
Pilot-Q05 - The computer screen is legible and does not have reflections
Pilot-Q06 - The lighting is distributed well
Response Scale: 7=Very Strongly Agree, 6=Strongly Agree, 5=Agree, 4=Neither Agree or Disagree, 3=Disagree, 2=Strongly Disagree, 1=Very Strongly Disagree

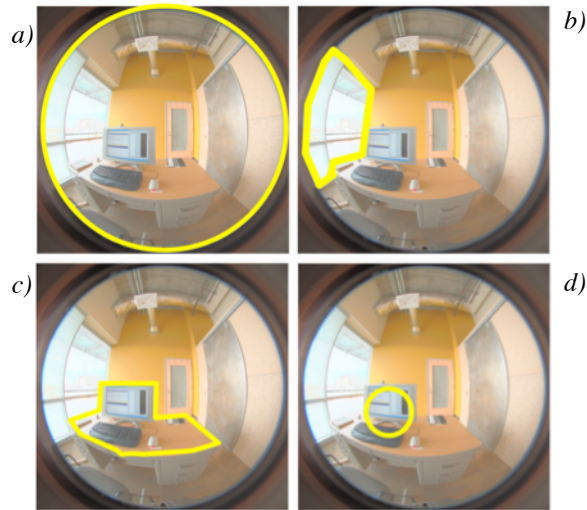


Figure 6 – Pilot study scene masks

(a) scene-based mean luminance threshold area, (b) predetermined absolute luminance threshold area, (c) task area defined as [desk+monitor], (d) task position defined as a subtended solid angle encompassing the screen and keyboard, © 2010 The Illuminating Engineering Society of North America, (Van Den Wymelenberg et al., 2010)

2.4.1.1 Predetermined absolute luminance threshold

Predetermined luminance values (including 500, 1000, 2000, and 3000 cd/m^2) were statistically able to differentiate between “P” and “JD” scenes (paired $t < 0.01$) and, surprisingly, there were only small differences in $\text{adj}I^2$ values for these thresholds when compared to the Likert question items. Question 3 showed consistently higher $\text{adj}I^2$ values than other questions. All “P” scenes had less than ~10% of pixel values that exceeded 2000 cd/m^2 (Figure 7a) and less than 7% of pixel values that exceeded 3000 cd/m^2 (Figure 7b). However, below the threshold there is a mix of “P” and “JD” scenes. Therefore, it is not possible to set a simple binary threshold to differentiate “P” and “JD” scenes. As expected, there is wide variability between subjects.

Sensitivity analyses were conducted to determine the effectiveness of absolute luminance values used to identify glare sources. Among these, the single best predictor of participant satisfaction (relative to all questions) was typically the DGI values derived from a 500 cd/m^2

threshold glare source identifier. However, for QU3, 2000 cd/m² was a strong candidate. For DGP, the single best predictor of participant satisfaction (relative to all questions) was typically the DGP values derived from a 2000 cd/m² threshold glare source identifier.

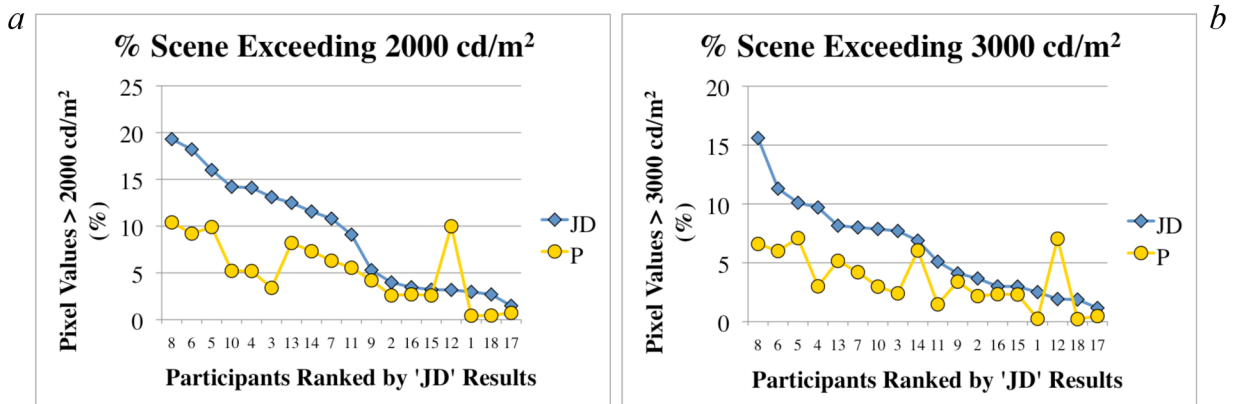


Figure 7 - Percent of scene pixels exceeding the absolute luminance values (a) 2000 cd/m² and (b) 3000 cd/m²

© 2010 The Illuminating Engineering Society of North America, (Van Den Wymelenberg et al. 2010)

2.4.1.2 Scene-based mean luminance threshold

The scene-based mean luminance threshold metric is consistent within-subjects (paired- $t < 0.01$) and, as was found for the absolute luminance threshold approach, a one-way threshold for mean luminance of the scene can be identified at ~ 800 cd/m². This metric produced a relatively strong $\text{adj}r^2$ value (0.44) with QU3. The percentage of pixel values that exceed 7*mL for each scene proved to be inconsistent and was not significant.

Figure 8a shows the results of the default *findglare* output for DGI. The results of this investigation are not well explained by DGI with sources identified by 7*mL. Figure 8b shows the improved ability of DGP 7*mL to differentiate between “P” and “JD” scenes (paired- $t < 0.01$). Sensitivity analysis (3*mL, 5*mL, 7*mL, or 10*mL) showed the multiplier that produced the highest $\text{adj}r^2$ value for all questions was DGP 10*mL.

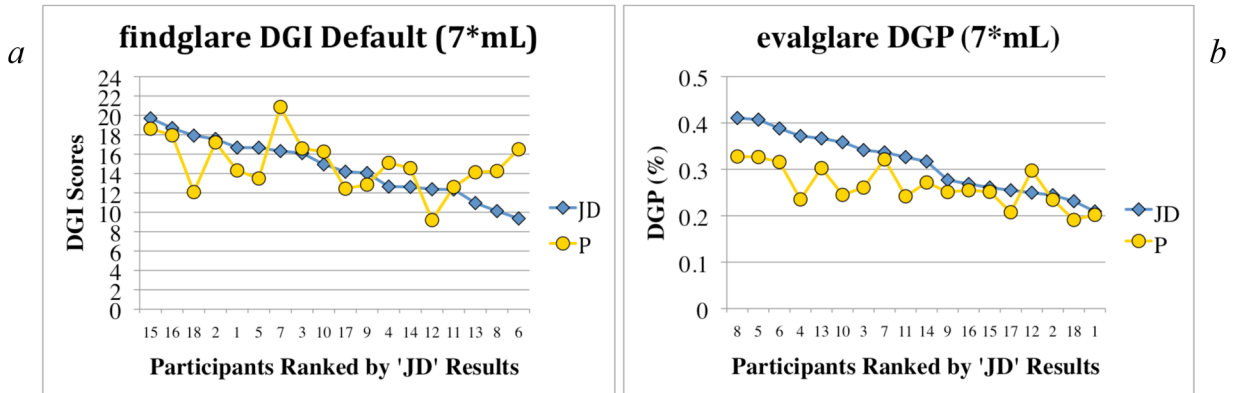


Figure 8 – Pilot study results for DGI from *findglare* (a) and DGP from Evalglare (b)

using 7*mL for glare source identification, © 2010 The Illuminating Engineering Society of North America, (Van Den Wymelenberg et al. 2010)

2.4.1.3 Task-based mean luminance threshold

The mean luminance of the task area encompassing the desktop and monitor (Figure 6c) accounts for the highest $adjr^2$ values for most questions ($adjr^2 = \text{pilot-QU3 } 0.59, \text{ pilot-QU5 } 0.51$). The results for the default DGP calculations (using DGP5*mL task where the task is as shown in Figure 6d) were not as strong (e.g. for pilot-QU3, $adjr^2 = 0.38$) as the relatively simple measure of mean luminance of the desktop and monitor (for pilot-QU3, $adjr^2 = 0.59$).

2.4.1.4 Other candidate metrics

In total, over 150 different illuminance and luminance metrics were tested for their ability to explain the variance in subjective responses. The single highest $adjr^2$ values for several Likert items are shown in Figure 9.

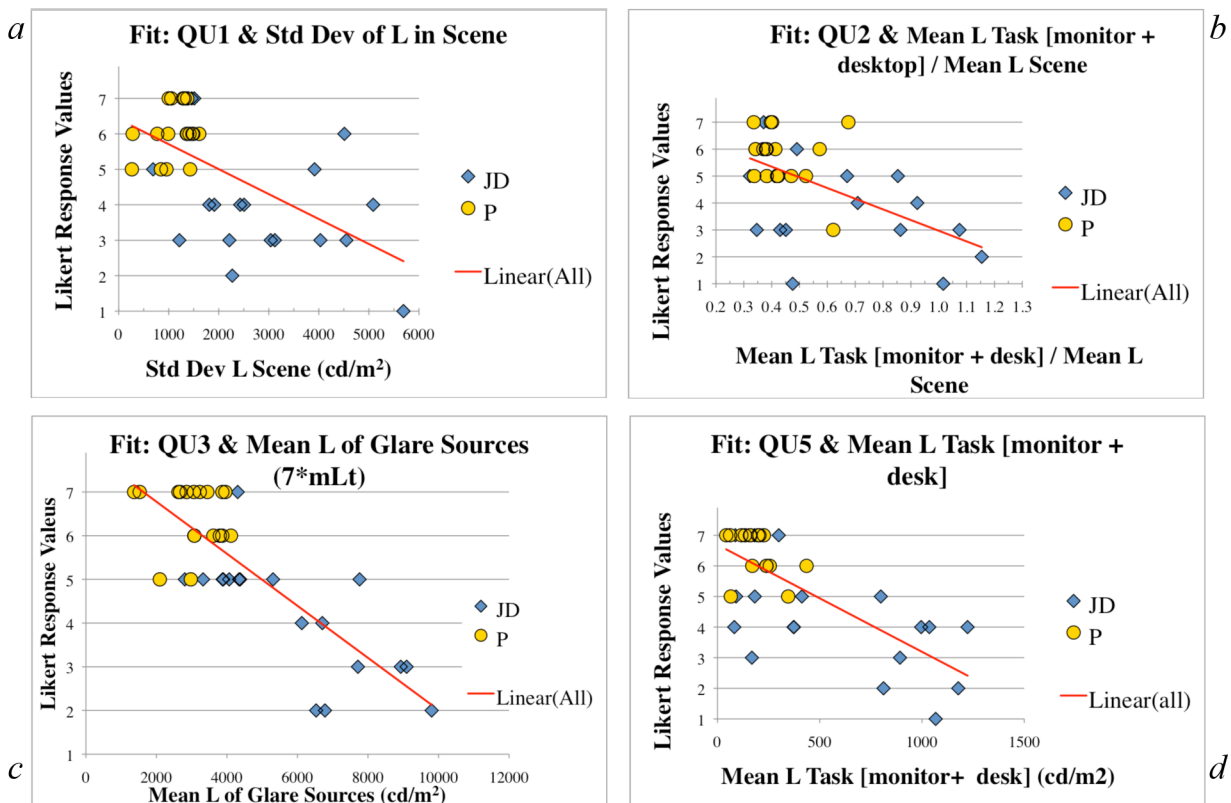


Figure 9 – Pilot study regressions

(a) Model of fit for pilot-QU1 and standard deviation of the luminance in the scene, (b) pilot-QU2 and the ratio of the mean luminance of the task [monitor+desktop] to the mean luminance of the scene, (c) pilot-QU3 and the mean luminance of the glare sources based upon the glare source identification threshold of 7* the mean luminance of the task position, (d) pilot-QU5 and the mean luminance of the task [monitor+desktop], © 2010 The Illuminating Engineering Society of North America, (Van Den Wymelenberg et al. 2010)

2.4.1.5 Pilot discussion and next steps

The pilot investigated the ability of common illuminance and advanced luminance measures to differentiate between participants' "P" and "JD" scenes and explain the variance in subjective ratings. Pilot-QU3 and pilot-QU5 generally show the highest $adjR^2$ values, likely due to the nature of the work conducted. Ceiling illumination was not statistically capable of

differentiating between participants' "P" and "JD" scenes, while E_monitor was better able to explain the variance in responses to pilot-QU3 than either E_desk or E_Veye. Predetermined absolute luminance thresholds (e.g. 2,000 cd/m²) were of limited value without identifying a complimentary scene proportional (e.g. ~10% of scene pixels) threshold value. As shown in Figure 8a, DGI tests were incapable of distinguishing between "P" and "JD" scenes. DGP produced with various glare source identifiers consistently produced higher $adjr^2$ values than the equivalent DGI tests; however, in some cases relatively simple metrics performed equally well or better than DGP. Task-based mean luminance thresholds produced the highest $adjr^2$ value out of the three distinct luminance analysis methods previously practiced.

The most meaningful finding from the pilot study was that "mean luminance of glare sources" metrics based upon various task and scene mean luminance multipliers consistently emerged as most capable of describing the variance of subjective responses. Aspects of task and scene luminance as well as luminance adaptation are accounted for with this metric based upon the glare source identification mechanism and the relative intensity of the glare sources. This metric (mean luminance of glare sources identified by 7* mean luminance of the task) represented the best overall correlation ($adjr^2 = 0.64$) with any question (pilot-QU3) of all metrics tested. Standard deviation of scene luminance was a consistent metric within-subjects and shows that all preferred scenes are below $\sigma=1,610$ cd/m². This metric appears to correlate fairly well with participants' responses related to general visual appearance (pilot-QU1) and luminous distribution (pilot-QU6). Adaptation luminance is affected both from the average and the variance of luminance distribution (Ishida & Iriyama 2003). Adequate luminance variations create a stimulating and interesting environment that improves the preference ratings of the occupants, whereas excessive luminance variability tends toward creating uncomfortable spaces.

In addition to beginning to prioritize candidate metrics that are capable of explaining the variability in subjective comfort assessments, several other objectives emerged from the pilot study. Due to the limited nature of the pilot, the effects associated with age, time of day, time of year could not be investigated and were therefore planned into the experiment. Additionally, participant sensitivity to brightness was added to the experimental design and a larger participant sample sought. The pilot research focused on the difference between “P” and “JD” scenes under daylighting conditions only and as manipulated by manual louver blinds. The experiment was designed to examine a broader array of daylighting conditions in order to more completely understand the preferred range of the preference-acceptance spectrum as well as the acceptance threshold. Additionally, the experiment was designed to incorporate integrated daylighting and electric lighting scenes. Finally, several objective human visual performance tests and creativity tests were planned. These modifications improve the capability of the data to support the specific aims listed in Section 1.2: to determine which lighting metrics are more strongly associated with subject visual preference ratings (*Aim 1*), to determine if differences exist between objective visual performance and creativity results in different scenes (*Aim 2*), and to provide guidance to integrated luminous environmental control systems and building performance design stage analysis (*Aim 3*).

3 Methods

Laboratory research included daylong, longitudinal (one day in summer and one day in fall), repeated measure experiments with 48 participants (45 repeated) in a mock private office space in Boise, Idaho. Each participant spent one working day, during two different times of the year (total of 93 participant-days), in the mock office environment. They assessed a range of visual conditions from very bright to very dim, under high sun angles to low sun angles (time of day and year), under naturally occurring sky conditions, and experienced multiple prescribed and user-defined light modifying elements (blind height, blind tilt, ambient electric lighting levels). This longitudinal laboratory research built upon the methods employed in two pilot studies (G.R. Newsham et al., 2008; Van Den Wymelenberg & M. N. Inanici, 2009). Extensive illuminance and luminance data were collected. Luminance data were collected with validated HDR photography techniques with 180° lens. HDR photographs were carefully calibrated, analysis masks for regions of interest were applied, and extensive luminance-based metrics were calculated for each of 23 different masks. A total of nearly 1,500 HDR photographs were analyzed for the participants' conditions described above.

3.1 Experimental Design

The control, independent and dependent variables for the experiment are summarized in Table 4.

Table 4 - Experimental variables

Control Variables (levels)	Time of day (8:30-12:00, 13:00-16:00), time of year (Jun 29-Sept 20; Sept 21- Dec 19), sky cover (naturally occurring, organized into five bins), room design and all lighting conditions between equipment and participant rooms, blind height, blind tilt of upper “daylight” louvers, blind tilt of lower “view” louvers, electric lighting level (0-100 % dimmed)
Independent Variables (levels)	16 environmental lighting conditions were tested and are described in detail in Section 3.4.5
Moderating Variables (levels)	Gender (M,F), general sensitivity to brightness (1-7), measured sensitivity to brightness (1-8), participant age (18-29 years, 30-49 years, 50-70 years)
Dependent Variables (levels)	Human: subjective preference ratings (semantic differential and Likert scales, etc.), objective performance on several tests (color-word, Landolt rings, typing, creativity, etc.) (see Section 3.5.5) Environmental: several luminance metrics from identical eye position, irradiance, illuminance, lighting energy use for each electric light source, etc. (see Section 3.5.1)

3.2 Research Setting

Human factors tests were conducted using two identical rooms (Figure 10) in Boise, Idaho (43° N and 116° W). Each room measured 4.4m x 3.7m, 16.3 m² (14’ - 4” x 12’ - 3”, 176 ft²) and had a southwest-facing window (35.5° west of South). One room was for the research participant (participant room) while the other room hosted the lighting data collection instrumentation (equipment room) to ensure data accuracy and to provide a natural working environment for participants (G.R. Newsham et al., 2008; Wienold & Christoffersen, 2006).

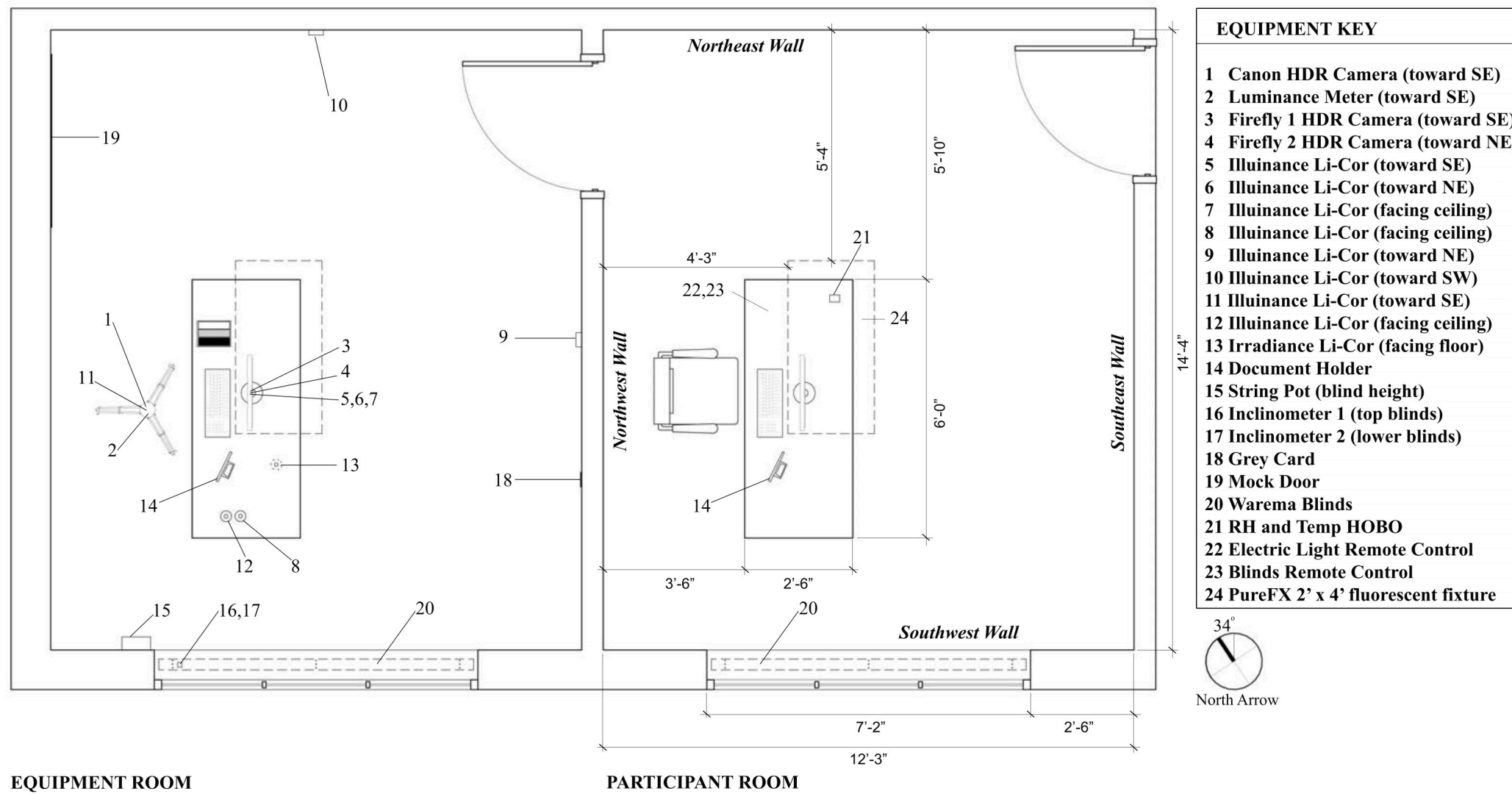


Figure 10 - Plan of equipment and participant rooms with data collection locations and description

Each room had a double-pane window (0.64 visible light transmission⁵) centered on the southwest wall with aluminum frames that extended from the floor to 2.7m high, and measured 2.3m wide. A daylight guidance semi-perforated motorized louver blind⁶ was mounted inside the window frame. The automated blind controls were disabled and the participants controlled the motorized blinds manually from the computer interface or with a remote control. A single 0.6m x 1.2m (2' x 4') recessed direct electric light source⁷ was located approximately in the center of the room above the desk (see dashed line in Figure 10) and was controlled with a remote control. This dimmable T5 high-output fixture provided a range of illumination between 30-800 lux as measured on the desktop. For more details on the electric light distribution see Section 3.2.1 and Figure 12. The lighting power density ranged from 7 watts/m² (0.65 watts/ ft²) to less than 0.01 watts/m² (0.1 watts/ ft²) depending on the dimming level selected. This, and the light output per unit power can be seen in Figure 11.

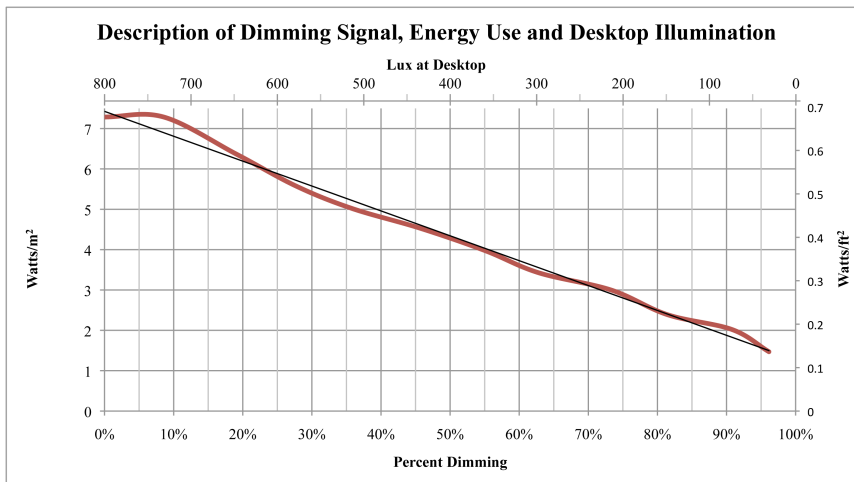


Figure 11 - Dimming signal, energy use and desktop illumination provided from the electric light only

⁵ Solarban 70 XL Starphire Clear glass

⁶ Warema light guidance blind: type E 80 L, TLT, 80mm slats, concave top, color RAL 9016 with 82% reflectance, convex bottom side color RAL 7030 matt, climatronic® computer desktop control and EWFS remote control

⁷ Phillips Leadalite Pure FX with Airware wireless handheld remote control

One rectangular desk measuring 1.83m x 0.76mm (6' x 2'-6") was positioned approximately 1m away from the window wall. The room was painted white and the participants faced southeast normal to the wall. Reflectances in the room were as follows: white walls (73.7%), ceiling (80.8%), floor (10.8%) desk (39.3%) and back of blinds when closed (20.3%). A 0.56m (diagonal screen dimension) LCD computer monitor⁸ (max screen luminance of 130 cd/m² measured at a distance of 1m) was set on the desk perpendicular to the window wall. The desk also had a traditional black keyboard and mouse for computer control. A paper document holder was located near the southwest edge of the desk.

Any time the electric lights were dimmed or switched, or the blinds were repositioned, the change occurred in both rooms simultaneously. The consistency of the visual conditions within the "participant" room and the "equipment" room was found to be essentially identical as described in Section 3.2.2. The equipment room was instrumented with multiple sensor types as detailed in Section 3.5.

3.2.1 Electric lighting distribution

At full output, the average horizontal illumination (0.81m, 32" above finish floor) across the entire room is 383 lux while the average of the illumination on the desk is 611 lux. The maximum illumination directly below the light fixture is 785 lux and the minimum in the corner of the room is 135 lux. Horizontal lux values are plotted on a plan of the room in Figure 12. To support data analysis, HDR photographs were captured at nighttime for each of 12 electric lighting dimming conditions ranging from full output to minimum output (approximately every 8.5% increment from 100% down to 4%). This was done for three blind conditions, once with

⁸ Dell 2208 WFPt, 22 inch LCD monitor.

blinds closed (providing a view to dark exterior and window reflections), once with blinds down and rotated closed, and once with blinds down and rotated open.

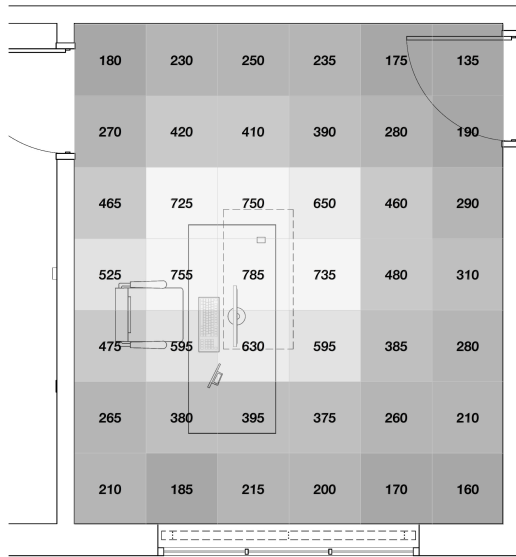


Figure 12 - Electric lighting illumination distribution in participant room at night with blinds closed (lux)

3.2.2 Difference between equipment room and participant room under daylight conditions

Tests were conducted using HDR techniques to document any differences between the equipment room and participant room. There was approximately a 3% difference in mean scene luminance (X01_mean). Essentially, the rooms have identical mean luminance and luminance patterns. The view out the windows is somewhat different due to the shift in point of view; however, there are no trees or large buildings that would cause any substantial differences in daylight or shadow patterns. One factor that could not be controlled was potential differences between the two rooms regarding reflections from parked cars outside the windows. However, the rooms are lifted about 1.3m from the street level, thus participants' seated eye position is approximately 2.5m above the street level. Furthermore, the near side of the street prohibits parking so the only cars were across the street. Luminance comparisons between the rooms are

provided for both a sunny day from the seated participants' eye position (Figure 13) and on a cloudy day from the back of the rooms looking toward the windows (Figure 14).

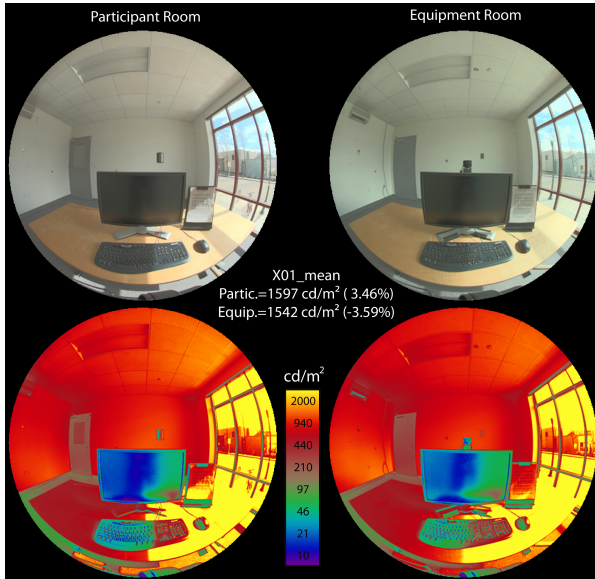


Figure 13 – Luminance comparison between participant room (left) and equipment room (right) from perspective of seated participant on a sunny day

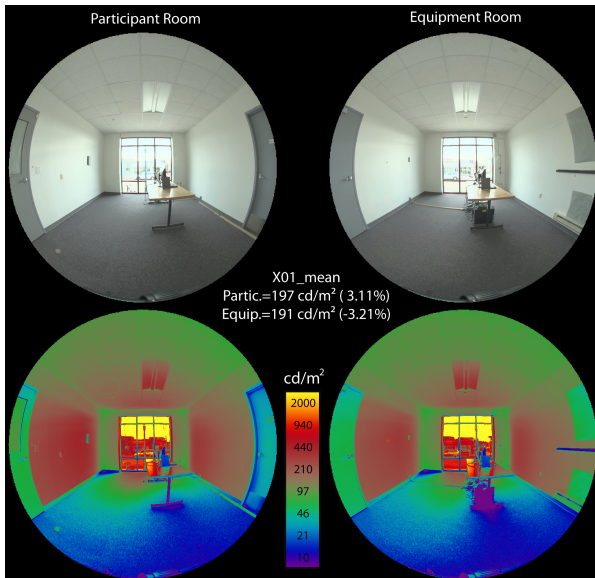


Figure 14 - Luminance comparison between participant room (left) and equipment room (right) looking toward the window on a cloudy day

3.3 Participants

A total of 48 people (24 female, 24 male) participated in the first round (day 1) of the study and 45 (22 female, 23 male) participated in the second round (day 2) of the study. Age ranges and gender for the participant groups are outlined in Table 5. Additional demographics of the participants are summarized in Table 6.

Table 5 - Group design by age and gender for round one and two of the study

Age (years)	Day 1 (6/29-9/20)		Day 2 (9/21-12/19)	
	Female	Male	Female	Male
18-29	8	8	8	7
30-49	8	8	7	8
50-70	8	8	7	8
Totals	24	24	22	23
	48		45	

Table 6 - Other participant demographics

Typical Vision Correction <i>(participants could select more than one)</i>	
I do not need vision correction	12.5% (6)
contact lenses	14.5% (7)
reading glasses	10.2% (5)
distance glasses	12.5% (6)
bi or trifocals	8% (4)
multi-focals or graduals	8% (4)
a combination of those above	33.3% (16)
Vision Correction on First Study Day	
I do not need vision correction	19% (9*)
contact lenses	28% (13)
reading glasses	12.5% (6)
distance glasses	20% (10)
bi or trifocals	8% (4)
multi-focals or graduals	12.5% (6)
<i>*(3) participants forgot their optional vision correction on the first study day</i>	

(Continued)

Vision Correction on Second Study Day	
I do not need vision correction	27% (12 ^{**})
contact lenses	27% (12)
reading glasses	9% (4)
distance glasses	17% (8)
bi or trifocals	7% (3)
multi-focals or graduals	13% (6)
<i>** (6) participants forgot their optional vision correction on the second study day</i>	
Color blindness	
I do not have any color blindness	98% (47)
yes, total color blindness	0% (0)
yes, red/green color blindness	2% (1)
yes, blue/yellow color blindness	0% (0)
Eye color	
blue	29% (14)
blue-green	11% (5)
brown	25% (12)
green	6% (3)
hazel	29% (14)

3.3.1 Participant Recruitment

Participants were identified using a recruitment email (8.2) sent to individuals within the University of Idaho Boise general community and alumni by program administrators at the University of Idaho. Since only program administrators distributed the email messages, anonymity was preserved and there was no risk of coercion. Prospective participants having received the e-mail initiated contact with the investigator.

Experienced computer users between the ages of 18-70 were sought. Participants were required to read, write, speak and understand spoken English since all instructions and questionnaires were provided in English. Participants had to be proficient with basic computer tasks such as word processing and mouse use since they were required to answer questionnaires

on the computer and complete computer-based performance tests. All subjects had to be well sighted or have corrected vision.

3.3.2 Participant Compensation

Participants chose to be compensated in one of two ways. The participant either elected to be entered into a raffle with a chance to win an Apple I-Pad valued at approximately \$500, or elected to be paid \$10 per hour (\$75.00 per day). For 79 of 93 participant-days (85%) participants selected to be paid \$75 per day, and in 14 of 93 cases (15%) participants selected to be entered into the raffle.

3.4 *Procedures*

The experiment was conducted between June 29th and December 19th, 2011 from 8:30-16:00 for a total of 93 participant-days. As expected, sky conditions varied throughout this period, but sunny days were most prevalent (83%). In the first round of the study (June 29th-September 20th) 94% of the study hours were “sunny,” 2% had “few” or “scattered” clouds, and 4% were “broken” overcast or fully “overcast.” In the second round of the study (September 21st – December 19th) 71% of the study hours were “sunny,” 7% had “few” or “scattered” clouds, and 22% were “broken” overcast or fully “overcast.” Figure 15 provides a graphical representation of the hourly sky conditions over the period of study. In Boise, the solar altitude at solar noon ranged from 69.6° to 23°, the sunrise azimuth ranged from 56.7° to 123.4° (east of north) and the sunset azimuth ranged from 302.1° to 235.9° (east of north) throughout the study period.

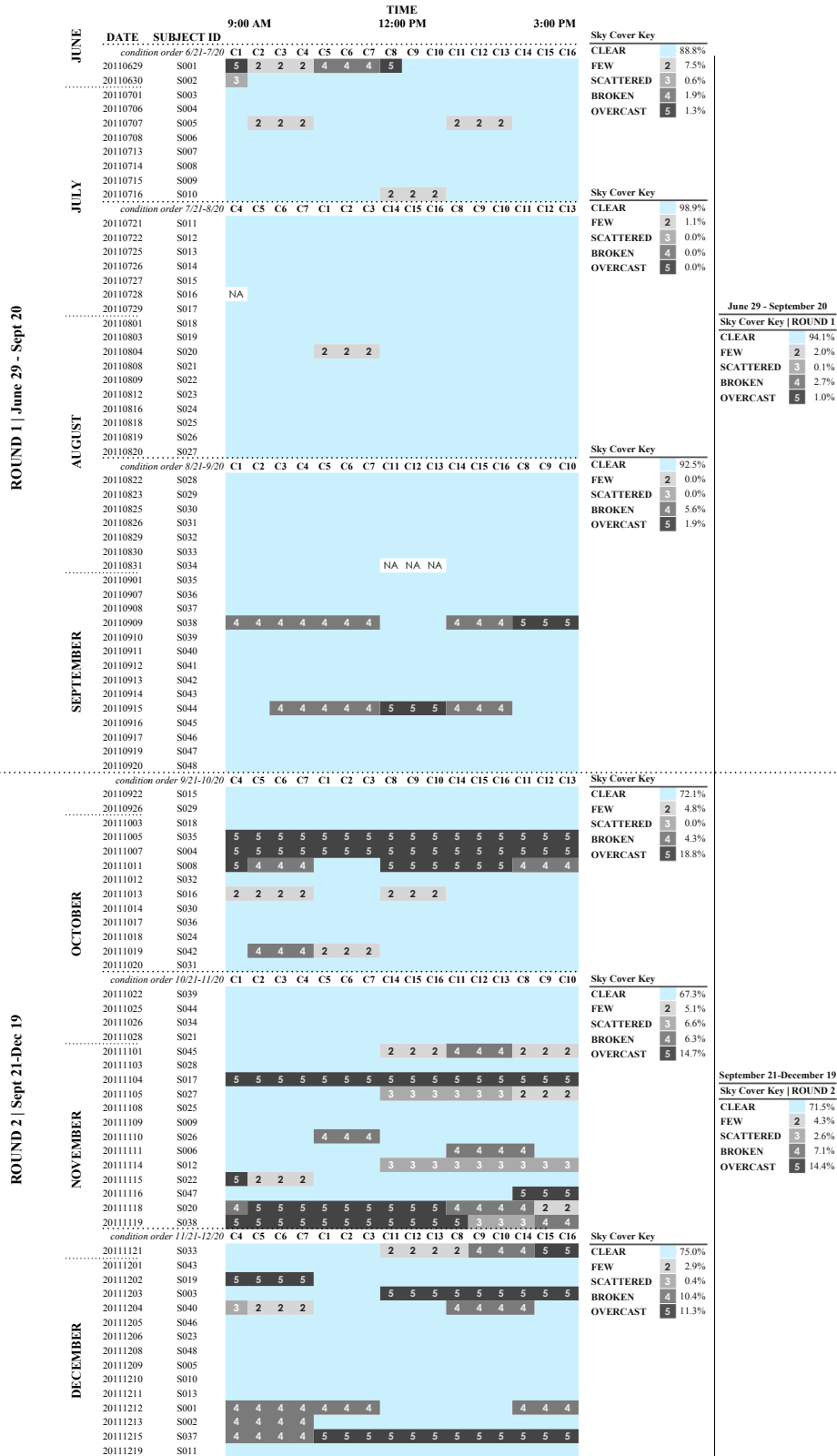


Figure 15 - Sky cover throughout study

3.4.1 Typical participant's day

Table 7 provides a timeline for a typical participant's day. It also provides a high-level overview of the data types collected during the study. The research measures are detailed in Section 3.5. The presentation orders of the experimental conditions were changed on a monthly basis to avoid sequence bias as shown in Section 3.4.6.

Table 7 - Typical participant's day

Data Key: SPCF=Subjective Preference, Comfort, and Fatigue questionnaire data; OP=All Objective Performance data; OPa=Omni-directional pointing, OPb=Proof-reading, OPc=Typing, OPd=Landolt rings, OPe=Number verification, OPf=Stroop color-word; OL=Objective Lighting data; C=Creativity. (Condition order was changed to avoid bias as shown in Section 3.4.6.)				
Time(minute)	Activity	Description	Round 1 Data	Round 2 Data
8:40(10)	Consent	Complete participant consent procedures		
8:50(20)	Sensitivity to brightness test	Objective sensitivity to brightness test	Sensitivity	Sensitivity, C
Put blinds down and rotated closed and electric lights on at full power to begin each participant-day.				
9:10(10)	Set up rooms	Workstation set to fit participant using published standards (Workers' Compensation Board of British Columbia 1996)		
9:20(20)	Participant training	Train participants on how to control light sources and complete performance tests		
9:40(10)	Demographic questionnaire	Participants complete on-screen demographic questionnaire	Answers recorded	
9:50(50)	Conditions 1-3 by participant	C1 - Participant directed to create Most Preferred (MP) daylight environment	SPCF, OP, OL	SPCF, OP, OL, C
		C2 - Participant directed to improve environment by adding electric light	SPCF, OPa, OPe, OL	SPCF, OPa, OPe, OL
		C3 - Participant directed to worsen environment by adjusting electric light	SPCF, OPa, OPe, OL	SPCF, OPa, OPe, OL
10:40(10)	Morning Break	Put blinds all the way up and turn the electric lights off.		
10:50(50)	Conditions 4-6 by participant	C4 - Participant directed to create Just Uncomfortable (JU) glare daylight environment	SPCF, OP, OL	SPCF, OP, OL, C
		C5 - Can participant improve environment adding electric light?	SPCF, OPd OPe, OL	SPCF, OPd OPe, OL
		C6 - Participant directed to just correct the glare problem by adjusting blinds	SPCF, OPd OPe, OL	SPCF, OPd OPe, OL
11:40(20)	Condition 7 by participant	C7 - Participant directed to create MP integrated lighting environment	SPCF, OP, OL	SPCF, OP, OL
12:00(60)	Lunch Break	Put blinds all the way up and turn the electric lights off.		
13:00(50)	Conditions 8-10 by researcher with participant confirmation	C8 - Participant directed to create MP daylighting environment	SPCF, OP, OL	SPCF, OP, OL
		C9 - Researcher sets an intentionally dark scene (blinds all the way down, and no electric lights)	SPCF, OPb, OPf, OL	SPCF, OPb, OPf, OL, C
		C10 - Participant directed to create JU glare scene from daylight alone	SPCF, OPb, OPf, OL	SPCF, OPb, OPf, OL, C
13:50(20)	Afternoon Break	Put blinds all the way up and turn the electric lights off.		
14:10(50)	Conditions 11-13 by researcher with participant confirmation	C11 - Participant directed to create and maintain their MP integrated lighting environment	SPCF, OP, OL	SPCF, OP, OL
		C12 - Leaving electric light as previous, researcher closes blinds all the way	SPCF, OPc, OPd, OL	SPCF, OPc, OPd, OL
		C13 - Leaving electric light as previous, Participant directed to open blinds just enough to create a JU glare scene	SPCF, OPc, OPd, OL	SPCF, OPc, OPd, OL
Put blinds all the way up and turn the electric lights off.				
15:00(50)	Conditions 14-16 by researcher with participant confirmation	C14 - Participant directed to create and maintain their MP integrated lighting environment	SPCF, OP, OL	SPCF, OP, OL
		C15 - Leaving blinds as pervious, participant directed to dim electric light until just too dim (or until off)	SPCF, OPa, OPb, OL	SPCF, OPa, OPb, OL
		C16 - Leaving blinds as previous, participant directed to increase electric lights until just too bright (or until on full)	SPCF, OPa, OPb, OL	SPCF, OPa, OPb, OL
15:50(10)	Debrief/dismiss	Participants debriefed and dismissed		

3.4.2 Researcher setup procedures

A research coordinator arrived each day at 7:30 to save data from the previous participant, prepare all the data collection devices for the new study day, ensure that the remote controls for the electric lights and blinds were functional, and run a test to verify the operation of all the automated questionnaire and data collection triggers within LabView. When the participants arrived each day, the researcher greeted them and directed them to review the consent form, ask any questions, and sign it if they wished to proceed with the study. Participants were given a copy of the consent form for his or her records and were asked to proceed to a room to test their sensitivity to brightness. Only one individual participated on a given day.

3.4.3 Sensitivity to brightness test

Each participant was tested for his or her general sensitivity to brightness in order to support correlation data analysis. A room without daylight (see Figure 17), measuring approximately 2.5m x 2.5m x 2.5m (8' x 8' x 8'), with white walls, floor and ceiling and a 55-watt dimmable compact fluorescent torchiere⁹, which provides a low level of background lighting, was used for this test. The participants were seated in a chair facing a 0.56m (diagonal screen dimension) LCD computer monitor¹⁰. They completed the sensitivity to brightness questionnaire data (Table 8). There were two dimmable high-intensity light boxes¹¹ positioned at a 45° view angle relative to the monitor at a distance of 0.85-0.9m (34"-36") from the seated

⁹ F552D/830 Polylux (CFS55W/GR10Q)

¹⁰ Dell 2208 WFPT, 22 inch LCD monitor

¹¹ An UltraLux® I Light Box produces 5,000 lux at 0.64m (25") and measures 0.23m by 0.28m (9"x11") it total size with an illuminated area that measures 0.15m by 0.22m (6" x 8.75") (available at http://www.fullspectrum solutions.com/ultraluxi_light_box_301_prd1.htm)

users' eye position. Eight preset dimming conditions were established for the light boxes using an equidistant linear scale from darkest to brightest (Table 9). (To support data analysis, HDR photographs were captured from the participants' eye position for each of the eight preset levels prior to the study beginning in June 2011.) Every participant experienced each of the eight presets in random succession. The first preset, which was also randomized, was presented a second time to avoid sequence bias. Each preset was presented for approximately 10 seconds. Participants were asked to direct their view toward the computer monitor and assess the level of glare produced by the light boxes using the scale shown in Table 10. The light boxes were turned off after the participant rated each condition and remained off until the participant was ready to rate another preset, usually a 10-20 second break. After each preset had been presented once in random order, the participant was also asked to select the preset level described as JU glare beginning with the dimmest and working toward the brightest.

Table 8 – Sensitivity to brightness questionnaire

Sensitivity to brightness questionnaire	
Question	Response
In general, I am sensitive to glare.	7-point Likert (Very Strongly Agree [7] - Very Strongly Disagree [1])
What is your eye color?	drop down
Do you have any vision related health issues?	y/n
<i>If so, please explain.</i>	write in
What time do you usually wake up?	write in
What time did you wake up today?	write in

Table 9 - Sensitivity to brightness test conditions

Sensitivity to Brightness Test		
Dimming setting	E_v measured at 0.37m (14.5") normal to light intensity boxes (lux)	E_v measured at 0.44m (17.5"), at the seated user's eye (lux)
E, 1= brightest	8791	1385
F, 2	7423	1175
G, 3	5473	893
H, 4	4273	707
I, 5	3310	565
J, 6	2550	452
K, 7	1881	357
L, 8= dimmest	1234	262

Table 10 - Glare assessment scale

Glare Assessment Scale
9- Intolerable Glare
8- Just Intolerable Glare
7- Between (Just Uncomfortable and Just Intolerable)
6- Just Uncomfortable Glare
5- Between (Just Acceptable and Just Uncomfortable)
4- Just Acceptable Glare
3- Between (Just Noticeable and Just Acceptable)
2- Just Noticeable Glare
1- No Noticeable Glare

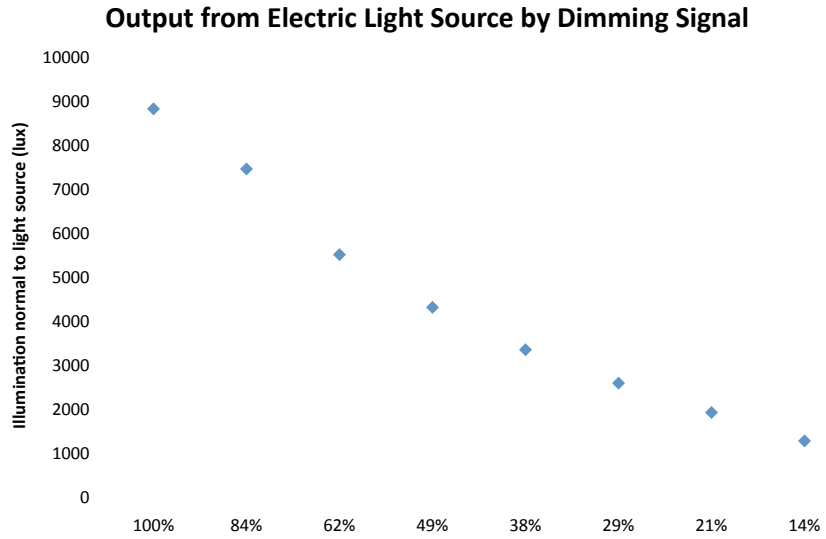


Figure 16 – Illumination normal to light source through dimming range for sensitivity to brightness test

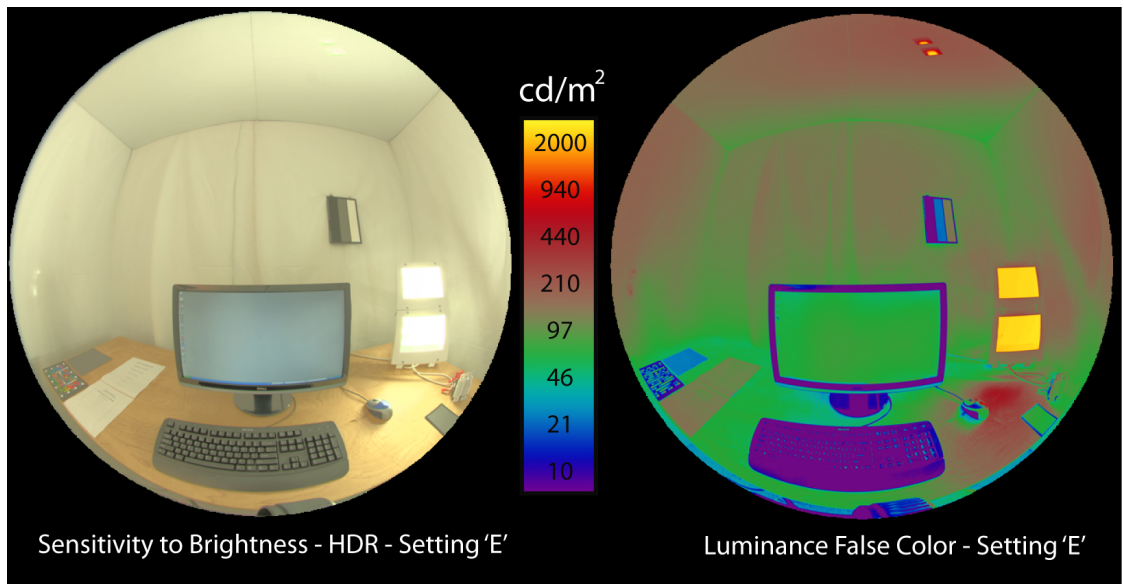


Figure 17 - Sensitivity to brightness chamber, at brightest setting (E, 8)

3.4.4 Participant room set up and training

After the sensitivity to brightness tests, each participant was brought into the participant study room with the electric lights on full and the blinds down and rotated closed. The research staff adjusted the room, chair and monitor according to an ergonomics checklist and workstation setup guide (Workers' Compensation Board of British Columbia 1996). The participant was then given verbal instructions and a tutorial on how to adjust the electric lights and blinds, how to complete the computer questionnaire and each of the objective performance tests. Then, the participant completed a full round of practice objective performance tests while the research staff was present. The research staff member confirmed that the participant understood the process for each test and the participant was able to ask questions as needed.

3.4.5 Condition description

Condition 1 – the participant was instructed to create his or her MP daylighting condition for normal office work from a seated position by adjusting the blind height and louver rotation only (no electric light).

Condition 2 – the participant was instructed to ensure that the blinds were still adjusted to his or her MP setting from a seated position, readjust them as necessary to achieve his or her MP setting, and then to turn on and adjust the electric lighting to try to improve the visual conditions for office work.

Condition 3 – the participant was instructed to ensure that the blinds were still adjusted to his or her MP setting from a seated position, readjust them as necessary to achieve his or her MP setting, and then to adjust the electric lighting to try to worsen the visual conditions for office work.

Condition 4 – the participant was instructed to create a JU glare setting for normal office work by adjusting the blind height and louver rotation only. JU glare was described as more severe than glare that is “just noticeable” and less severe than glare that is “just intolerable.” It is the visual environment under which the participant would normally correct a blind position because of disturbing glare from daylight/sunlight.

Condition 5 – the participant was instructed to ensure that the blinds were still adjusted to create a JU glare setting from a seated position, readjust the blinds as necessary to create a JU setting, and then to adjust the electric lighting to try to improve the visual conditions for office work.

Condition 6 – the participant was instructed to readjust the blinds as necessary just until the glare problem was eliminated (no instruction was given regarding electric lighting).

Condition 7 - the participant was instructed to create his or her MP integrated lighting environment (daylight and electric light) by adjusting the blind height, louver rotation and electric lighting for normal office work (electric lights must be on but could be dimmed to any level).

Condition 8 – same as Condition 1.

Condition 9 - the researcher created an intentionally dark setting with the blinds all the way down and rotated closed with no electric lights.

Condition 10 – the researcher created an intentionally JU daylight glare setting by adjusting the blind height and louver rotation only with no electric lights. This required some interaction with each participant to ensure the scene was precisely JU for the individual participant.

Condition 11 – same as Condition 7.

Condition 12 – leaving the electric lights as set from the previous condition, the researcher positioned the blinds all the way down and rotated closed.

Condition 13 – leaving the electric lights as set from the previous condition, the researcher created an intentionally JU daylight glare setting with confirmation from the participant.

Condition 14 – same as Condition 7.

Condition 15 - leaving the blinds as set from the previous condition, the researcher slowly dimmed the electric lights until the participant said “the scene is just too dim.” If the participant never said it is “just too dim” the researcher turned the electric lights completely off.

Condition 16 – leaving the blinds as set from the previous condition, the researcher increased the electric lights until the participant said “the scene is just too bright.” If the participant never said it is “just too bright” the researcher turned the electric lights to full output.

3.4.6 Condition sequence

In order to avoid sequence bias, the order that each group of conditions was presented was changed every month of the study as shown in Table 11. The groups of conditions that occurred in the morning and afternoon remained in the morning and afternoon, but the order in which they were presented within the morning and within the afternoon changed. The order within each group of conditions (Conditions 1, 2, and 3 for example) remained in the same order because they intentionally build upon one another.

Table 11 - Condition sequence by month of study (C = condition)

Presentation Order	Jun 21 – Jul 20	Jul 21 – Aug 20	Aug 21 – Sep 20	Sep 21 – Oct 20	Oct 21 – Nov 20	Nov 21 – Dec 20
1st - AM	C 1,2,3	C 4,5,6,7	C 1,2,3	C 4,5,6,7	C 1,2,3	C 4,5,6,7
2nd - AM	C 4,5,6,7	C 1,2,3	C 4,5,6,7	C 1,2,3	C 4,5,6,7	C 1,2,3
3rd - PM	C 8,9,10	C 14, 15, 16	C 11,12,13	C 8,9,10	C 14, 15, 16	C 11,12,13
4th - PM	C 11,12,13	C 8,9,10	C 14, 15, 16	C 14, 15, 16	C 11,12,13	C 8,9,10
5th - PM	C 14, 15, 16	C 11,12,13	C 8,9,10	C 11,12,13	C 8,9,10	C 14, 15, 16

3.4.7 Participant breaks and end of day debrief

Participants were given a 10-minute morning break, a 60-minute lunch break and a 20-minute afternoon break. The participants were allowed to go outside or stay in the study room during breaks. At the end of the day, participants were asked a few wrap up questions about their experience, were given the opportunity to ask any questions they wished of the researcher and finally, they were dismissed.

3.5 Measures

3.5.1 Physical measures in the equipment room

Objective lighting data collected in the equipment room included measures of luminance, illuminance, irradiance, lighting power consumption and blind position. See Figure 10, and text below for a detailed description of the data collection hardware. Lighting power consumption data were recorded continuously throughout the entire six-month study on a one-minute interval and were downloaded monthly. Illuminance, irradiance and blind position data were recorded on a one-minute interval for a 10-hour period for each study day and were downloaded daily. Luminance data (including spot readings and HDR photographs) were recorded only as needed,

based upon a software trigger in LabView, for each of the 16 conditions throughout each study day.

Three cameras were located in the equipment room to capture HDR photographs to generate luminance data maps (Debevec & Malik 1997; Reinhard et al. 2005; Ward 2009). These cameras were held in a fixed position throughout the entire six-month study. A Canon EOS-1 Ds Mark III Digital SLR camera with a Sigma 8 mm F3.5 DG Circular Fisheye lens (180° horizontally and vertically) was positioned at the typical eye position of a seated participant as shown in Figure 18-right. For each Canon HDR scene (Figure 19), multiple exposure photographs were captured across a range of shutter speeds (1/4000 – 8 seconds) with a fixed aperture (5.6) and fixed white balance (daylight) and ISO (100) settings. Spot luminance values were recorded via a Konica Minolta LS-110 (1/3° measurement angle) before and after each HDR photograph sequence was recorded. The luminance meter was aimed at a X-rite ColorChecker[®] Gray Scale Balance Card positioned on the southeast wall. A second grey card was positioned at the north corner of the desk, mounted on the work surface, and within the FOV of the Canon camera. Additionally, two Point Grey Firefly MV 1/3-inch CMOS digital cameras (FMVU-12S2C-CS) with an Omnitech Robotics 3.4 mm F2.8 circular fisheye lens (190° horizontally and vertically) and UV/IR filter (450-680 nm transmission greater than 90%) were positioned on the top of the computer monitor (Figure 10) to support future research¹².

¹² FFMV406 faced southeast in the line of sight of the seated participant, FFMV3665 faced northwest toward the seated participant. Similar to the Canon, for each Point Grey HDR, multiple exposure photographs were captured across a range of “shutter speeds” with a fixed aperture, white balance and ISO. These data had to be written into the header in order to process HDRs.

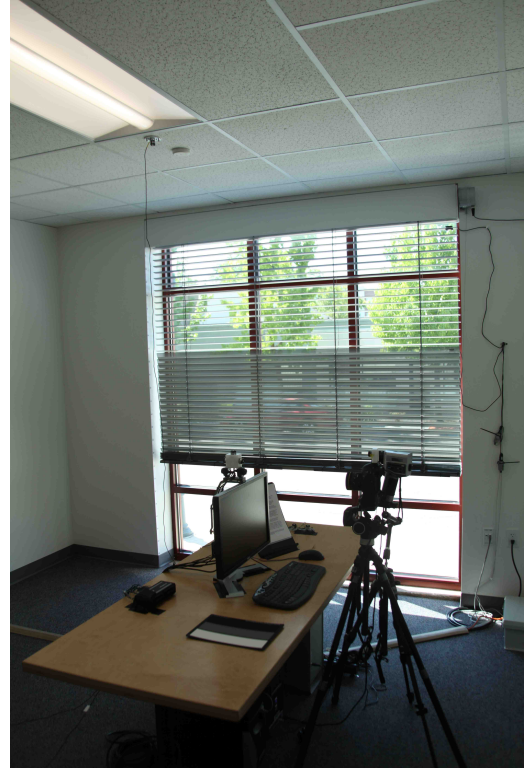


Figure 18 - Participant room (left), equipment room (right)

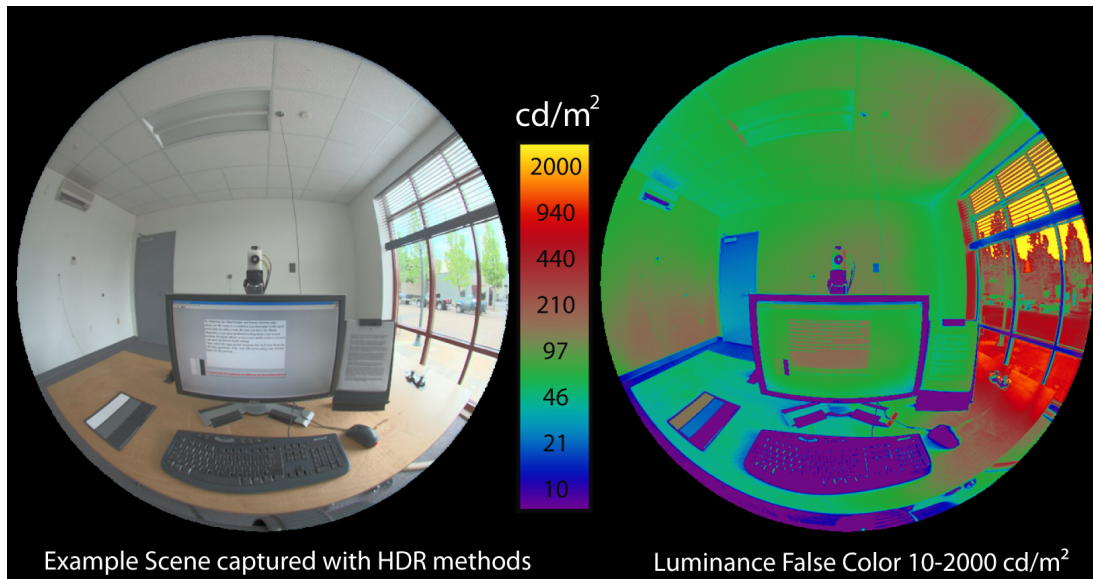


Figure 19 - Example HDR scene from Canon (left), corresponding luminance false color (right)



Figure 20 - Canon camera, luminance meter, Li-Cor 210sa from seated eye position

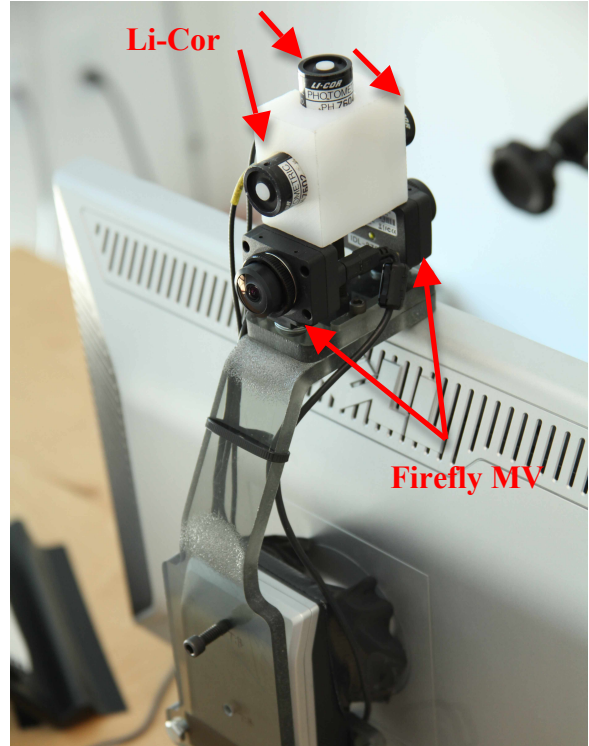


Figure 21 - Firefly MV cameras and Li-Cor 210sa illumination sensors on top of monitor

Illumination data were recorded using Li-Cor 210SA photometric sensors at the desktop, on the ceiling (toward the desktop), at the top of the computer monitor facing the ceiling and normal to the surface of the monitor in both directions (toward southeast and northwest walls), centered on the southeast and northeast walls, and next to the Canon Camera at the typical seated users' eye position looking toward the southeast wall. Irradiance data were recorded horizontally on the desktop using a Li-Cor 200 pyranometer. Electric lighting power levels were recorded using Dent Elite Pro data loggers with 20-amp current transducers attached to the light fixtures. Light fixture dimming levels were derived from the ratio of light to power (Figure 11). Blind tilt

was recorded using two SignalQuest USB inclinometers¹³. One was used for blind slats measuring higher than 1.67m (5'-6") above the floor and the other for blinds below. The vertical position of the blind was recorded using a Celesco string pot¹⁴.

3.5.2 Physical measures in the participant room

Participants were given the opportunity to adjust the temperature in the participant room to maintain thermal comfort as desired using the in-room heating and cooling unit. Therefore, temperature and relative humidity were measured in the participant room. The temperature in the equipment room was set to maintain 74 °F during cooling season and 70 °F during heating season, therefore there were thermal differences between the two rooms, but these pose no liability to the data collected.

3.5.3 Physical measures at the rooftop weather station

A weather station mounted on the roof of the study rooms, with an unobstructed view of the sky in all directions, recorded global horizontal illuminance, global horizontal irradiance, vertical southwest-facing irradiance (normal to façade), temperature and relative humidity data. In addition to the rooftop weather data, supplemental weather data were collected from the National Oceanic and Atmospheric Administration's National Climatic Data Center – Boise Air Terminal site¹⁵.

¹³ SignalQuest inclinometer part number: SQ-SI2X-360DA-3.0R-NP-HP-IND-S; SQ-ENCL-3; SQ-USB2-TTL

¹⁴ Celesco string pot part number SR1V

¹⁵ <http://www4.ncdc.noaa.gov/cgi-win/wwcgi.dll?wwDI~StnSrch~StnID~20005225>

3.5.4 Questionnaire items

Each participant completed a basic demographic questionnaire, a questionnaire for each lighting condition and an end of day questionnaire. The complete questionnaire is available in Section 8.5.

The demographics questionnaire included the following items:

1. What is your gender?
2. What is your age?
3. What type of vision correction do you normally require?
4. What type of vision correction do you have today?
5. What is your eye color?
6. Do you have any type of color blindness?
7. Do you have any other vision related health issues? (If yes, please explain)
8. What time do you usually wake up?
9. What time did you wake up today?
10. In general, I am sensitive to glare? (while in sensitivity to brightness room)

Each of the 16 lighting conditions included a questionnaire module with the following items:

1. Confirmation that the participant had created the lighting condition according to the given description.
2. Rate the following statements using the scale provided (7-point Likert type)
 - a. *This is a visually comfortable environment for office work.*
 - b. *I am pleased with the visual appearance of the office.*
 - c. *I like the vertical surface brightness.*
 - d. *I am satisfied with the amount of light for computer work.*
 - e. *I am satisfied with the amount of light for paper-based reading work.*
 - f. *The computer screen is legible and does not have reflections.*
 - g. *The lighting is distributed well.*
3. Rate the following using the scale from Too Bright – Too Dim provided
 - a. *When I look up from my desk the scene I see in front of me seems:*
 - b. *When I look to my left the scene that I see seems:*
 - c. *When I look to my right the scene that I see seems:*
 - d. *I find the ceiling to be:*
4. Rate the following using the scale from Least Preferred – Most Preferred (this item was only completed for Conditions 9, 10, 12, 13, 15, and 16).
 - a. *I find this lighting condition to be:*

5. Please click on the button to estimate how you think your personal productivity increased or decreased working under the present lighting conditions (this item was not asked for the first condition of each day).
 - a. -30%, -20%, -10%, 0%, +10%, +20%, +30%
6. Rate your level of fatigue using the scale provided.

Each participant completed a few end of day questionnaire items:

1. What was your strategy when using the electric lighting control?
2. What was your strategy when using the motorized blind control?
3. Were you trying to light a particular part of the room?
 - a. If yes, which parts of the room were you trying to light?
4. Rate the following using the scale provided (Likert scale from very strongly disagree to very strongly agree)
 - a. I would like to have these lights in my office:
 - b. I would like to have these blinds in my office:
5. Please describe any changes you would make to the office set up to make it more comfortable. For example, would you move the desk location or view direction? Would you change anything about the electric lights, blinds, walls or windows? Please explain below.

The subjective questions were drawn from the Office Lighting Survey (Boyce, Veitch, et al. 2003; Eklund & Boyce 1996) which dealt with elements of uniformity and distribution, comfort, color rendering and sufficiency, and from the COPE Field Study Questionnaire (Charles et al. 2003; Veitch et al. 2002) which dealt with privacy and acoustics, ventilation, lighting, job satisfaction and overall environmental satisfaction. A perceptual intensity Borg scale and semantic differential scales (E. Borg & G. Borg 2002; G. Borg 1990; G. Borg 1982; Neely et al. 1992) were used with regard to preference, acceptance, glare and fatigue.

3.5.5 Objective performance measures

A series of objective performance tests were conducted in order to provide meaningful office environment activity to help inform subjective assessments made by participants and to determine if the lighting condition experienced affected participant performance. Each objective performance test is described in detail.

3.5.5.1 *Omni-directional pointing with a mouse*

Using a mouse, participants clicked targets that moved from one location of the computer monitor to another in a circular fashion. Speed and accuracy were measured by software. Movement time and click time were recorded. The success rate (0 or 1) was recorded and the distance from the center of each target to the pointer location was also recorded. This test (Figure 22) follows Blackstone, Karr, Camp, & Peter W. Johnson, (2008).

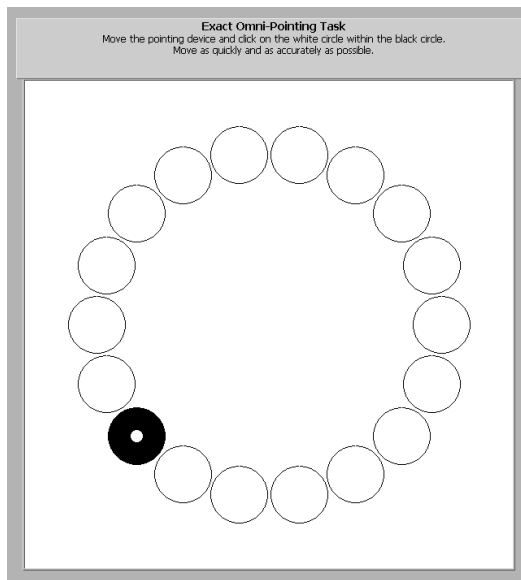


Figure 22 - Omni-directional pointing with a mouse

3.5.5.2 *Proofreading on computer screen*

Participants read one randomly selected (of 20 possible) approximately 225-word passage and searched for spelling errors for a period of up to two minutes. The total number of errors was measured by software. The text title, the number of accurate corrections, and the number of new errors were recorded. This test follows Newsham et al. (2008).

3.5.5.3 Manuscript typing

Participants retyped one randomly selected approximately 400-word passage (of 10 possible) from a paper document with 12-point font located on a fixed position document holder adjacent to the computer screen. Participants were given three minutes to type the passage. The passage was always too long for anyone to type. Accuracy was measured by software. The text title, the total number of errors, and the number of missing characters were recorded. Each character counted as one possible error such that an incorrectly typed character counted as one error and each character that was not typed (due to time limit) was counted as an error. This test follows Newsham et al. (2005). Scores were calculated two ways. One way used a standardized word count that just exceeded the longest type passage and scored the percentage of correctly typed words from that maximum possible correct value. The second way used the actual word count typed on an individual passage basis and reported the percentage of correctly typed words within that individual passage.

3.5.5.4 Visual search

Participants repeatedly searched a field of Landolt “C” rings (C-shaped rings with small gaps, facing in various directions) to find rings with gaps facing a specified direction. Each grouping of five rings (four rings surrounding the reference ring in the middle) was presented for 200 milliseconds. Speed and accuracy were measured by software. The time (in seconds) that it took to select an answer and the accuracy (correct or incorrect) were recorded. This test follows multiple authors (Berman et al. 1993; Berman et al. 1993; H. R. Blackwell & O. M. Blackwell 1977; H. R. Blackwell & Scott 1973) and is illustrated in Figure 23.

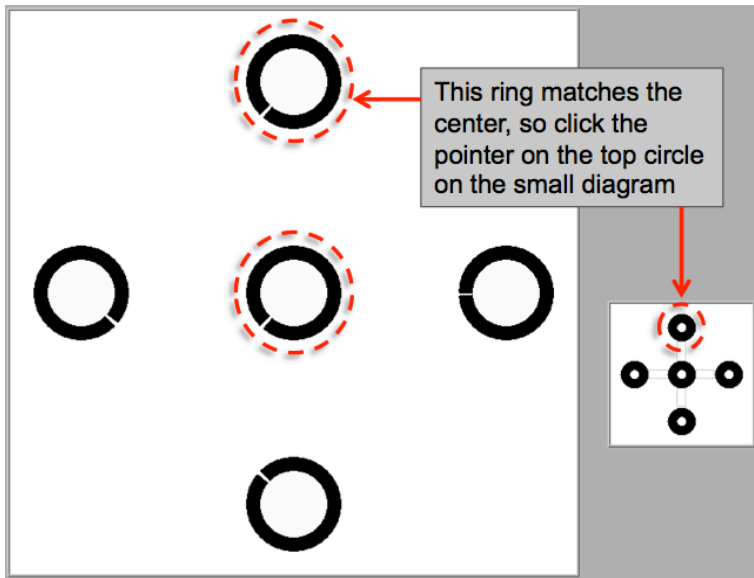


Figure 23 - Visual search test showing Landolt C rings

3.5.5.5 Numerical verification

Two adjacent lists of numbers, one to the left of the other, were presented on the computer screen (Figure 24) following Rea (1981). Participants scanned the list to identify any pairs of numbers that did not match. Speed and accuracy were measured by software. The time (in seconds) it took to complete each trial, the false positive errors, the number of misses, as well as the true number of differences that were to be found for each trial were recorded. The results were scored as follows: $(20 \text{ trials} - (\text{misses} + \text{false positives}) / \text{time in seconds})$.

62513	62513	SAME
10147	10147	SAME
49891	49891	SAME
68495	78495	DIFF
44783	44783	SAME
92467	92467	SAME
40964	40964	SAME
85939	85939	SAME
95085	96085	SAME
86762	86762	SAME
92600	92600	SAME
31360	31360	SAME
60281	60281	SAME
73693	73693	SAME
41583	41583	SAME
94631	94631	SAME
49835	49845	SAME
38152	38152	SAME
74068	74068	SAME
28399	28399	SAME

Figure 24 - Numerical verification test

3.5.5.6 Stroop color-word

Participants were presented with three types of the Stroop color-word tests using red, green, yellow, blue and black words, colored texts, and colored fields in different combinations. Stroop Type 1 consisted of black font of a color word such as “RED,” and the participants selected that color using the arrow keys. Stroop Type 2 consisted of a colored field, and the participants selected that color using the arrow keys. Stroop Type 3 consisted of a colored font of a differing color word, such as the word “YELLOW” in blue font, and the participants selected the font color using the arrow keys. Speed and accuracy were recorded by software.

This test follows multiple authors (Hammes 1973; N. J. Stone & Irvine 1993; Van der Elst et al. 2006) and is detailed in Figure 25, Figure 26 and Figure 27.

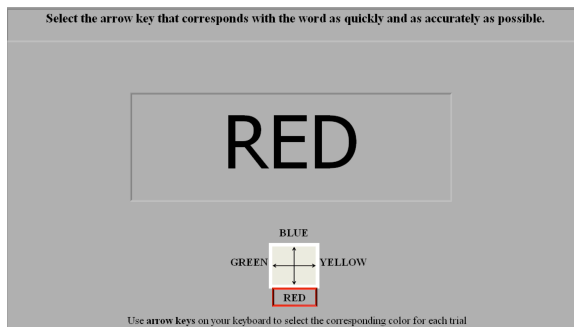


Figure 25 - Stroop color-word type 1

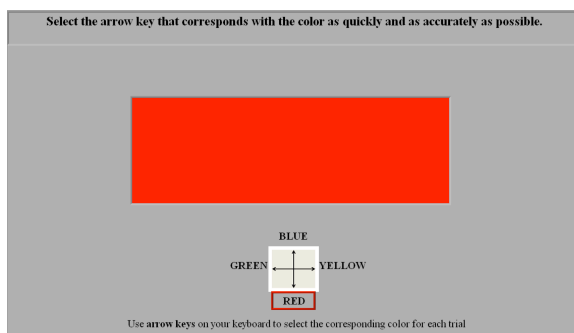


Figure 26 - Stroop color-word type 2

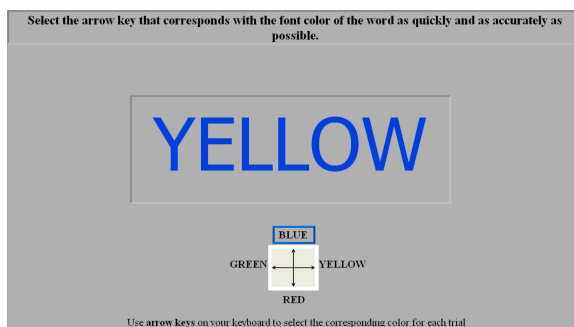


Figure 27 - Stroop color-word type 3

3.5.6 Word association creativity test

A creativity test was administered for five selected conditions during the second round of the study only (September 21-December 19) to assess the effect of varying lighting conditions on participants' creativity. One of five words or phrases (barrel, tin of boot polish, paper clip, blanket, brick) were randomly presented to participants during the conditions listed below, and participants were asked to list as many novel uses as they could think of for each object. These five words were used in Hudson's (1967) work on intelligence, convergent thinking and divergent thinking. Participants were timed with a stopwatch until they ceased writing new uses or reached the 15-minute limit. The creativity tests were administered under the following conditions:

- Right after the sensitivity to brightness test using the participant's selected JU glare condition; this occurred at the beginning of each day
- Condition 1- MP daylight-only (no electric light)
- Condition 4- JU glare under daylight-only (during morning)
- Condition 9 – electric lights off, blinds all the way down and rotated closed
- Condition 10 – JU glare under daylight-only (during afternoon)

“Creativity” and a “creativity speed” scores were generated as follows:

- Creativity = total number of novel uses suggested for common objects
- Creativity Speed = average time (seconds) per novel use suggested

This test spawns from Mednick's (1962) theory of creativity in which he related word associations to cognitive representation. Creativity is defined “in terms of the formation of new associations or combinations of cognitive elements that are in some way useful” (Isen et al. 1987). Divergent thinking tests are frequently used to assess the quality and quantity of creative ideas and are predicated on the assumption that divergent thinking is essential to creativity. Divergent thinking is a thought process or method used to generate creative ideas by exploring

several possible solutions (Runco & Albert 1990). This type of creativity test methodology has been used in lighting studies by Veitch and Gifford (1996), in which participants had differing levels of control over lighting conditions.

3.6 *Data Analysis*

3.6.1 HDR image processing and calibration workflow

Several important steps were taken to ensure accuracy of the HDR luminance maps in preparation for data analysis. In order to process any HDR image, it is first necessary to develop an accurate luminance response curve for each camera, and if fisheye or wide-angle images are used it is necessary to derive a vignetted correction function for each camera and lens combination. The process of developing these data, as well as the step-by-step approach used for post-processing HDR images is documented below. Additional background information on HDR techniques, calibration steps and accuracy of results are available elsewhere (Debevec & Malik 1997; Inanici 2006; Ward 2009).

For the Canon camera used in this study, three alternate scenes were photographed using HDR methods to ensure that an accurate luminance response curve was available. Scenes with large, uniform, light colored surfaces, and with extremes of very bright and very dark regions were selected for this purpose. Two of the three scenes studied produced relatively similar curves, and the one with the tightest curve between the red, green and blue channels was selected (Figure 28). The response curve was generated by Photosphere (Ward 2006) and that curve was applied to all HDR images captured with the Canon.

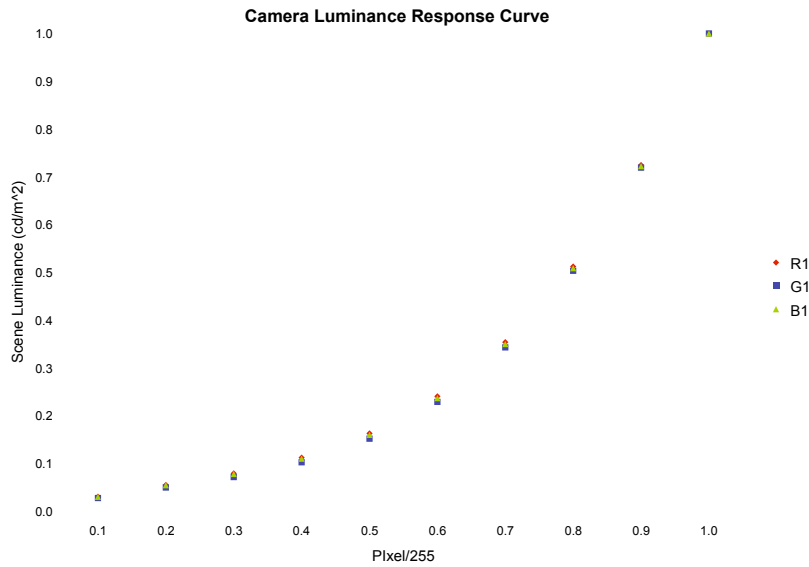


Figure 28 – Canon luminance response curve derived by Photosphere

A vignetting correction function was developed for the Canon camera and Sigma fisheye lens combination (Figure 29). The process involved capturing 19 individual HDR sequences, one for every five degrees of lens rotation between 0°-90°, in an environment with stable electric lighting, without daylight and with a grey card. Grey card luminance values were compared from each of the 19 HDRs relative to the known measured value from the physical environment. From these data, a polynomial fit function was developed using Excel (or Open Office) and that function converted to a greyscale image using MatLab (or ImageMagick) to create a tiff file of the same pixel resolution as the HDR images it would be applied to. Then, it was converted to a Radiance format (ra_tiff) and applied in Radiance to correct each HDR image following the steps detailed further in this Section.

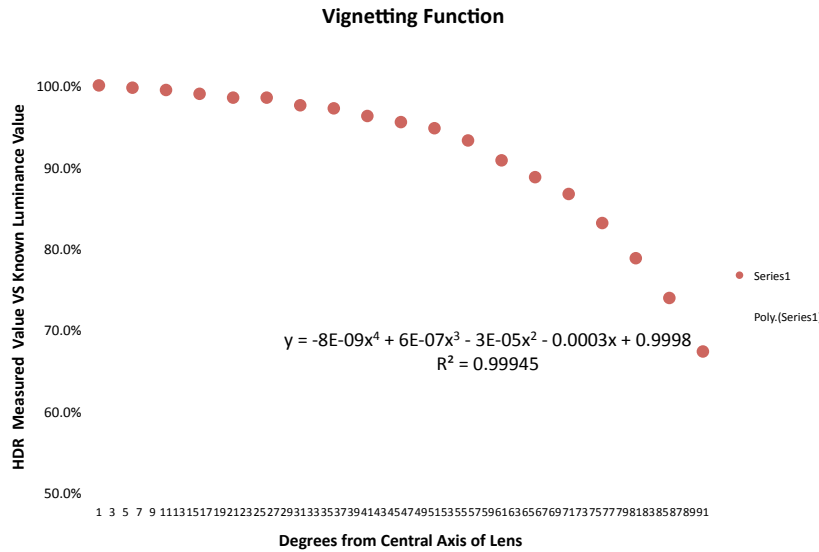


Figure 29 – Vignetting function for Canon 1DS Mark III with Sigma 8mm Lens

Once the luminance response and vignetting correction functions were available, the batch processing for calibration and image optimization could occur. Given that each camera captured 16 lighting conditions per study day, and there were ninety-three total study days, there were 1,488 total HDR capture sequences per camera. Therefore a great deal of automation was necessary to handle image calibration and post-processing in order to avoid human error and expedite the generation of results. The following text is meant to accompany Figure 31 in a step-by-step fashion, using the numeral sequence in the graphic.

Step 1 – Capture bracketed exposures

Each HDR capture sequence from the Canon resulted in 16 individual exposures (at F5.6 from 1/4000 seconds to eight seconds). This was programmed by modifying the HDRcapOSX script developed by Ward and updated by IESD, at De Montfort University (Ward et al. 2010). These sequences were intentionally over-bracketed to ensure that a full range of exposures (from

completely unsaturated to completely saturated pixels) was achieved, even for the wide range of lighting conditions (from full sun and specular solar reflections to near nighttime conditions) that occurred during this six-month study. Therefore, for a given capture sequence, it was highly probable that one or more exposures from each sequence had to be discarded in order to generate an accurate HDR image.

Step 2 – Select appropriate exposures for each sequence

Only the appropriate exposures from the photographic sequence were included in the formation of the HDR image. This was a two-part step where the first part was to set the RGB pixel values from the unusable region of the image to a known value (RGB 200, 200, 200) and the second part was to examine the pixels in the usable region to determine which exposures to include in the HDR compilation. To automate the first part, bash commands were used to call ImageMagick software. The usable region of the image (central 180° by 180° circular scene) was defined using the ImageMagick *convert* command, identifying the radius of the usable pixels, and converting the pixels in the unusable region to RGB 200, 200, 200. Then, a perl script used *if/else* commands to select any exposure that had an absolute maximum RGB pixel value of 255 and an absolute minimum RGB pixel value of less than 80. Furthermore, if there were exposures within a bracketed sequence with an absolute maximum RGB pixel value of less than 255 within the usable region, the highest of these was also included in the HDR compilation.

Step 3 – Combine exposures

The selected exposures were combined using the Radiance *hdrgen* command, which referenced the pre-prepared camera luminance response function. After this step, full-size uncalibrated HDRs were available. These were not used for results analyses.

Step 4 – Calibrations and optimizations

A series of additional calibrations and optimizations were applied as detailed in steps 4.1-4.4 in Figure 31. Step 4.1 is good practice, and simply adjusted the automatic exposure to a value of 1.0 using the Radiance *pfilt* command. Step 4.2 used the Radiance *pcomb* command to apply the vignetting correction function to the HDR. Step 4.3 accomplished absolute calibrations, and had two alternate pathways. In either pathway, the objective was to determine an exposure multiplier and write this into the header of the HDR. Luminance-based absolute calibration was prioritized if luminance data were available; otherwise, illuminance-based calibration was used. Most of the command line steps are identical for the two pathways. The luminance calibration pathway used Radiance *ra_xyze* to create a RGBE format, *pvlaue* was used to create a numeric string, *rlam* and *rcalc* were used to isolate a masked area (in this case the grey card), and *awk* (a bash scripting command) was used to capture the mean luminance value within masked region. The only difference with the illuminance calibration pathway is that it began with the Radiance *pinterp* command to convert the image from equidistant to orthographic projection and ended with taking mean luminance of the entire scene (rather than just the grey card region as in the luminance calibration pathway) and converting it to a E_v value (by multiplying with π). The outputs of these methods were compared with the physical grey card

luminance reading or a E_v reading respectively. This comparison provided a calibration multiplier that was applied to the HDR image header.

In the physical space, absolute luminance values were captured with a Minolta LS-110 ($1/3^\circ$ measurement angle) spot luminance meter focused on a grey card fixed in the center of the scene. The luminance meter was positioned as close as possible to the center of the camera lens (less than 1/3m away). For redundancy, a Li-Cor 210sa illuminance sensor was fixed vertically to the flash shoe on top of the Canon. These sensors can be seen in Figure 20. The luminance meter failed on 60 of the 1,488 (4%) HDR photographs. Of these, two were determined to be unreasonable values and 58 were due to mechanical failures. The illuminance meter failed on 51 of the 1,488 (3%) HDR photographs. Of these, two were determined to be unreasonable values and 49 were due to a mechanical failure. None of the equipment failures occurred simultaneously. Whenever possible (96% of scenes), HDR images that were derived from the luminance calibration pathway were used in results analysis.

Finally, in step 4.4, the full-resolution HDR images were cropped to a square encompassing the circular scene using Radiance *pcompos* and resized to 800 by 800 pixels using *pfilt* to expedite results generation.

Step 5– Masking and calculations

This step took the calibrated HDRs and passed them through a series of scripts to produce the desired results for analysis. One pathway generated glare indices using Evalglare and *findglare-glarendx*, and the other pathway generated descriptive statistics associated with each masked region using perl scripts and *awk* commands. These results are described in greater detail in Section 3.6.2

Step 6– Parsing results

This step took the nearly 200,000 disparate text files and reorganized them into a single matrix for use with statistical analysis software. Extensive data cleaning routines were conducted to ensure accuracy as described in 3.6.3.

Step 7– Results analysis

Results analyses were carried out using the R Package for Statistical Computing and details for the statistical methods used are provided in 3.6.4.

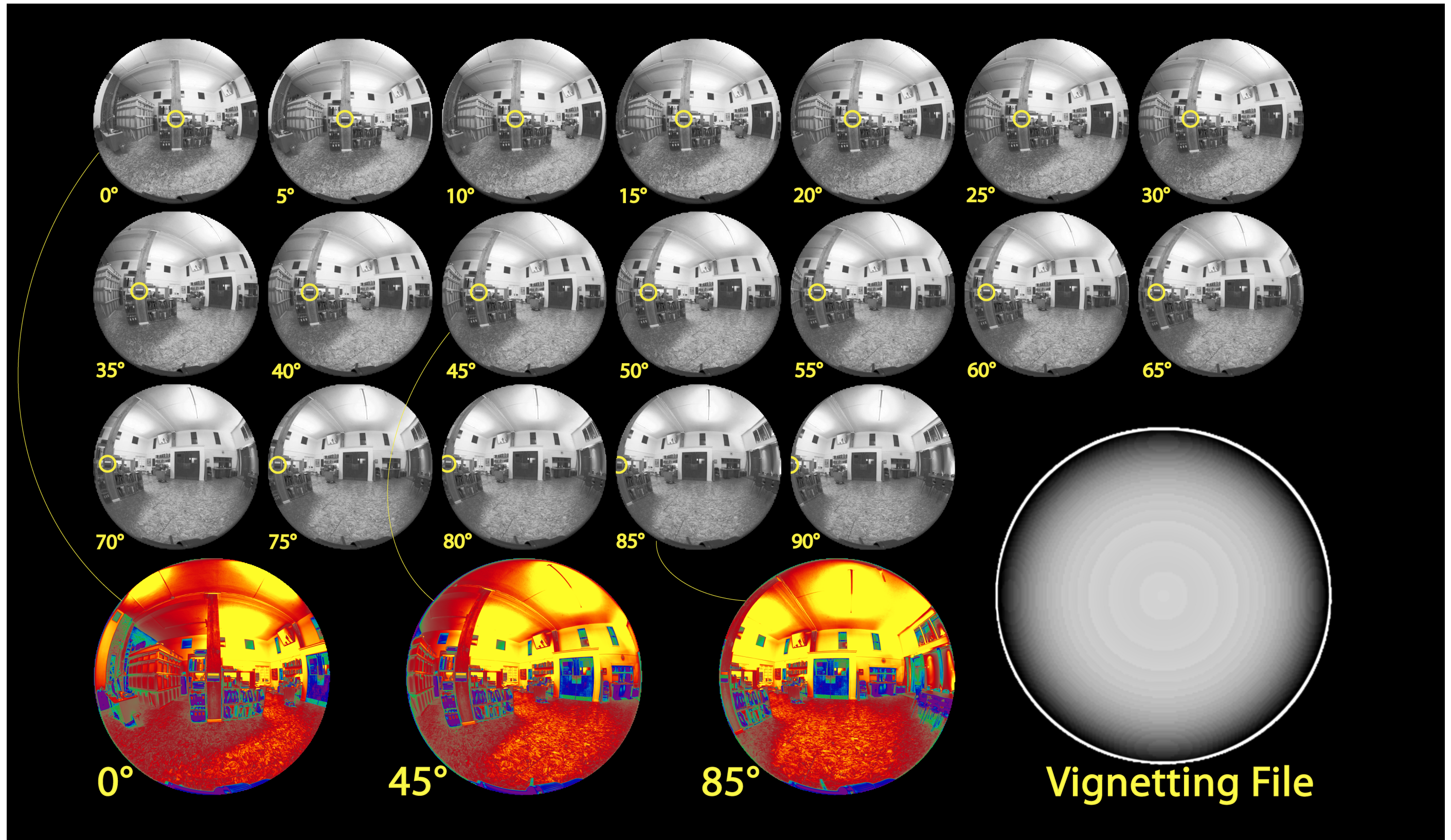


Figure 30 – Process to develop lens vignetting function

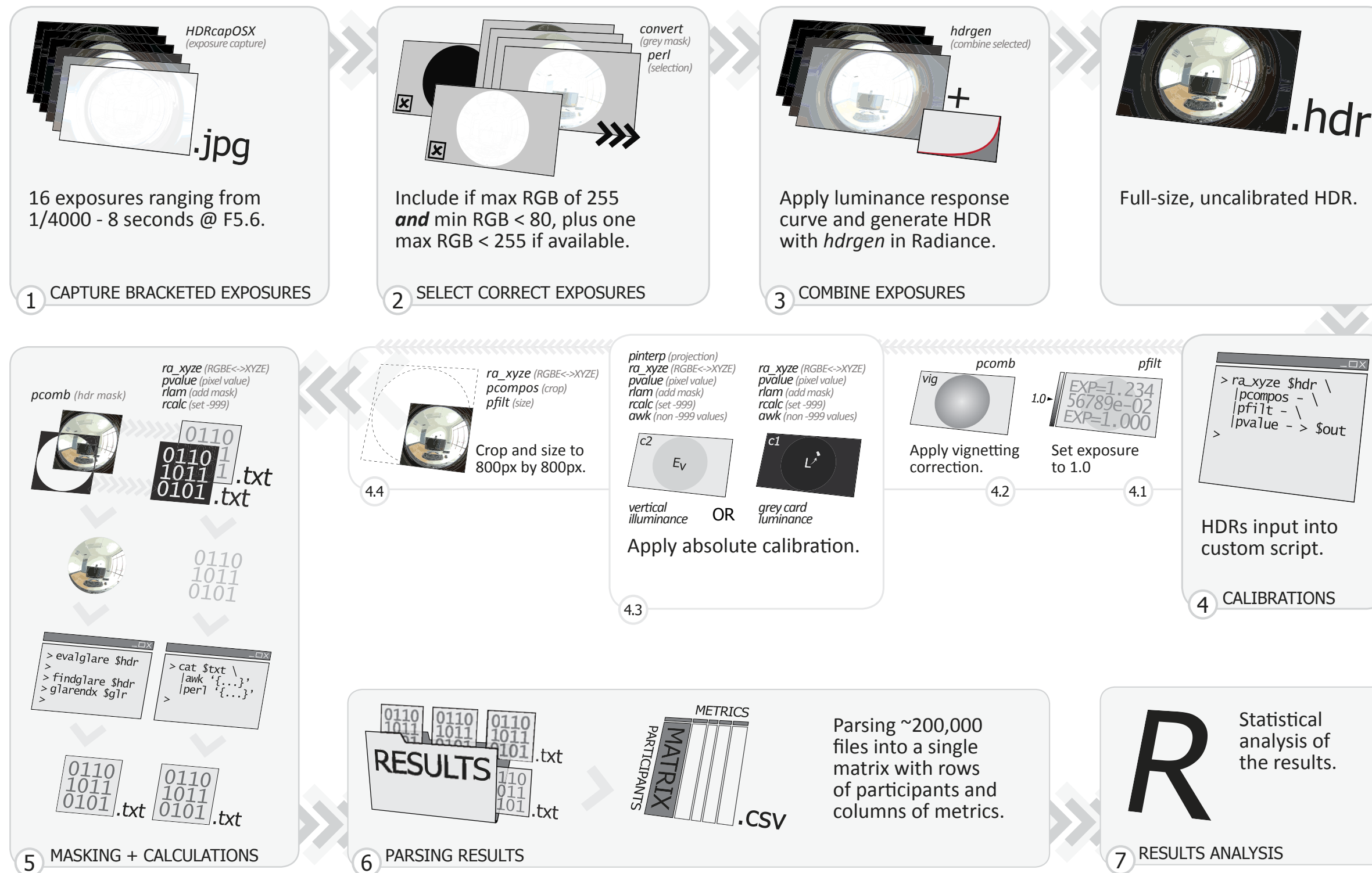


Figure 31 – HDR capture, calibration, and data processing workflow

3.6.2 Luminance metrics and scene masks

The pilot study (Van Den Wymelenberg et al. 2010) examined approximately 150 illuminance- and luminance-based metrics summarized in Section 2.4.1. Since the pilot study encompassed a limited duration, these metrics, along with several others, were examined for the six-month dataset. The pilot study examined luminance values in four regions within each scene as shown in Figure 6. In order to better understand specific areas within the scene, 23 masked regions were examined for the six-month dataset as shown in Figure 32. The pixels within the dark shaded areas were excluded from the analysis when a specific mask was applied. Several masks are space-dependent while others are space-independent. Some of the masks (X16-X19) represent different regions the FOV and others represent concentric bands from the scene center (X21-X23) and were adapted from Stein and Reynolds (1999) and Inanici (2004) respectively.

The six-month study examined 198 metrics for each of mask 01 (X01) and mask 03 (X03) and 80 metrics for each of masks X02 and X04-X23. Eighteen additional metrics were developed to encompass luminance data from two or more masks. Given that this represents over 2,000 unique luminance metrics they are only described generally. In addition to the 2,000 luminance metrics, illuminance and irradiance data collected (described in Section 3.5) were also examined.

Statistics such as minimum, maximum, mean (\bar{x}), standard deviation (σ), coefficient of variation (σ / \bar{x}), several percentiles (2nd, 10th, 50th, 75th, 90th, 98th), ratios of these (e.g. 2nd percentile : 98th percentile), percentage of scene pixels above or below certain absolute luminance thresholds (below 5, 10, 40, 50, 100, 250, 500, 1000 cd/m²; above 1500, 2000, 2500, 3000, 4000, 5000 cd/m²), and ratios of these (e.g. % below 5 cd/m² : 5000 cd/m²) were calculated for every mask. Additionally, for X01 several existing glare metrics were calculated using

Evalglare version 0.9f including DGP, DGI, VCP, UGR, CIE Glare Index (CGI), and the average luminance of the glare sources identified. Evalglare output was generated using two glare source identification methods. One method was based upon mean luminance multipliers ($3\bar{x}$, $5\bar{x}$, $7\bar{x}$, $10\bar{x}$) and the second used absolute luminance values (1500, 2000, 2500, 3000, 4000, 5000 cd/m^2) to identify glare sources. Once the glare sources were identified the glare indices were calculated. For X03, the same mean luminance multipliers ($3\bar{x}$, $5\bar{x}$, $7\bar{x}$, $10\bar{x}$) were used to identify glare sources and the circle task defined by X03 was used as the basis for mean luminance. Radiance *findglare* and *glarendx* programs were used to calculate DGI for X01 using the default method glare source identification method ($7\bar{x}$) and the same six absolute luminance values. A small number of additional metrics were calculated using data from multiple masks as outlined in Table 12. These include basic luminance ratios, contrast ratios and comparisons of mean and standard deviation values between several masks. The luminance ratio metrics examine simple ratios between mean values of the task (using X03, X01) and either adaptation background values (X01_mean, X22_mean, X23_mean), background variability (X01_standard deviation, X23_standard_deviation), or high scene luminance values (X01_90th_percentile, X01_98th_percentile, X08_mean). The luminance contrast metrics comprise two combinations of masks to develop task (X01, X22) to background (X01, X22) luminance contrast ratios. The mean to standard deviation ratios examine the brightness of the central 60° of vision to the variation of luminance in the entire scene (X01) or the non-central vision (X23).

Table 12 – Luminance-based metrics with multiple masks or multiple metric components involved.

Luminance Ratios	Luminance Contrast Ratios
X03 \bar{x} : X01 \bar{x} ; (X03_mean_to_X01_mean)	$\frac{X01\bar{x} - X03\bar{x}}{X01\bar{x}}$
X21 \bar{x} : X01 \bar{x} , (X21_mean_to_X01_mean)	(X01_to_03_contrast)
X21 \bar{x} : X22 \bar{x} ; (X21_mean_to_X22_mean)	
X21 \bar{x} : X23 \bar{x} ; (X21_mean_to_X23_mean)	
X21 \bar{x} : X01 σ ; (X21_mean_to_X01_standard_deviation)	$\frac{X22\bar{x} - X21\bar{x}}{X22\bar{x}}$
X21 \bar{x} : X23 σ ; (X21_mean_to_X23_standard_deviation)	(X22_to_21_contrast)
X21 \bar{x} : X01 $_{90^{th}}$ % ; (X21_mean_to_X01 $_{90^{th}}$ _percentile)	
X21 \bar{x} : X01 $_{98^{th}}$ % ; (X21_mean_to_X01 $_{98^{th}}$ _percentile)	
X08 \bar{x} : X03 \bar{x} ; (X08_mean_to_X03_mean)	
Where: X01 $_{90^{th}}$ % is the luminance value of the 90 th percentile brightest pixel in mask 01, X01 $_{98^{th}}$ % is the luminance value of the 98 th percentile brightest pixel in mask 01.	

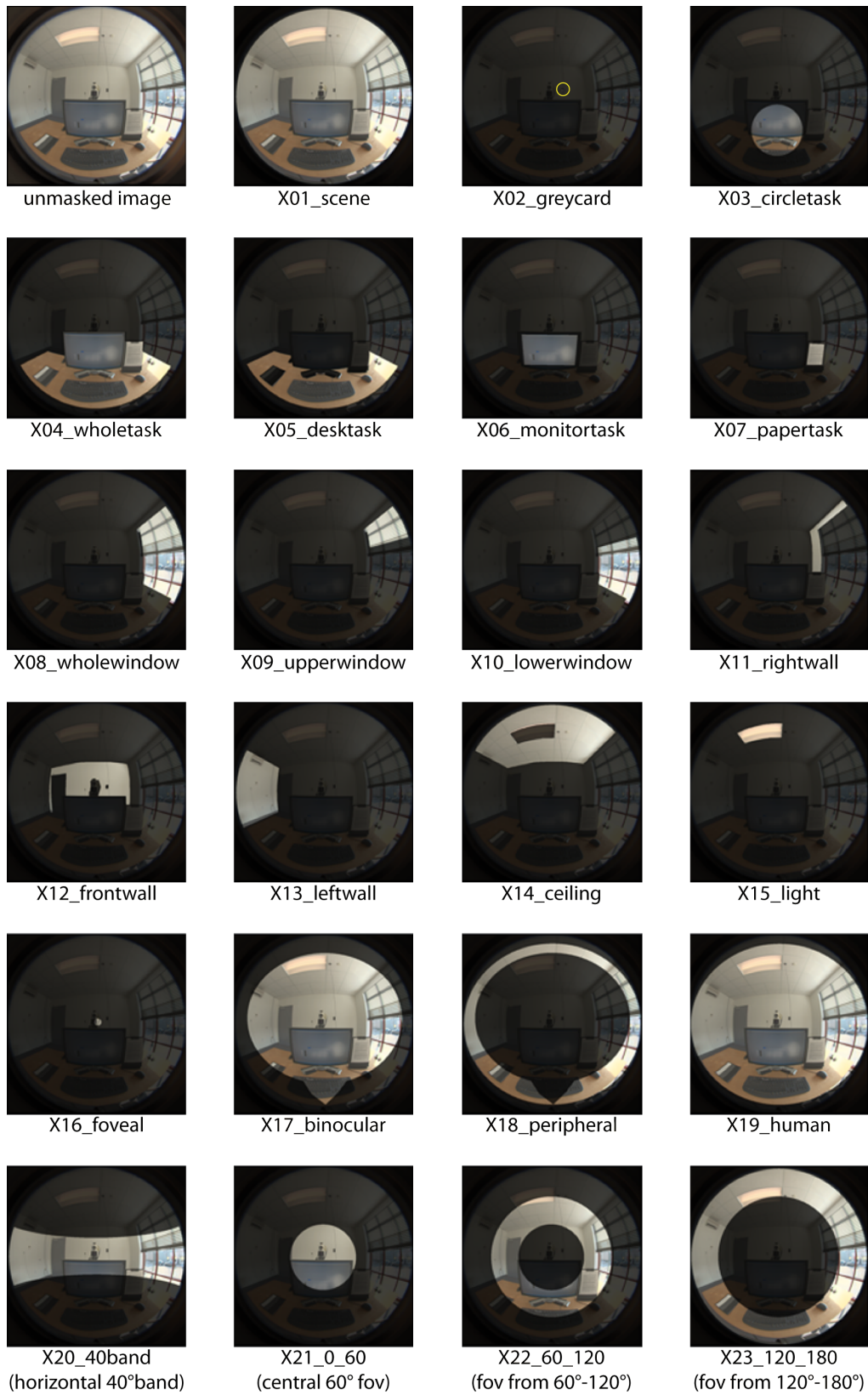


Figure 32 – Masks applied to an example scene

3.6.3 Data cleaning

All data were collected in discrete files, and scripts were used to conduct data cleaning and organization. After initial cleaning and organization was complete, extensive spot-checking of data was conducted to ensure accuracy. Scripts helped to reduce human error and revealed structural data issues that were corrected. Spot-checking routines confirmed the accuracy of the scripting procedures. Any data that required manual generation or database entry (e.g. scoring the typing tasks and inputting the results) was conducted simultaneously by two people and crosschecked to ensure accuracy.

The data were very clean and complete with a few exceptions. The Canon capture script failed on six of the 1,488 (<0.005%) HDR photographs. The Firefly MV HDR data are available from 2011/06/29-2011/10/19. Due to the incomplete Firefly MV HDR dataset, the Canon data were prioritized for analysis. Illuminance on the SE wall, ceiling and desktop, and irradiance on the desktop are available from 2011/06/29-2011/09/20. Illuminance on the NE wall, horizontally at the top of the monitor, and vertically at the top of the monitor facing the participant are available from 2011/06/29-2011/11/15.

As described in Section 3.6.2, extensive luminance-based metrics were developed from the calibrated HDRs and applied to several masked scene areas within each scene. When applied to some scenes or masked areas within scenes, these mathematical tests reported values of *-nan* or *-inf* for “not a number” and “infinity” respectively. These were converted to NA (not available) or “0” respectively so that the statistical analysis software would interpret them appropriately.

The validated HDR capture procedure described in Section 3.6.1 has been shown to result in less than 10% error in scene luminance values (Inanici 2006). However, if the daylighting conditions change substantially during the HDR capture sequence (lasting about one minute) there is less confidence in the usefulness of the results since successive exposures may have been captured during physically different lighting conditions. Konis et. al (2011) found that if the E_v adjacent to the camera exceeded 5% difference throughout the exposure sequence then error increased from 5% to 14% (for mean luminance of the masked window).

For this dissertation, the participant-scenes with greater than 10% difference between pre and post spot luminance measurements on the grey card were removed from the data set unless the grey card luminance values were low (less than 30 cd/m^2) for pre and post measurements. If the grey card luminance values were less than 30 cd/m^2 for pre and post measurements, conditions with greater than 20% difference between pre and post luminance measurements were removed. As noted previously, 60 conditions had missing luminance data, therefore an alternate checking method was needed. Of these, conditions with greater than 10% difference between pre and post E_v measurements were deleted unless the E_v values were less than 200 lux for pre and post measurements. If the E_v values were less than 200 lux for pre and post measurements, conditions with greater than 20% difference between pre and post E_v measurements were deleted. In total, this process reduced the data set by 100 conditions (7%).

Additionally, a thumbnail plot for each of the 16 conditions on each of the 93 participant-days was generated for additional spot-checking. Two versions of the “93x16 plots” were created, one with tone-mapped HDR photographs (Figure 33-top), and one with false color luminance data (Figure 33-bottom). Examining these plots revealed that the scripted condition labels on one participant-day were incorrect and that four participants had mistakenly left the

electric light on during conditions intended to be under daylight conditions only (C1 and C4). The incorrect labels were manually corrected for one participant-day in the database and the four participant-scenes that had mistakenly left electric lights on were removed from the dataset. Some participants chose to turn the electric lights off during conditions intended to be MP integrated lighting but these were not removed from the data since the participants were instructed that this was acceptable if they inquired about it.

As noted previously, given the 93 participant-days and 16 conditions per day, there were 1,488 HDRs captured. In summary, the Canon camera failed on five participant-scenes, the excessive daylight variability during the HDR capture sequence resulted in removing 100 participant-scenes, and spot-checking the 93x16 plots resulted in removing four participant-scenes because participants had electric lights on when they were supposed to be off. Therefore, results from a total of 1,379 HDR scenes are reported herein.

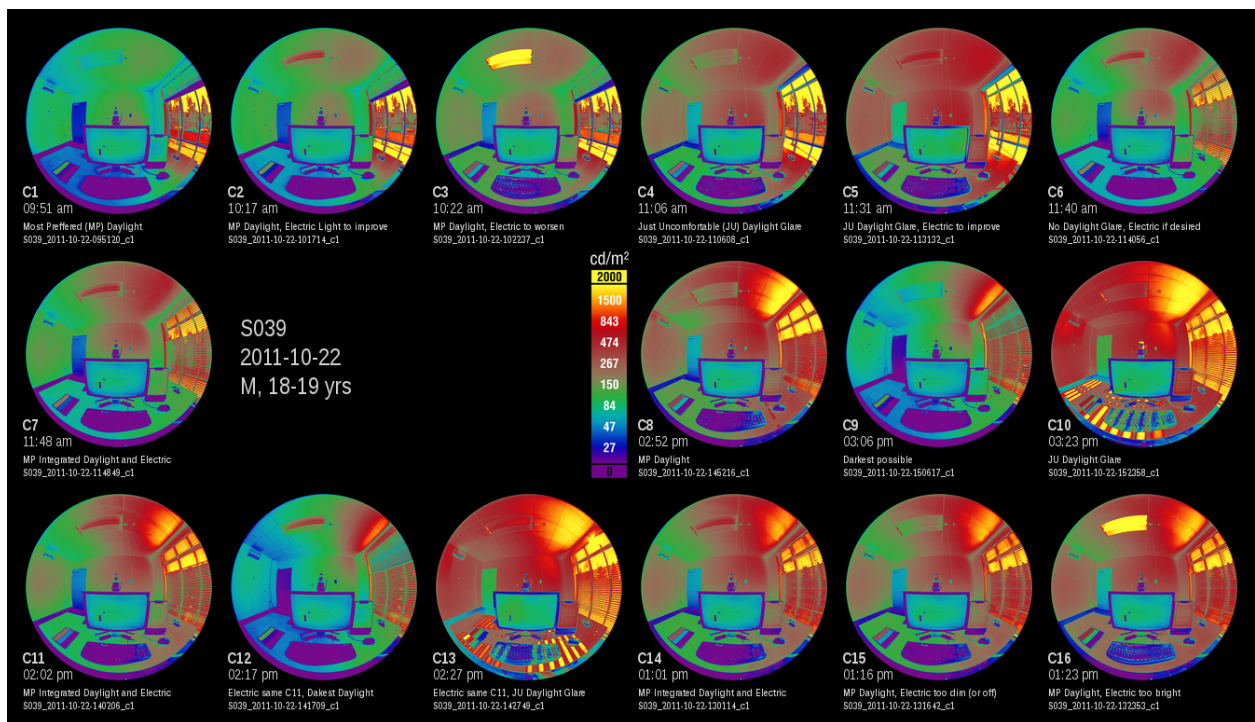


Figure 33 – Tone-mapped plot of 16 conditions for example participant-day (top), luminance false-color plot for the same participant-day (bottom)

3.6.4 Statistical methods

The statistical methods employed in this study are as follows:

- Descriptive statistics
 - Luminance-based descriptive statistics available for each masked region of a scene are outlined in Section 3.6.2
 - Other descriptive statistics are outlined in Section 3.5.1-3.5.3
- Inferential statistics
 - T-tests: to determine statistical significance between groups of continuous data, using 95% confidence interval; these could be one-way or two-way, paired or unpaired
 - Friedman tests: to determine statistical significance between groups of ordinal data
 - Pearson correlation: to determine the relationship between variables
 - Spearman correlation: to determine the relationship between variables; used sparingly and not reported; used only to confirm that Pearson methods were adequate for use with ordinal data
 - ANOVA: to determine whether individual variables in multiple-regression models were statistically significantly improving the model

The purpose of the subjective visual preference and acceptance measures (*Aim 1*) was to identify which of several candidate metrics (or combinations of metrics) derived from the objective lighting data could best fit (“explain” or “predict”) the variance of the participants’ evaluations. Human visual preference and acceptance were measured using subjective responses to Likert-type and semantic differential questionnaire items (see Section 3.5.4 and 8.5). Objective lighting data (see Section 3.5.1) were collected simultaneously and were used to determine the degree of correlation with human visual preference and acceptance. Likert data are ordinal (whereas the illuminance and luminance metrics tested to describe the variability in Likert data are continuous, either interval or ratio data) and there is substantial controversy regarding the use of parametric statistical tests with ordinal data (J. Choi et al. 2010). However, parametric tests such as Pearson correlations and t-tests have been shown to be robust, even

when dealing with the potential challenges of non-normality, skewness and unequal differences between scaled responses as sometimes found with Likert data (Norman 2010). Therefore, this study employed both Spearman and Pearson correlations to discern which objective lighting metrics best explained the variability in participants' subjective responses on Likert items. Spearman correlations are suggested for use with ordinal data but are not as common in practice. While moderate differences were found in the resultant coefficients of determination (r^2), the strongest metrics tended to be stable regardless of the correlation method used. Essentially, Pearson and Spearman correlations yielded similar results in terms of the relative performance of individual metrics. Because of this finding, as well as its general robustness reported above, and due to its prevalent use in practice, Pearson correlations are reported herein.

Metrics that performed well in correlation analysis were also examined with qualitative methods to examine their consistency, that is their ability to differentiate between a single participant's MP and JU conditions within a short time period (e.g. C8 versus C10 or C11 versus C13). Furthermore, several moderating variables, including participant age and sensitivity to brightness, were examined for their ability to further explain the variance of the data and were built into multiple regression models. ANOVA methods were used to characterize these relationships. Friedman tests were used to examine the statistical differences in Likert scores between the 16 conditions studied and to determine if there were any consistent outliers with regard to the 48 participants and their responses to the seven Likert items. Objective human performance measures (*Aim 2*) were examined using t-tests to identify if there were significant differences in performance results between MP and JU conditions.

4 Results

4.1 MP versus JU conditions

4.1.1 Descriptive statistics of lighting characteristics of MP and JU scenes

The range of several illuminance- and luminance-based metrics for all MP scenes, MP daylit scenes and MP integrated lighting scenes are available in Table 13 – Table 15, and for all JU scenes in Table 16. Note that when examining data for different metrics the tables report summary data, not paired data, so direct comparisons between individual results is not suggested because the results are unlikely to come from the same participant-scene. It is useful to examine the results of several of these illuminance- and luminance-based metrics in a graphical format and a selection are shown in Figure 34 – Figure 37.

Table 13 – All MP scenes (C1C2C6C7C8C11C14) with score of five or higher on QUI

All MP Scenes (C1C2C6C7C8C11C14) with score of five or higher on QUI							
	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.	σ
<i>Illuminance</i>							
E_desktop (lux)	52	459	903	1101	1508	4973	852
E_ceiling (lux)	25	477	810	1042	1507	3030	735
E_vertical_eye (lux)	17	455	707	798	1027	5607	501
<i>Luminance</i>							
X01_mean (cd/m ²)	32	165	252	294	379	1682	183
X01_standard_deviation (cd/m ²)	54	418	679	762	962	7300	636
X01_cov	1.23	2.09	2.50	2.57	2.92	6.94	0.77
X01_98 th _percentile (cd/m ²)	175	1220	2152	2452	3360	12450	1602
X01_percent_below_30_cd/m ²	2.7%	11.1%	13.7%	15.3%	16.4%	85.0%	10.4%
X01_percent_above_2000_cd/m ²	0.0%	1.0%	2.2%	2.5%	3.6%	9.3%	1.8%
X08_mean_to_03_mean	0.58	8.44	13.96	14.43	19.78	56.84	7.96
X01_findglare_dgi_default	1.10	7.68	10.91	10.01	12.52	16.43	3.22
X03_evalglare_mL0005_dgp	16.5%	19.6%	21.4%	21.6%	23.0%	44.0%	3.1%
X08_standard_deviation	33	788	1412	1509	2069	6842	982
X08_mean (cd/m ²)	29	509	929	1033	1446	3618	662

Table 14 – MP integrated lighting scenes (C7C11C14) with score of five or higher on QU1

MP Integrated Lighting Scenes (C7C11C14) with score of five or higher on QU1							
	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.	σ
<i>Illuminance</i>							
E_desktop (lux)	100	551	1014	1268	1810	4973	878
E_ceiling (lux)	53	589	1143	1291	1887	3030	773
E_vertical_eye (lux)	17	516	842	917	1259	5607	579
<i>Luminance</i>							
X01_mean (cd/m ²)	32	182	280	335	466	1682	216
X01_standard_deviation (cd/m ²)	54	436	742	875	1101	7300	807
X01_cov	1.33	1.97	2.43	2.55	2.93	6.94	0.86
X01_98 th _percentile (cd/m ²)	175	1276	2152	2635	3696	12450	1810
X01_percent_below_30_cd/m ²	2.7%	9.3%	12.8%	13.6%	15.7%	74.0%	8.7%
X01_percent_above_2000_cd/m ²	0.0%	1.0%	2.2%	2.6%	3.8%	9.3%	2.0%
X08_mean_to_03_mean	1.29	7.50	12.99	13.78	19.04	56.37	8.02
X01_findglare_dgi_default	1.71	6.89	9.94	9.53	12.18	16.36	3.22
X03_evalglare_mL0005_dgp	17.1%	19.6%	21.5%	22.1%	24.0%	44.0%	3.6%
X08_standard_deviation	53	737	1497	1608	2285	6842	1127
X08_mean (cd/m ²)	60	481	916	1076	1560	3374	731

Table 15 – MP daylit scenes (C1C8) with score of five or higher on QU1

MP Daylit Scenes (C1C8) with score of five or higher on QU1							
	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.	σ
<i>Illuminance</i>							
E_desktop (lux)	52	419	950	1119	1387	4910	994
E_ceiling (lux)	33	345	759	1026	1526	3013	787
E_vertical_eye (lux)	55	352	665	708	976	2602	436
<i>Luminance</i>							
X01_mean (cd/m ²)	35	142	241	268	358	805	164
X01_standard_deviation (cd/m ²)	57	370	598	696	953	4588	530
X01_cov	1.23	2.13	2.57	2.58	2.89	5.83	0.76
X01_98 th _percentile (cd/m ²)	195	1050	2056	2249	3080	8992	1534
X01_percent_below_30_cd/m ²	4.7%	11.6%	14.0%	17.3%	17.7%	85.0%	13.1%
X01_percent_above_2000_cd/m ²	0.0%	0.7%	2.1%	2.1%	3.1%	6.5%	1.6%
X08_mean_to_03_mean	1.60	10.38	15.50	15.88	20.45	56.84	8.40
X01_findglare_dgi_default	1.10	7.43	11.12	10.19	12.60	16.38	3.40
X03_evalglare_mL0005_dgp	16.5%	19.7%	21.4%	21.4%	23.0%	34.6%	2.7%
X08_standard_deviation	101	862	1386	1567	2250	4805	982
X08_mean (cd/m ²)	74	577	1001	1068	1473	3618	659

Table 16 – All JU scenes (C4C5C10C13) with score of three or lower on QUI

All JU Scenes (C4C5C10C13) with score of three or lower on QUI							
	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.	σ
<i>Illuminance</i>							
E_desktop (lux)	418	1435	2004	4288	2649	40920	7142
E_ceiling (lux)	115	1295	1688	1904	2385	3799	815
E_vertical_eye (lux)	51	1061	1402	1467	1755	4816	626
<i>Luminance</i>							
X01_mean (cd/m ²)	35	385	515	535	640	1568	233
X01_standard_deviation (cd/m ²)	93	976	1451	1587	2040	5278	867
X01_cov	1.39	2.21	2.85	2.93	3.42	8.37	0.90
X01_98 th _percentile (cd/m ²)	463	3392	4272	4426	5540	14530	1893
X01_percent_below_30_cd/m ²	0.3%	6.3%	9.2%	9.7%	11.8%	80.6%	8.3%
X01_percent_above_2000_cd/m ²	0.0%	3.7%	4.5%	4.6%	5.2%	15.0%	2.1%
X08_mean_to_03_mean	3.62	18.26	23.59	22.87	27.32	51.82	7.40
X01_findglare_dgi_default	0.00	10.92	12.75	12.18	14.20	18.39	2.97
X03_evalglare_mL0005_dgp	16.8%	23.4%	25.4%	25.5%	27.2%	38.7%	3.4%
X08_standard_deviation	218	2086	3191	3775	5054	12560	2189
X08_mean (cd/m ²)	162	1702	2171	2123	2511	6128	803

MD_daq08_illuminance_desktop Variability per Participant

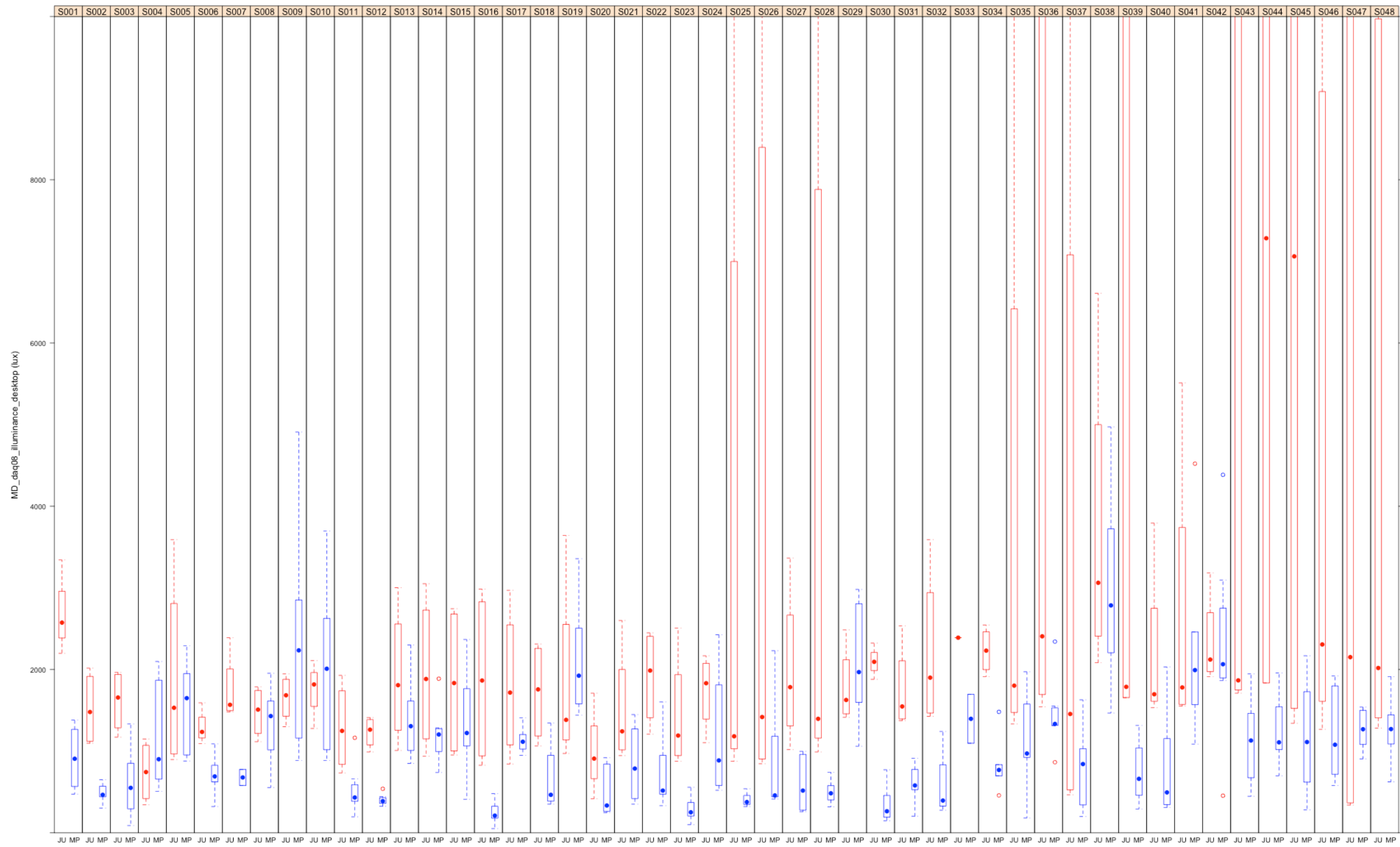


Figure 34 – Variability of E_{desktop} by participant for MP (blue) and JU (red) conditions

X08_mean_to_03_mean Variability per Participant

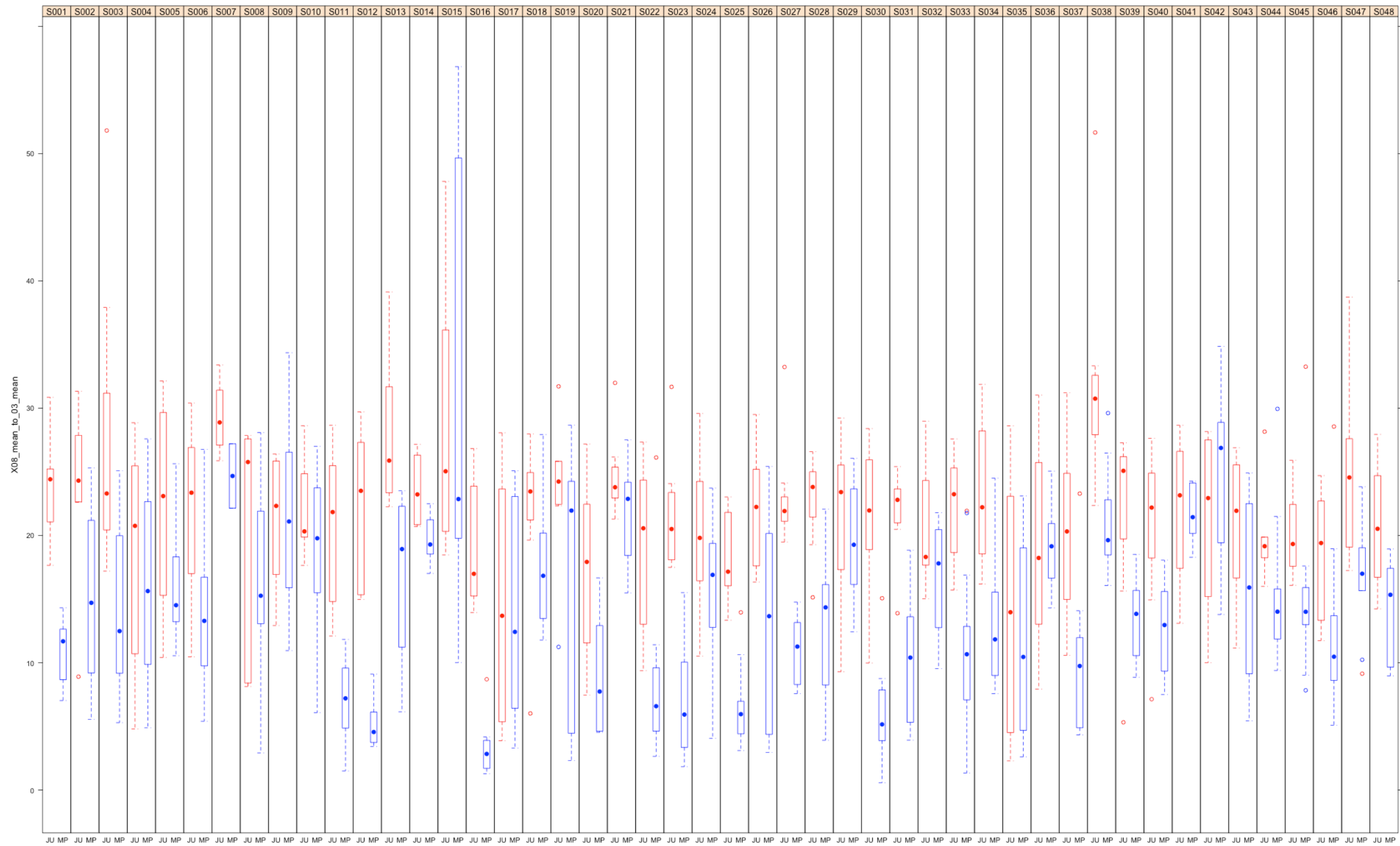


Figure 35 – Variability of luminance ratios (daylight source:task) by participant for MP (blue) and JU (red) conditions

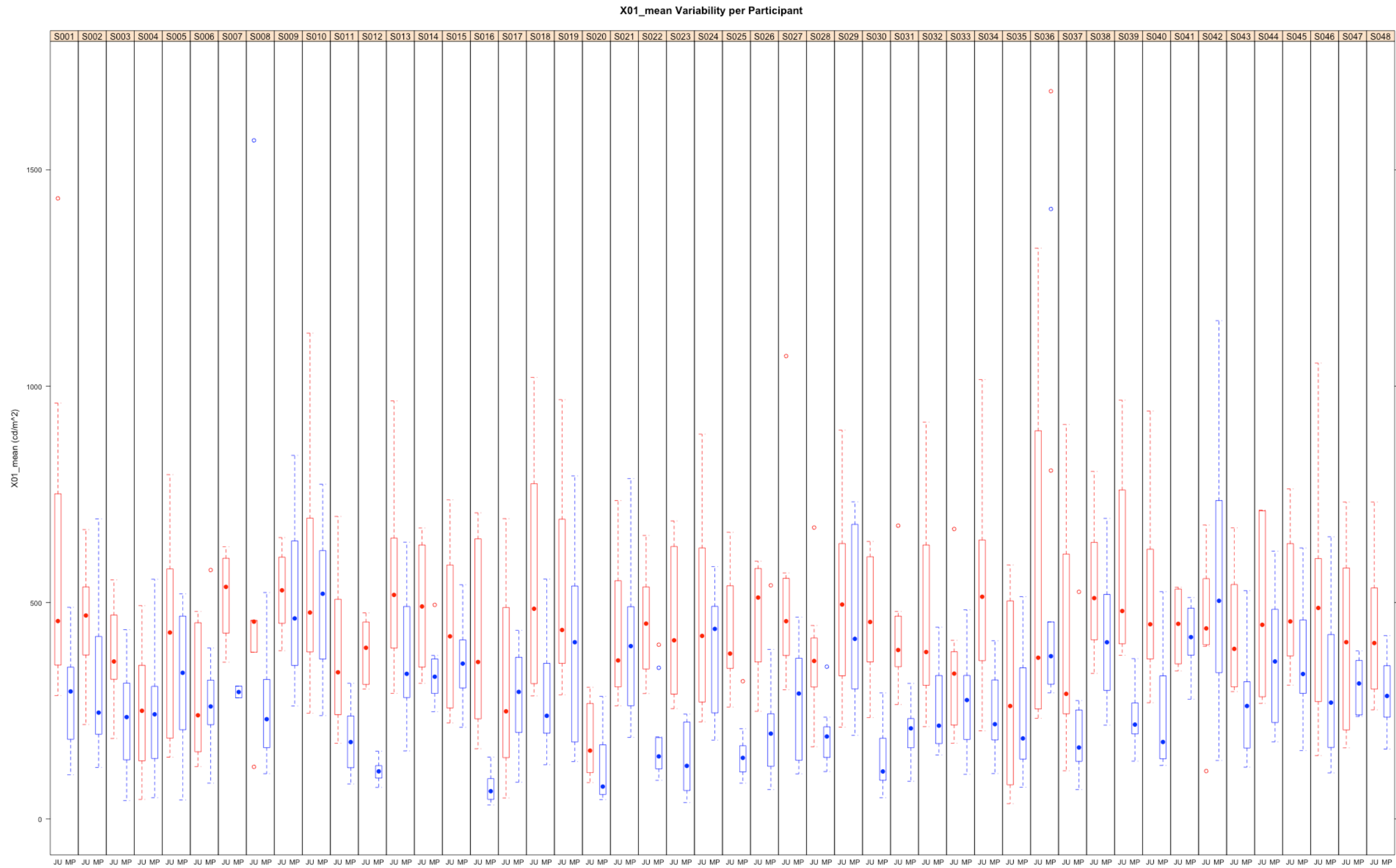


Figure 36 – Variability of mean scene luminance for mask 01 by participant for MP (blue) and JU (red) conditions

X03_evalglare_mL0005_dgp Variability per Participant

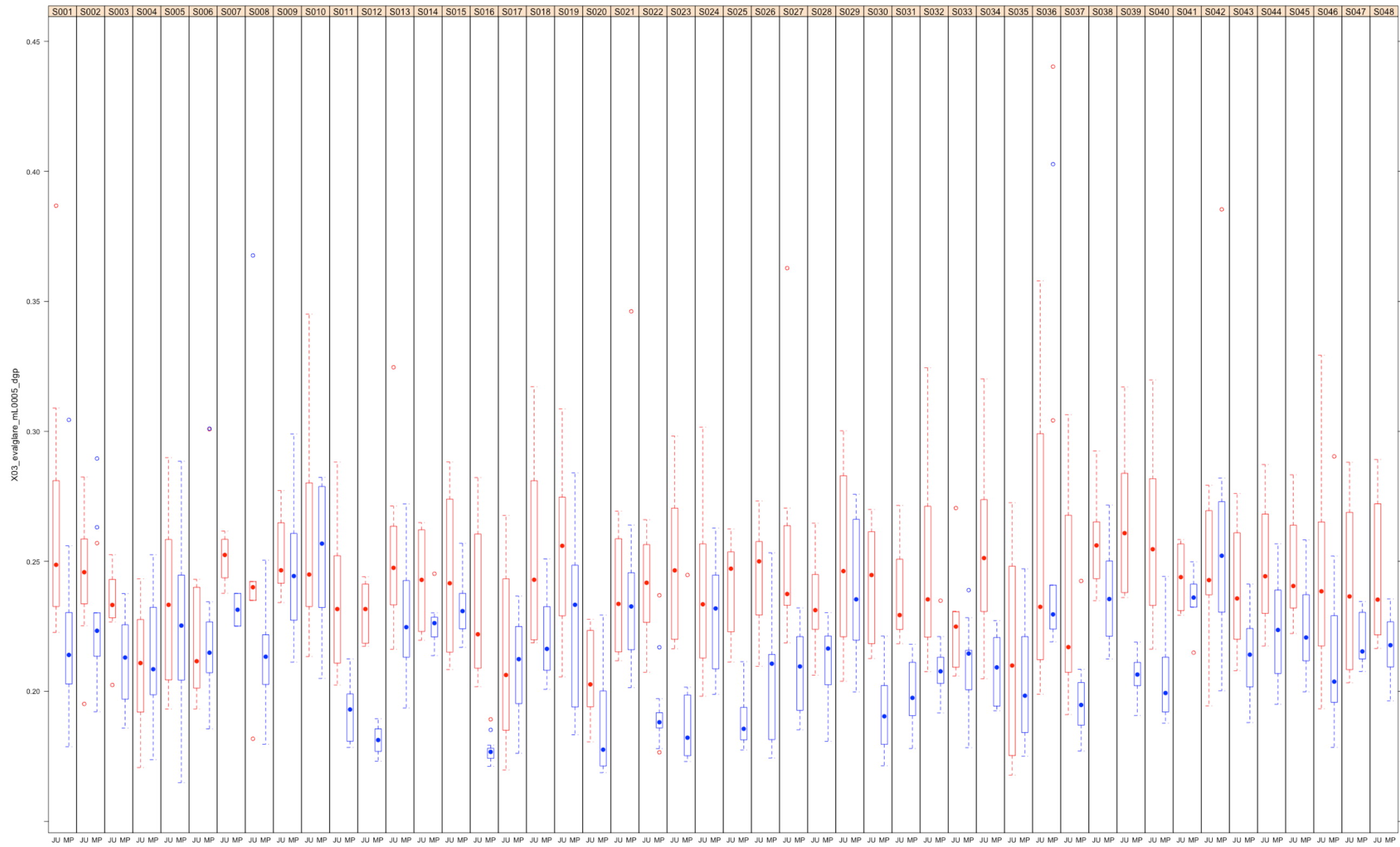


Figure 37 – Variability of DGP values (using five times the mean of X03 circle tasks mask to identify glare sources) by participant for MP (blue) and JU (red) conditions

4.1.2 Significant differences between MP and JU metric results

Tests of significant difference were done using Welch two-sample, one-way t-tests. The same selected metrics as presented in Section 4.1 were tested for their difference between the MP group (C1,C2,C6,C7,C8,C11,C14) and the JU group (C4,C5,C10,C13) as shown in Table 17. So as not to bias the results, the t-tests were conducted on all participant-scenes, not just those with Likert responses higher than five for MP conditions or lower than three for JU conditions. Therefore, the sample mean results shown in Table 17 differ slightly from those shown in Table 13 and Table 16. Note that all metrics reported are statistically different for MP and JU conditions at the 99% confidence level. While not every metric is presented, metrics that were found to be particularly meaningful for space analysis had statistically different results for MP and JU at the 99% confidence level.

Table 17 – Results of paired one-way Welch t-tests

MP Scenes (C1C2C6C7C8C11C14) versus JU Scenes (C4C5C10C13) one-way t-test					
	t-value	df	p-value	MP \bar{x}	JU \bar{x}
<i>Illuminance</i>					
E_desktop (lux)	-4.92	185.72	<0.01	1098	3178
E_ceiling (lux)	-7.54	338.35	<0.01	1041	1607
E_vertical_eye (lux)	-10.81	579.09	<0.01	796	1234
<i>Luminance</i>					
X01_mean (cd/m ²)	-11.40	621.27	<0.01	293	453
X01_standard_deviation (cd/m ²)	-10.21	594.94	<0.01	755	1263
X01_cov	-3.30	690.22	<0.01	2.56	2.74
X01_98 th _percentile (cd/m ²)	-13.02	671.66	<0.01	2446	3943
X01_percent_below_30_cd/m ²	6.07	832.05	<0.01	15.4%	11.5%
X01_percent_above_2000_cd/m ²	-13.31	679.44	<0.01	2.5%	4.2%
X08_mean_to_03_mean	-15.01	801.01	<0.01	14.34	21.79
X01_findglare_dgi_default	-11.26	835.47	<0.01	9.97	12.18
X03_evalglare_mL0005_dgp	-12.08	678.51	<0.01	21.6%	24.2%
X08_standard_deviation	-12.22	444.75	<0.01	1492	2917
X08_mean	-16.18	636.18	<0.01	1031	1845

4.1.3 Significant differences between subjective ratings for MP and JU conditions

Friedman tests (Table 18) were used to test for significant differences between conditions for each Likert and semantic-differential item. Conditions without significant differences in the responses to the Likert and semantic-differential item share the same alpha code in the column labeled with double asterisks (**). MP conditions are colored blue and JU conditions are colored red. The most important finding is that only one question (QU5) had any MP conditions that were significantly similar to JU conditions. This analysis confirmed that the subjective responses on Likert items were statistically different between MP and JU conditions.

The Friedman sum of ranks is denoted with a single asterisk (*). The condition with the lowest sum of ranks for each Likert question (QU1-QU7) indicates it as the least preferred condition for that question. Typically, C10 had the lowest sum of ranks. It is not necessary to use Friedman tests on the semantic-differential data since it is continuous, not ordinal. However, for the sake of consistency, selected semantic-differential data are presented using Friedman tests. The semantic differential question needs to be interpreted differently than the Likert items. The question “*When I look to my right the scene that I see seems: Too dim – Too bright*” is abbreviated “*right_scene*”. A score of 50 means “just right,” a score of zero means very dim and a score of 100 means very bright. Therefore, the sum of ranks is ordered by conditions generally rated as too bright to those that were rated as too dim. As expected, the JU conditions were rated as too bright, while MP conditions were rated near the middle, or “just right.”

Table 18 – Friedman test results by condition (*sum of ranks, **significant difference code)

Cond.	QU1*	QU1**	Cond.	QU2*	QU2**	Cond.	QU3*	QU3**
C7	650.5	b	C7	642.5	b	C7	626	b
C11	647	b	C11	630.5	b	C11	617.5	b
C14	612	bc	C14	626	b	C14	600	bc
C2	565.5	cd	C2	588.5	bc	C2	563.5	bcd
C1	557	d	C1	555	cd	C1	538.5	cde
C8	544.5	d	C6	527	d	C8	522	de
C6	530	d	C8	510.5	d	C6	497.5	e
C15	399	e	C15	412.5	e	C15	391	f
C12	365	ef	C5	386	e	C5	373	f
C5	365	ef	C4	324.5	f	C4	333.5	fg
C4	329	f	C12	308	fg	C12	287.5	gh
C9	249	g	C16	257.5	gh	C16	265.5	hi
C16	240.5	g	C9	240	hi	C3	252	hi
C3	175	h	C13	193.5	ij	C13	246	hi
C13	161.5	h	C3	177.5	j	C10	214	i
C10	146.5	h	C10	157.5	j	C9	209.5	i

Cond.	QU4*	QU4**	Cond.	QU5*	QU5**	Cond.	QU6*	QU6**
C7	615.5	b	C14	629.5	b	C1	588.5	b
C11	608.5	b	C11	618.5	b	C7	580.5	b
C14	608	b	C2	600.5	b	C11	559	b
C2	576.5	bc	C7	594.5	b	C2	545	bc
C1	544.5	cd	C1	499.5	c	C14	531.5	bcd
C6	531	cd	C6	491.5	c	C6	486	cde
C8	494.5	d	C8	455	cd	C8	483	de
C15	398.5	e	C5	426.5	d	C12	441.5	ef
C12	388.5	e	C16	353	e	C15	441	ef
C5	387	e	C4	331.5	e	C9	420.5	fg
C4	318	f	C15	331	e	C4	365	gh
C9	285	fg	C12	316	ef	C5	322	h
C16	252.5	g	C13	265.5	fg	C3	242.5	i
C3	189	h	C3	254	fg	C16	220.5	ij
C13	180.5	h	C10	202.5	gh	C10	168.5	jk
C10	159.5	h	C9	168	h	C13	142	k

QU1 – This is a visually comfortable environment for office work
QU2 – I am pleased with the visual appearance of the office
QU3 – I like the vertical surface brightness
QU4 – I am satisfied with the amount of light for computer work
QU5 – I am satisfied with the amount of light for paper-based reading work
QU6 – The computer screen is legible and does not have reflections

(Continued)

Cond.	QU7*	QU7**	Cond.	Right_scene*	right_scene**
C11	632	b	C13	705	b
C14	599.5	bc	C10	697	b
C7	589.5	bc	C4	571.5	c
C2	578.5	bc	C5	553	c
C6	553.5	c	C16	486	d
C1	540	cd	C3	408.5	e
C8	490.5	d	C2	390.5	ef
C15	400	e	C8	372	ef
C5	380	ef	C1	361	efg
C12	363.5	ef	C14	359	efg
C4	335.5	fg	C15	352.5	efg
C9	277.5	gh	C6	349	fg
C16	235.5	hi	C11	336.5	fg
C3	217	ij	C7	312	g
C13	181	ij	C12	169.5	h
C10	163.5	j	C9	114	h

QU7 – The lighting is distributed well
right_scene – When I look to my right the scene that I see seems: (too dim – too bright)

The Friedman test “sum of ranks” on Likert items show that participants preferred integrated lighting conditions (C7C11C14) over conditions with daylight alone (C1C8). All Likert item responses were combined into an overall satisfaction value described as “Likert_all” and a Welch two-sample, two-way t-test was calculated with results shown in Table 19. While there is a significant difference between the groups, the effect size is not large. Still, the difference between means of 2.42 out of 49 possible represents approximately a 5% increase in overall preference for integrated MP conditions over daylight-only MP conditions.

Table 19 – MP daylit scenes versus MP integrated scenes

MP Daylit Scenes (C1C8) versus MP Integrated Scenes (C7C11C14)						
	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
C1C8 Likert_all	15	33	37	37.33	42	49
C7C11C14 Likert_all	28	35	40	39.75	43	49
	t-value	df	p-value			
Two-way t-test	-3.94	279.28	0.0001			

It is probably not appropriate to attribute all of this effect to the conditions themselves since some of the difference could be due to the fact that two-thirds of the MP integrated lighting scenes occurred in the afternoon with the potential for higher daylight levels in the southwest-facing study space and only half of the MP daylight-only scenes occurred in the afternoon. Nonetheless, it seems that the availability of personally controlled electric lighting to supplement daylight is preferable to daylight alone. This is discussed further in Section 4.2.

4.2 Understanding electric lighting use in integrated lighting environments

The mean response to “I was able to improve the environment by adding electric light” was 5.0 (agree) for C2 compared to C1, with more than 80% of the participants agreeing with the statement. The mean response for “I was able to worsen the environment by adding electric light” was 5.5 (agree-strongly agree) for C3 compared to C1, with more than 95% of the participants agreeing with the statement.

As was shown in Section 4.1.3, there is a statistically significant preference for MP integrated lighting over MP daylight-only scenes. It is interesting to note that in MP integrated lighting conditions (C7C11C14) participants chose a mean electric lighting value of almost 75% dimmed (Table 20), thus adding approximately 125-200 lux of supplemental electric lighting at the desktop (depending on desktop measurement location, see Figure 11 and Figure 12).

Table 20 – Desktop illumination from daylight & electric light, and dimming signal for MP integrated lighting conditions

MP Integrated Scenes (C7C11C14)						
	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
Electric_light_percent_dimmed	0.0%	57.9%	84.3%	72.9%	100.0%	100.0%
E_desktop_total (lux)	100	548	1003	1257	1766	4973
E_desktop_daylight (lux)	100	453	871	1139	1642	4864
E_desktop_electric (lux)	0	0	78	136	210	500

In all MP integrated lighting scenes, 30% of the participants elected to turn the electric lights off and only 10% of participants elected to dim electric lights by less than 10%. In C15, participants were instructed to leave blinds as they were for the MP integrated lighting in C14, and dim the electric lights until “the scene is just too dim,” and if they felt the scene did not get too dim, to turn the electric lights off if they wished. For this condition (C15), all participants chose to dim electric lights by at least 40%, while the mean was 96% dimmed, and 83% of participants elected to turn the electric lights off. In C16, participants were instructed to leave blinds as they were for the MP integrated lighting (in C14), and brighten the electric lights until “the scene is just too bright,” and if they felt the scene did not get too bright, to turn the electric lights all the way on (0% dimmed) if they wished. For this condition (C16), 6% of the participants indicated that adding any electric light whatsoever made “the scene too bright.” The mean response for “the scene is just too bright” was to dim the electric lights by 35% dimmed (65% on), while almost 40% of participants elected to turn the electric lights essentially all the way on (less than 10% dimmed) without indicating “the scene was just too bright.” In open-ended comments, only two participants indicated that they felt the electric light fixture itself was inherently too bright or glaring.

4.3 Single regressions and subjective responses

Table 21 and Table 22 present squared correlation coefficients, using the Pearson pairwise method, between selected lighting metrics and questionnaire items for conditions C1, C2, C4, C6, C7, C8, C10, C11, C13 and C14 (hereafter C1C2C4C6C7C8C10C11C13C14 or composite data set). Section 3.6.4 discusses the use of Pearson as opposed to Spearman correlation methods. Note that some conditions (C3, C5, C9, C12, C15, C16) were ignored from these analyses since these conditions had unique characteristics meant for other purposes. Furthermore, for some analyses, data were filtered to remove scenes from JU conditions (C4, C10, C13) that were rated by participants as four or higher on QU4. Similarly, data were filtered to remove scenes from MP conditions (C1, C2, C6, C7, C8, C11, C14) that were rated as four or lower by participants on QU4. This was done to remove data that were not rated as uncomfortable from JU conditions since it was sometimes not possible to create uncomfortable scenes (e.g. due to sky cover). When data were filtered this way they are denoted with “Computer_split53” appended at the end of the condition string (e.g. composite_data_set_Computer_split53).

In Table 21 and Table 22 results from seven Likert items, four semantic differential (too dim – too bright) items, and the overall scene preference semantic differential (least preferred – most preferred) item are summarized for selected illuminance- and luminance-based lighting metrics. These results are presented in ranked order by the item “right_scene” since this item had the highest overall squared correlation coefficient. (For the top 20 metrics ranked by squared correlation coefficients for each subjective item individually see Section 8.1.) The item right_scene rates whether the scene toward the participants’ right side was too dim or too bright; thus, it is the assessment of the brightness of the window wall, the window and the scene out the

window. Table 21 depicts the 20 highest squared correlation coefficients for `right_scene`, and Table 22 includes other commonly referenced, or otherwise selected, metrics of interest. The metrics' rank with regard to `right_scene` is in the leftmost column of each table, and the abbreviated metric names are in the next column to the right. These abbreviations are self-explanatory. For example, the metric abbreviated "X08_standard_deviation" is the standard deviation of the luminance within mask eight (X08), which is the entire window. Each mask and the associated reference number are depicted in Figure 32. Additionally, **bolded 12 pt** text indicates the metrics' r^2 value ranked in the top 10 for a specific question, and **bolded 14 pt** text indicates the metrics' r^2 value ranked highest for a specific question. **Pink** fill indicates the metrics' r^2 value was greater than or equal to 0.20 while **yellow** fill indicates the metrics' r^2 value was greater than or equal to 0.10 but less than 0.20. The results in Table 21 and Table 22 represent r^2 values. These values are generally higher than *adjusted*- r^2 ($adjr^2$) values; however, given the substantial size of this sample data, the r^2 and $adjr^2$ figures are almost identical. For example, for X08_standard_deviation relative to `right_scene`, the $r^2 = 0.4252$ as shown in Table 21 is inconsequentially lower than the $adjr^2 = 0.4244$. This example is based upon a single regression with 690 degrees of freedom ($F_{1,690}$), where $F_{1,690} = 510.4$, and has significance at $p < 0.00001$ (written, $adjr^2 = 0.42$, $F_{1,690} = 510.4$, $p < 0.01$).

Luminance metrics based upon X08, X10 and X20 are the most common among the top 20 metrics for `right_scene`. X08_standard_deviation has the highest squared correlation coefficient for six of the seven Likert items as well as `right_scene`. There are several metrics based upon the horizontal 40° band within the FOV (X20) in the top 20 including X20_mean, X20_percent_below_1000_cd (percent of scene pixels below 1000 cd/m²) and X20_75th_percentile. No metrics based upon the entire scene (X01) rank in the top 20, nor do

any based upon illuminance or irradiance data, nor for DGI/DGP or any other glare indices, nor for luminance ratios or contrast ratios as discussed in Table 12. As noted above, right_scene is the item with the overall highest squared correlation coefficient. However, QU1, QU4 and QU6 are clustered together as the next highest and address a different construct than right_scene, namely a more holistic assessment of human visual preference and acceptance. Of these, QU1 represents the most general characterization of visual comfort and is therefore used in addition to right_scene in the detailed metric-by-metric analysis in Sections 4.3.1 through Section 4.3.10.

Table 21 – Top 20 ranked r^2 values ordered by “right_scene” (using composite_data_set_Computer_split53)

Rank	Top 20 Metrics (ordered by right_scene)	QU1	QU2	QU3	QU4	QU5	QU6	QU7	Likert_all	front_scene	left_scene	right_scene	ceiling	light_in_scene
1	X08_standard_deviation	0.2983	0.2543	0.1635	0.3019	0.1495	0.2809	0.2322	0.2875	0.0908	0.0721	0.4252	0.1133	0.0646
2	X10_25 th _percentile	0.2713	0.2240	0.1410	0.2887	0.1334	0.2690	0.2178	0.2636	0.1243	0.1004	0.3890	0.0790	0.0770
3	X10_50 th _percentile	0.2447	0.1921	0.1256	0.2511	0.1149	0.2239	0.1853	0.2283	0.1452	0.1034	0.3697	0.0616	0.0847
4	X08_25 th _percentile	0.2570	0.2233	0.1590	0.2874	0.1304	0.2877	0.2163	0.2662	0.1130	0.1127	0.3589	0.1009	0.0418
5	X08_mean	0.2411	0.1931	0.1280	0.2502	0.1165	0.2367	0.1777	0.2291	0.1132	0.0917	0.3401	0.0769	0.0790
6	X20_mean	0.2436	0.1939	0.1301	0.2518	0.1130	0.2358	0.1892	0.2315	0.1247	0.1098	0.3312	0.0670	0.0793
7	X13_75 th _percentile	0.2421	0.2080	0.1564	0.2630	0.1224	0.2698	0.2070	0.2506	0.1233	0.1715	0.3242	0.1028	0.0934
8	X14_10 th _percentile	0.2261	0.1916	0.1347	0.2486	0.1079	0.2535	0.1849	0.2293	0.1177	0.1444	0.3214	0.0988	0.1051
9	X10_10 th _percentile	0.2406	0.2066	0.1237	0.2573	0.1355	0.2494	0.2092	0.2431	0.0802	0.0718	0.3199	0.0763	0.0440
10	X20_percent_below_1000_cd	0.2149	0.1594	0.1130	0.2276	0.0913	0.2031	0.1560	0.1982	0.1341	0.1067	0.3185	0.0517	0.1140
11	X23_50 th _percentile	0.2306	0.1995	0.1431	0.2549	0.1098	0.2682	0.1952	0.2384	0.1046	0.1356	0.3147	0.1005	0.0782
12	X20_75 th _percentile	0.2299	0.1907	0.1348	0.2539	0.1076	0.2687	0.1898	0.2336	0.1189	0.1399	0.3135	0.0924	0.0814
13	X14_25 th _percentile	0.2188	0.1855	0.1315	0.2417	0.1049	0.2494	0.1802	0.2232	0.1074	0.1399	0.3097	0.0938	0.0847
14	X20_25 th _percentile	0.2250	0.1883	0.1302	0.2474	0.1082	0.2672	0.1914	0.2307	0.1026	0.1262	0.3084	0.1064	0.0738
15	X14_2 nd _percentile	0.2131	0.1806	0.1249	0.2355	0.1002	0.2407	0.1736	0.2157	0.1116	0.1361	0.3073	0.0937	0.1025
16	X20_90 th _percentile	0.2122	0.1592	0.1076	0.2175	0.0896	0.2026	0.1527	0.1941	0.1516	0.1122	0.3052	0.0517	0.0695
17	X18_50 th _percentile	0.2311	0.2026	0.1457	0.2518	0.1118	0.2716	0.1994	0.2407	0.0946	0.1221	0.3043	0.0970	0.0594
18	X20_50 th _percentile	0.2106	0.1787	0.1291	0.2355	0.0990	0.2467	0.1760	0.2168	0.1107	0.1415	0.2999	0.1014	0.0907
19	X19_25 th _percentile	0.2157	0.1889	0.1326	0.2420	0.1007	0.2695	0.1862	0.2265	0.0964	0.1218	0.2993	0.1126	0.0767
20	X08_50 th _percentile	0.2036	0.1604	0.1233	0.2209	0.0914	0.2145	0.1548	0.1989	0.1365	0.1078	0.2991	0.0723	0.0461
<p>QU1 – This is a visually comfortable environment for office work QU2 – I am pleased with the visual appearance of the office QU3 – I like the vertical surface brightness QU4 – I am satisfied with the amount of light for computer work QU5 – I am satisfied with the amount of light for paper-based reading work QU6 – The computer screen is legible and does not have reflections QU7 – The lighting is distributed well</p>										<p><i>front_scene</i> – When I look up from my desk does the scene I see in front of me seem: (too dim – too bright) <i>left_scene</i> – When I look to my left the scene that I see seems: (too dim – too bright) <i>right_scene</i> – When I look to my right the scene that I see seems: (too dim – too bright); this direct included the window <i>ceiling</i> – I find the ceiling to be: (too dim – too bright) <i>light_in_scene</i> – I find this lighting condition to be: (least preferred – most preferred), [C9,C10, C12, C13, C15, C16 only]</p>				

Table 22 – Selected r² values ordered by “right_scene” (using composite_data_set_Computer_split53)

Rank	Other metrics of interest (by right_scene)	QU1	QU2	QU3	QU4	QU5	QU6	QU7	Likert_all	front_scene	left_scene	right_scene	ceiling	light_in_scene
21	MD_daq02_illuminance_topFF406 (E _v)	0.2389	0.2004	0.1500	0.2602	0.1182	0.2833	0.2132	0.2496	0.1044	0.1308	0.2982	0.0909	0.0494
58	X03_evalglare_mL0005_dgp	0.1983	0.1632	0.1079	0.2156	0.0931	0.2257	0.1667	0.1989	0.0772	0.0861	0.2808	0.0703	0.0572
59	X20_standard_deviation	0.2107	0.1713	0.1155	0.2095	0.0976	0.1851	0.1694	0.1982	0.0757	0.0582	0.2805	0.0464	0.0164
68	X01_evalglare_mL0005_dgp	0.1832	0.1510	0.1011	0.2010	0.0879	0.2109	0.1564	0.1855	0.0748	0.0859	0.2783	0.0740	0.0786
69	X01_mean	0.2001	0.1718	0.1152	0.2230	0.0968	0.2431	0.1681	0.2068	0.0852	0.1035	0.2780	0.0946	0.0645
91	X01_standard_deviation	0.2017	0.1793	0.1135	0.2185	0.1040	0.2231	0.1736	0.2070	0.0588	0.0595	0.2755	0.0894	0.0627
129	daq01_illuminance_topcanon	0.2068	0.1700	0.1210	0.2351	0.0968	0.2633	0.1814	0.2161	0.0846	0.1031	0.2667	0.1175	0.0102
162	X01_evalglare_mL0005_lum_sources	0.1945	0.1692	0.1061	0.2099	0.0994	0.2222	0.1623	0.1981	0.0666	0.0741	0.2596	0.0956	0.0527
164	X20_percent_above_2000_cd	0.1638	0.1206	0.0818	0.1618	0.0648	0.1460	0.1027	0.1429	0.1257	0.0966	0.2574	0.0447	0.1149
193	X01_brightest_10percent	0.1749	0.1500	0.0956	0.1932	0.0868	0.2089	0.1449	0.1791	0.0681	0.0762	0.2410	0.0785	0.0495
244	X01_98 th _percentile	0.1643	0.1382	0.0861	0.1782	0.0795	0.1820	0.1313	0.1632	0.0816	0.0796	0.2208	0.0632	0.0572
256	X01_percent_above_2000_cd	0.1516	0.1202	0.0820	0.1623	0.0598	0.1886	0.1126	0.1477	0.0897	0.0880	0.2138	0.0763	0.0553
309	X08_percent_above_2000_cd	0.1243	0.0840	0.0605	0.1299	0.0428	0.1232	0.0725	0.1072	0.1006	0.0720	0.1920	0.0367	0.0676
340	X01_findglare_dgi_th0500	0.1251	0.0927	0.0654	0.1383	0.0455	0.1401	0.0919	0.1182	0.0905	0.0670	0.1784	0.0480	0.0687
404	SW_vert_irradiance_adjusted	0.1070	0.1003	0.0669	0.1321	0.0608	0.1447	0.1058	0.1217	0.0380	0.0704	0.1487	0.0514	0.0078
408	X08_mean_to_03_mean	0.0914	0.0581	0.0403	0.0963	0.0324	0.0682	0.0498	0.0736	0.0610	0.0281	0.1454	0.0156	0.0051
445	daq08_illuminance_desktop	0.1070	0.1132	0.0859	0.1178	0.1282	0.1136	0.1347	0.1369	0.0095	0.0198	0.1133	0.0183	0.0005
466	X21_mean_to_01_mean	0.0902	0.0751	0.0559	0.0926	0.0302	0.0998	0.0790	0.0883	0.0334	0.0298	0.0968	0.0410	0.0092
467	daq04_illuminance_topmonitor	0.0789	0.0755	0.0491	0.0867	0.0431	0.1194	0.0745	0.0892	0.0460	0.0524	0.0961	0.0739	0.0494
483	X21_mean_to_23_mean	0.0881	0.0734	0.0564	0.0872	0.0298	0.0907	0.0771	0.0851	0.0295	0.0249	0.0898	0.0375	0.0088
485	X01_percent_below_30_cd	0.0515	0.0423	0.0348	0.0785	0.0172	0.1057	0.0444	0.0607	0.0424	0.0517	0.0877	0.0350	0.0174
490	X12_mean_to_03_mean	0.0508	0.0334	0.0287	0.0681	0.0112	0.0636	0.0311	0.0469	0.0556	0.0583	0.0857	0.0253	0.0002
499	X22_to_21_contrast	0.0653	0.0526	0.0403	0.0793	0.0184	0.1007	0.0560	0.0681	0.0410	0.0411	0.0821	0.0364	0.0167
500	X21_mean_to_22_mean	0.0653	0.0526	0.0403	0.0793	0.0184	0.1007	0.0560	0.0681	0.0410	0.0411	0.0821	0.0364	0.0167
503	X01_to_03_contrast	0.0580	0.0424	0.0391	0.0762	0.0141	0.0854	0.0448	0.0591	0.0466	0.0415	0.0814	0.0276	0.0000
504	X03_mean_to_01_mean	0.0580	0.0424	0.0391	0.0762	0.0141	0.0854	0.0448	0.0591	0.0466	0.0415	0.0814	0.0276	0.0000
528	X21_mean_to_23_standard_deviation	0.0742	0.0635	0.0506	0.0609	0.0315	0.0547	0.0613	0.0679	0.0083	0.0042	0.0639	0.0244	0.0226
529	X21_mean_to_01_standard_deviation	0.0740	0.0630	0.0515	0.0625	0.0326	0.0559	0.0605	0.0685	0.0080	0.0030	0.0633	0.0221	0.0221
532	X21_mean_to_01_90 th _percentile	0.0335	0.0308	0.0231	0.0492	0.0077	0.0597	0.0344	0.0388	0.0334	0.0447	0.0621	0.0330	0.0095
535	X01_findglare_dgi_default	0.0456	0.0278	0.0188	0.0427	0.0151	0.0315	0.0235	0.0346	0.0240	0.0053	0.0583	0.0011	0.0045
563	X01_cov	0.0509	0.0504	0.0298	0.0382	0.0324	0.0306	0.0497	0.0484	0.0000	0.0003	0.0430	0.0171	0.0044
595	X21_mean_to_01_98 th _percentile	0.0473	0.0368	0.0273	0.0402	0.0131	0.0370	0.0373	0.0405	0.0196	0.0038	0.0303	0.0082	0.0203
616	X08_mean_to_12_mean	0.0283	0.0178	0.0128	0.0175	0.0192	0.0047	0.0154	0.0192	0.0034	0.0032	0.0267	0.0009	0.0000
	QU1 – This is a visually comfortable environment for office work QU2 – I am pleased with the visual appearance of the office QU3 – I like the vertical surface brightness QU4 – I am satisfied with the amount of light for computer work QU5 – I am satisfied with the amount of light for paper-based reading work QU6 – The computer screen is legible and does not have reflections QU7 – The lighting is distributed well									front_scene – When I look up from my desk does the scene I see in front of me seems: (too dim – too bright) left_scene – When I look to my left the scene that I see seems: (too dim – too bright) right_scene – When I look to my right the scene that I see seems: (too dim – too bright); this direct included the window ceiling – I find the ceiling to be: (too dim – too bright) light_in_scene – I find this lighting condition to be: (least preferred – most preferred), [C9,C10, C12, C13, C15, C16 only]				

The following sections present detailed results for several of the top rated, commonly cited, or otherwise selected metrics. These sections are structured to describe a range of characteristics for each metric. Note that none of the graphs used the “Computer_split53” data; instead they used the entire data set for the specified condition groups, C8 with C10 (hereafter, C8C10) and the composite data set.

First, each metric was investigated for its ability to consistently differentiate between MP and JU scenes within-subjects using results from C8C10. This pair of conditions was selected for two reasons. Firstly, C8 and C10 occurred within 30 minutes of one another, thus making these conditions ideal for analyses between MP and JU daylight scenes within-subjects because they excluded most temporal confounding factors (e.g. variable sky conditions, sun position). Secondly, C8 and C10 always occurred in the afternoon, thus increasing the potential of creating JU scenes for C10 given the southwest-facing aperture. In fact, as shown in Table 18, C10 was rated as one of the lowest in each of the subjective questionnaire items. The participants were instructed to create their MP scene for C8 and a JU scene for C10 using blind controls to adjust daylight levels and distribution, and were instructed to leave the electric light off. The blinds were closed for C9, and this condition was markedly darker than C8 or C10. However, there was ample time built into the study sequence (three to four minutes) to ensure adaptation before establishing C10. These plots (e.g. Figure 39) are useful in discerning whether there is a point at which the metric becomes inconsistent, or is unable to discern between MP and JU scenes within-subjects for each particular participant-day.

Next, scatter plots were created with a first-degree line of fit as well as a *loess* (locally weighted polynomial regression smoothing) polynomial line for each metric relative to both QU1 and right_scene. The $_{adj}r^2$ values noted in these figures (e.g. Figure 40 and Figure 41) represent

the first-degree line of fit. These plots are provided for both the C8C10 data set and the composite data set. Both data sets are shown since C8C10 is useful when examining variance across a relatively short time period (approximately 30 minutes) within-subjects, whereas the composite data set is useful when examining variance across the span of an entire day. These plots provide graphical representation of the relationship between each metric and a subjective rating, and thus provide insight to the overall predictive strength, sensitivity, and potential limitations of each metric with regard to design guidance and environmental control. The loess line is useful for determining if the relationship between various metrics and subjective responses is linear or nonlinear, and suggests the approximate degree and shape of nonlinearity. Loess methods are suggested for non-parametric and exploratory analyses (Cleveland & Devlin 1988) and are well-suited to the nature of this research. However, the adjusted correlation coefficients are reported for the first-degree line of fit so as not to be overstated due to the potential “overfitting” of the loess curve.

Then, each metric was plotted using C8C10 data, ordered by the metric result, with data points color-coded by the subject response to QU1. These plots are useful in discerning the most preferred and least preferred ranges of the metric as well as the typical changeover range, described hereafter as the bounded-borderline between comfort and discomfort (bounded-BCD). These plots, are therefore, the most useful for indicating recommended performance criteria; however, these must be considered preliminary in nature.

4.3.1 Standard deviation of window luminance (X08)



Figure 38 – Mask eight (X08) encompasses the entire window

The standard deviation of the luminance values within the entire window (X08_standard_deviation, X08 shown in Figure 38) represents the highest squared correlation coefficient for six of the seven Likert items (all except QU6) as well as right_scene for the composite data set. It is also one of the 10 highest for QU6 and the rating of “ceiling” brightness. Figure 39 shows the results for C8C10 with participant-days results ordered by C10 results. The metric correctly differentiates C10 (MP) from C8 (JU) scenes in most cases, especially where $C10 \sigma > 3000 \text{ cd/m}^2$. However, there are several cases where C10 scenes have lower X08_standard_deviation than other participant-day C8 cases. Figure 40 represents the ability of the metric to explain the variance in QU1 and right_scene for C8C10 and Figure 41 does the same for the composite data set. Each plot includes linear and loess polynomial fits with the $\text{adj}t^2$ value representing the first-degree linear fit. The single regression statistics can be seen in Table 23. Finally, Figure 42 takes the C8C10 data, organizes it by the metric result, and color-codes it by the response to QU1. This graphic reveals three preliminary thresholds for criteria development as described in Table 24.

Table 23 – X08_standard_deviation single regression results

C8C10: X08_standard_deviation (cd/m²)				
DV	adjR²	F-statistic:	DF	p-value
C8C10				
QU1	0.2880	70.98	172	1.39E-14
right_scene	0.3553	96.32	172	2.20E-16
Composite_data_set				
QU1	0.2667	314.10	860	2.20E-16
right_scene	0.3834	536.40	860	2.20E-16
C8C10Computer_split53				
QU1	0.3108	59.18	128	3.36E-12
right_scene	0.3526	71.26	128	5.81E-14
Composite_data_set_Computer_split53				
QU1	0.2973	293.40	690	2.20E-16
right_scene	0.4244	510.40	690	2.20E-16

C8C10: X08_standard_deviation

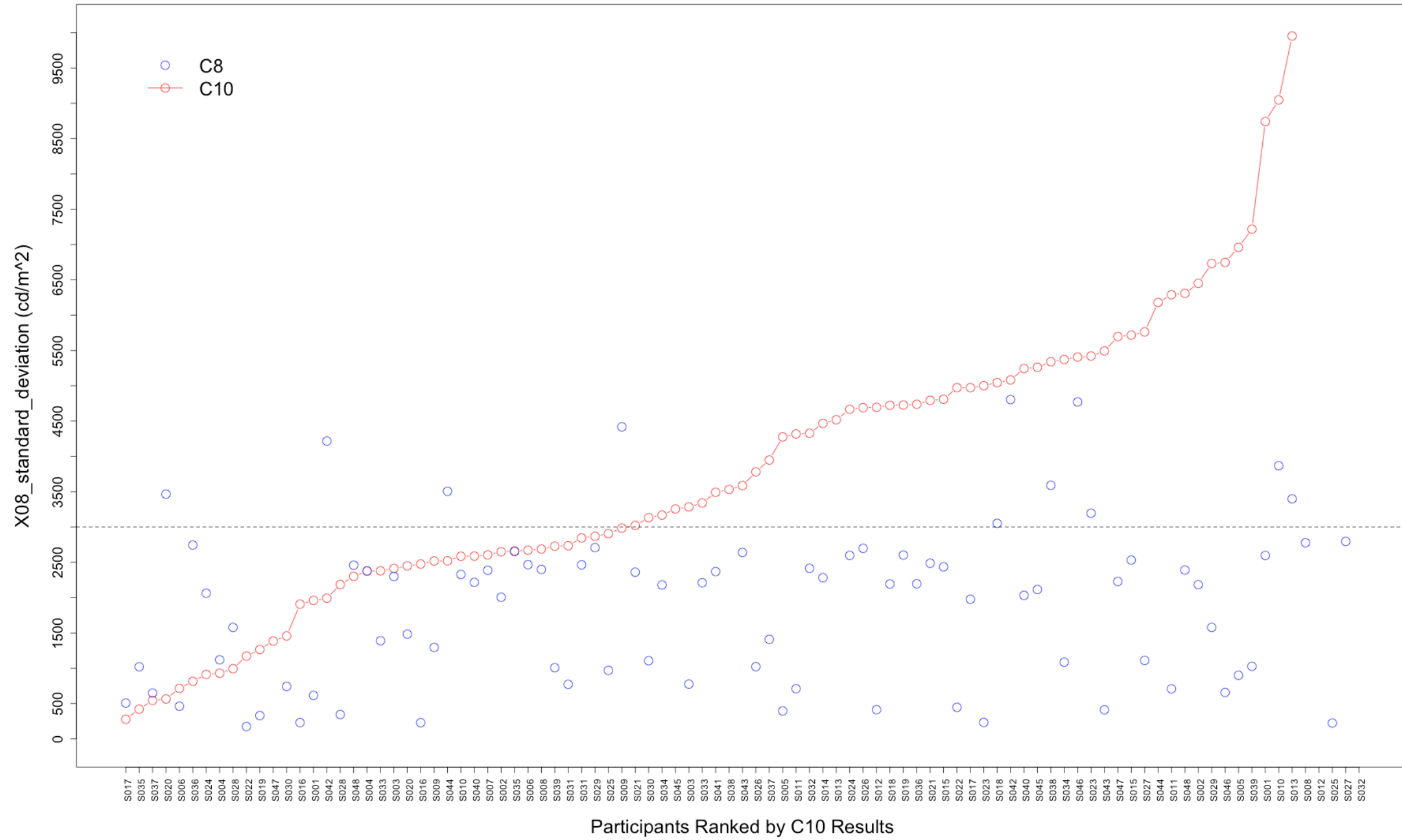


Figure 39 – Standard deviation of window luminance (X08) for C8 (MP) & C10 (JU), participant-days ranked by C10 results

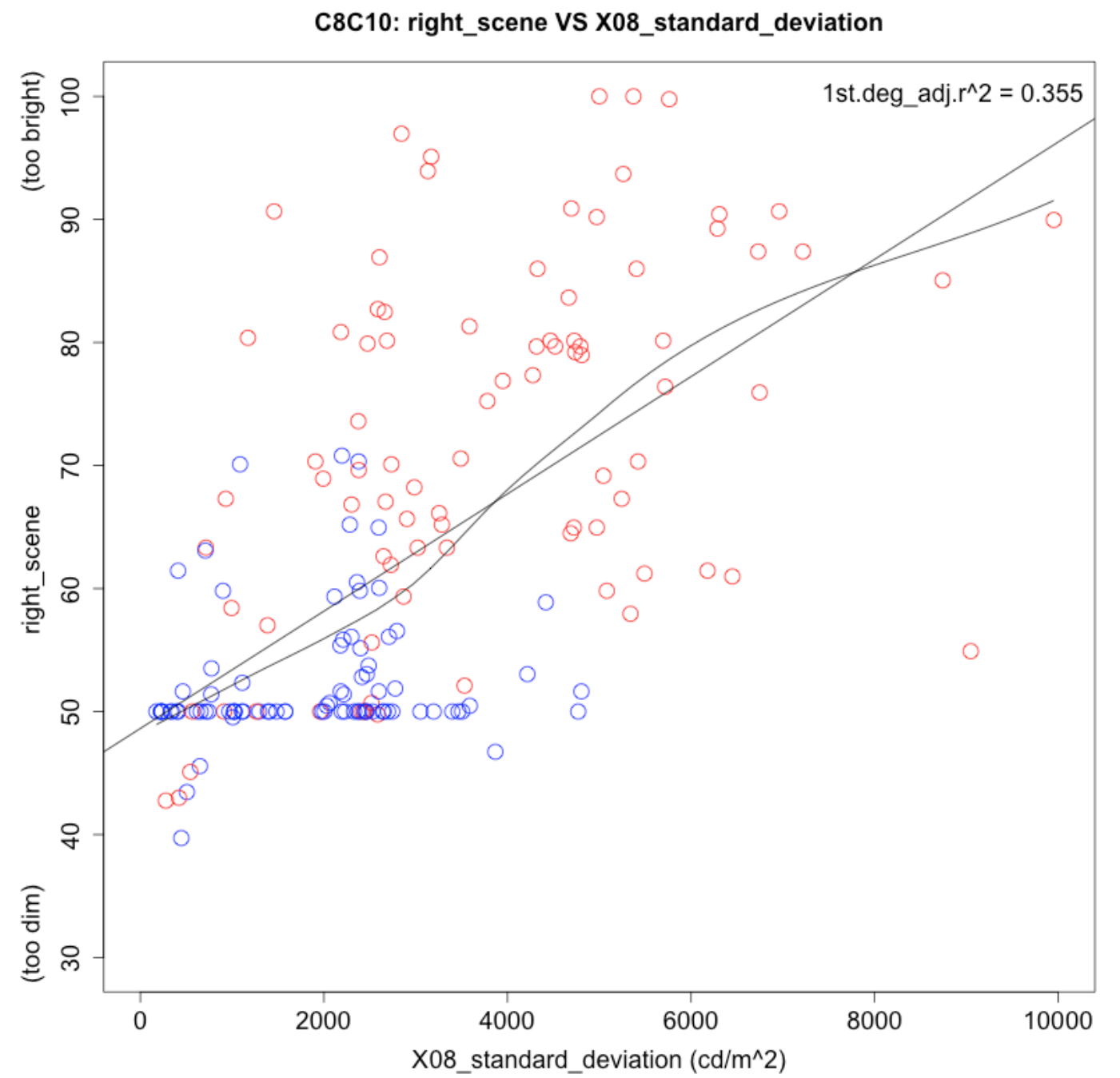
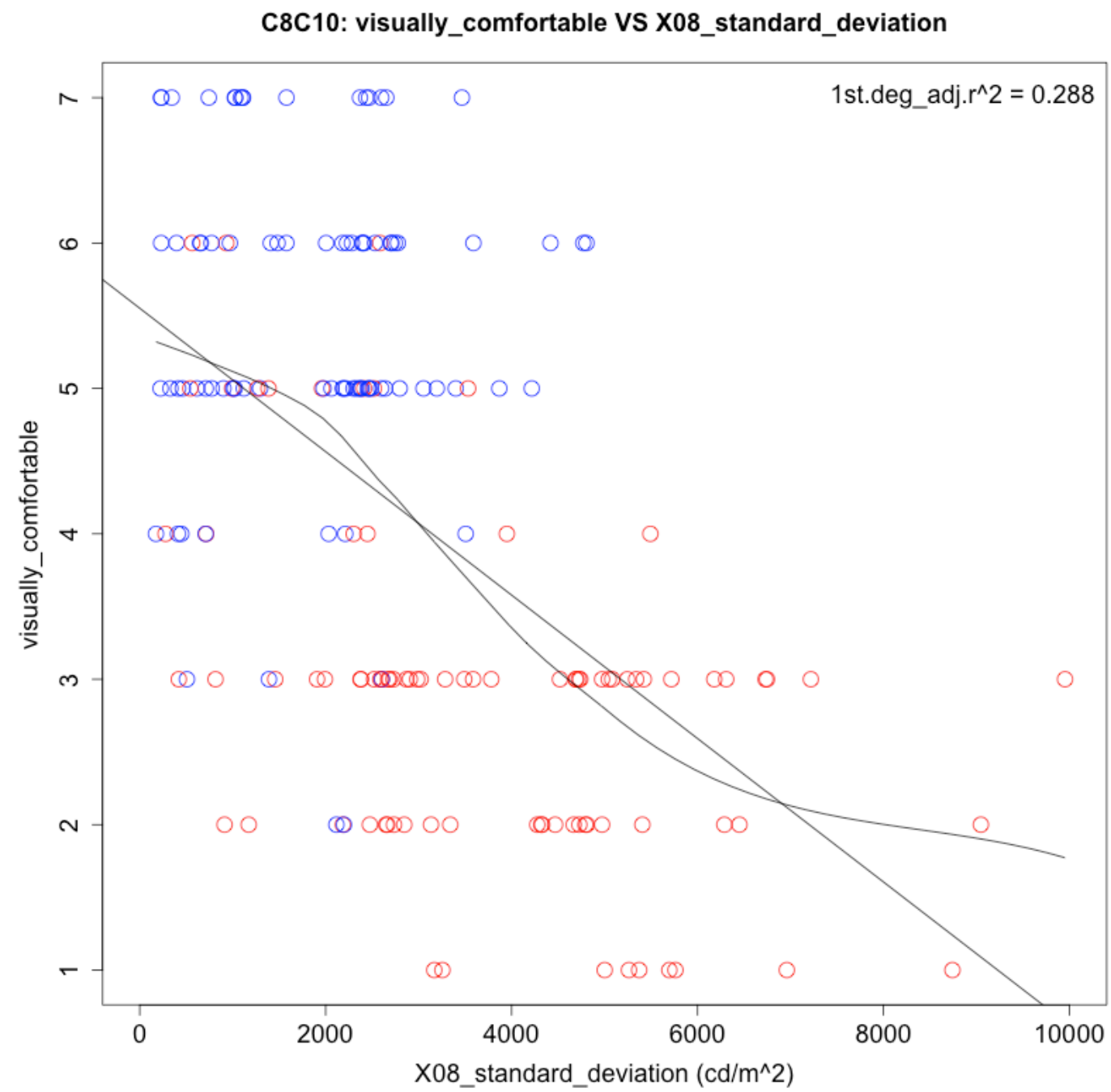


Figure 40 – Standard deviation of window luminance (X08) versus subjective ratings of QU1 (left) and right_scene (right) for C8C10, note $adjr^2$ value is for linear fit

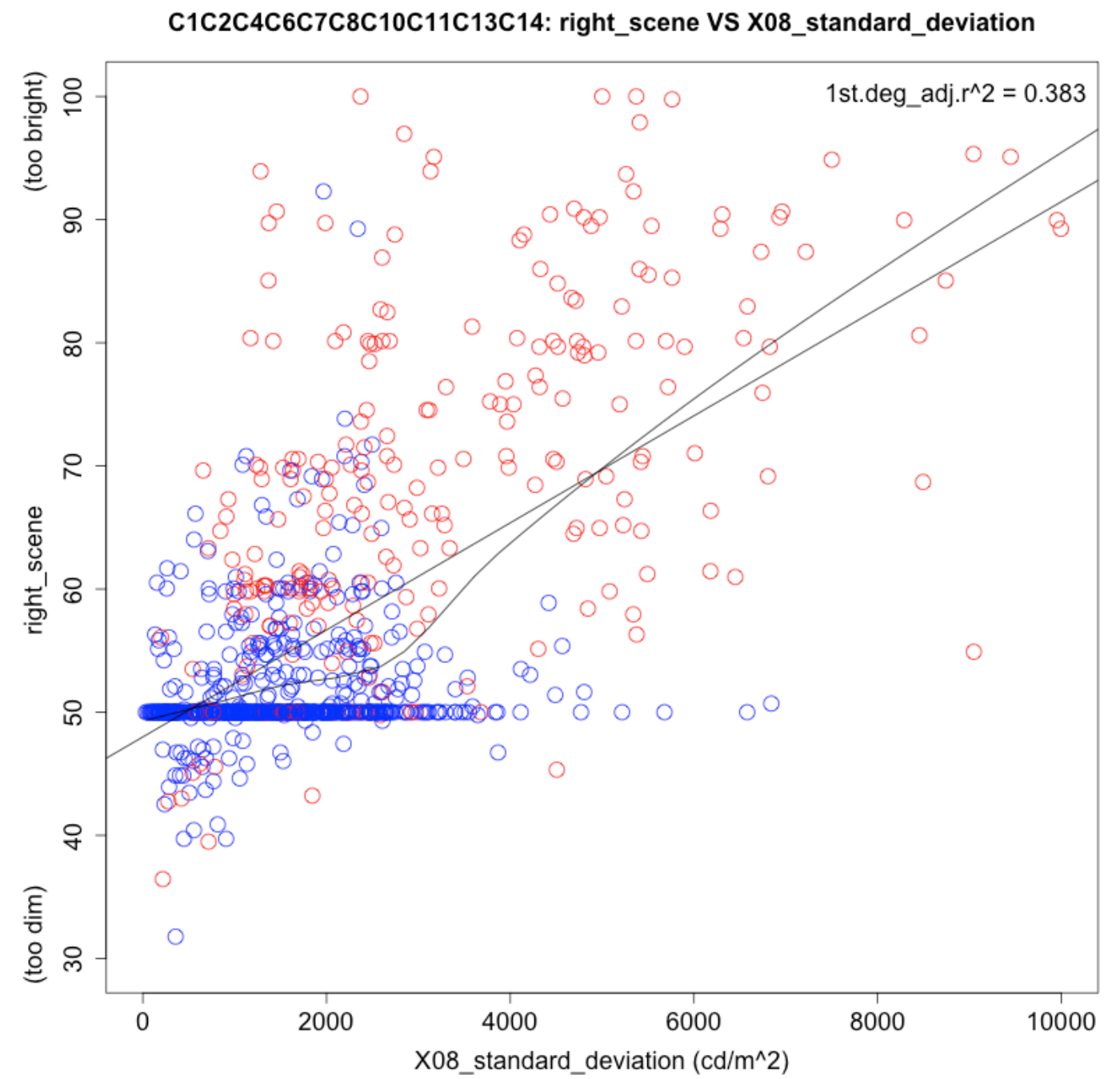
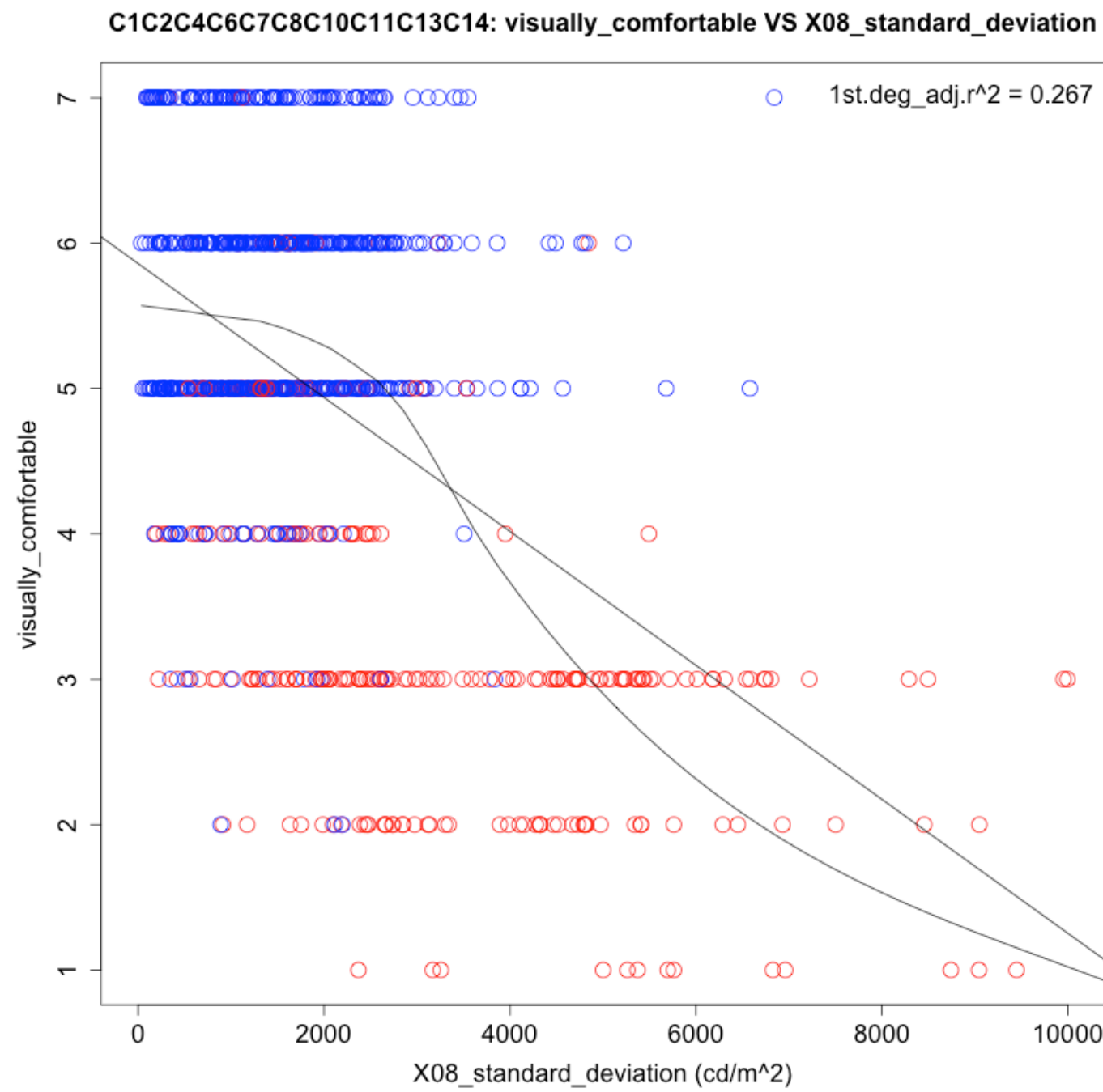


Figure 41 – Standard deviation of window luminance (X08) versus subjective ratings of QU1 (left) and right_scene (right) for the composite data set

C8 & C10: X08_standard_deviation & visually_comfortable

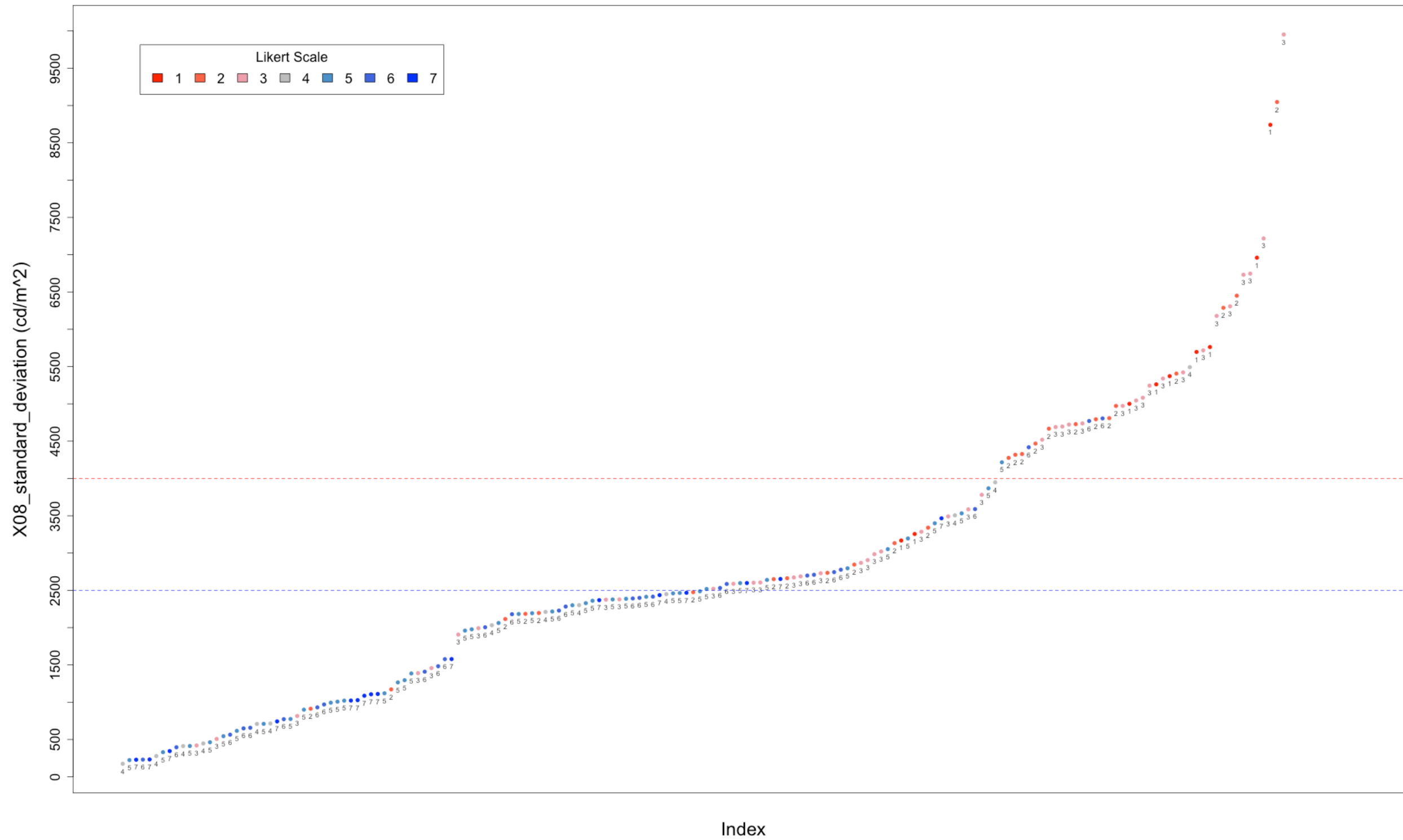


Figure 42 – Standard deviation of window luminance (X08) for C8 & C10, results ordered by metric and color-coded by response to QU1

Table 24 – X08_standard_deviation range and preliminary criteria

C8C10: X08_standard_deviation (cd/m ²) Range						
Min.	1 st Qu.	Median	Mean	3 rd Qu.	Max.	σ
175	1386	2503	2842	3928	9952	1892
Preliminary criteria:						
$x < 2500$			Likely to be comfortable			
$2500 > x < 4000$			Bounded-BCD			
$x > 4000$			Likely to be uncomfortable			

4.3.2 Mean luminance of 40° horizontal band (X20)



Figure 43 – Mask 20 (X20) encompasses the 40° horizontal band

The mean of the luminance values within the 40° horizontal band (X20_mean, X20 shown in Figure 43) represents the highest squared correlation coefficient for any metric based upon a space-independent mask (whereas some masks are space specific, e.g. X08). It is one of the 10 highest squared correlation coefficients for QU1, QU2, front_scene, and right_scene, and is in the top 20 for QU4, QU5, and QU7. Figure 44 shows the results for C8C10 with participant-days results ordered by C10 results. The metric correctly differentiates C10 (MP) from C8 (JU) scenes in most cases especially where $C10 \bar{x} > 700 \text{ cd/m}^2$. There are several cases where C10 scenes have lower X20_mean values than other participant-day C8 cases. Figure 45

represents the ability of the metric to explain the variance in QU1 and right_scene for C8C10 and Figure 46 does the same for the composite data set. Each plot includes linear and loess polynomial fits with the $\text{adj}r^2$ value representing the first-degree linear fit. The single regression statistics can be seen in Table 25. Finally, Figure 47 takes the C8C10 data, organizes it by the metric result, and color-codes it by the response to QU1. This graphic reveals three preliminary thresholds for criteria development as described in Table 26.

Table 25 – X20_mean single regression results

C8C10: X20_mean (cd/m²)				
DV	adjr²	F-statistic:	DF	p-value
C8C10				
QU1	0.2889	71.27	172	1.25E-14
right_scene	0.3230	83.54	172	2.20E-16
Composite_data_set				
QU1	0.2234	248.7	860	2.20E-16
right_scene	0.3075	383.3	860	2.20E-16
C8C10Computer_split53				
QU1	0.3615	74.02	128	2.38E-14
right_scene	0.3601	73.6	128	2.72E-14
Composite_data_set_Computer_split53				
QU1	0.2425	222.2	690	2.20E-16
right_scene	0.3302	341.7	690	2.20E-16

C8C10: X20_mean

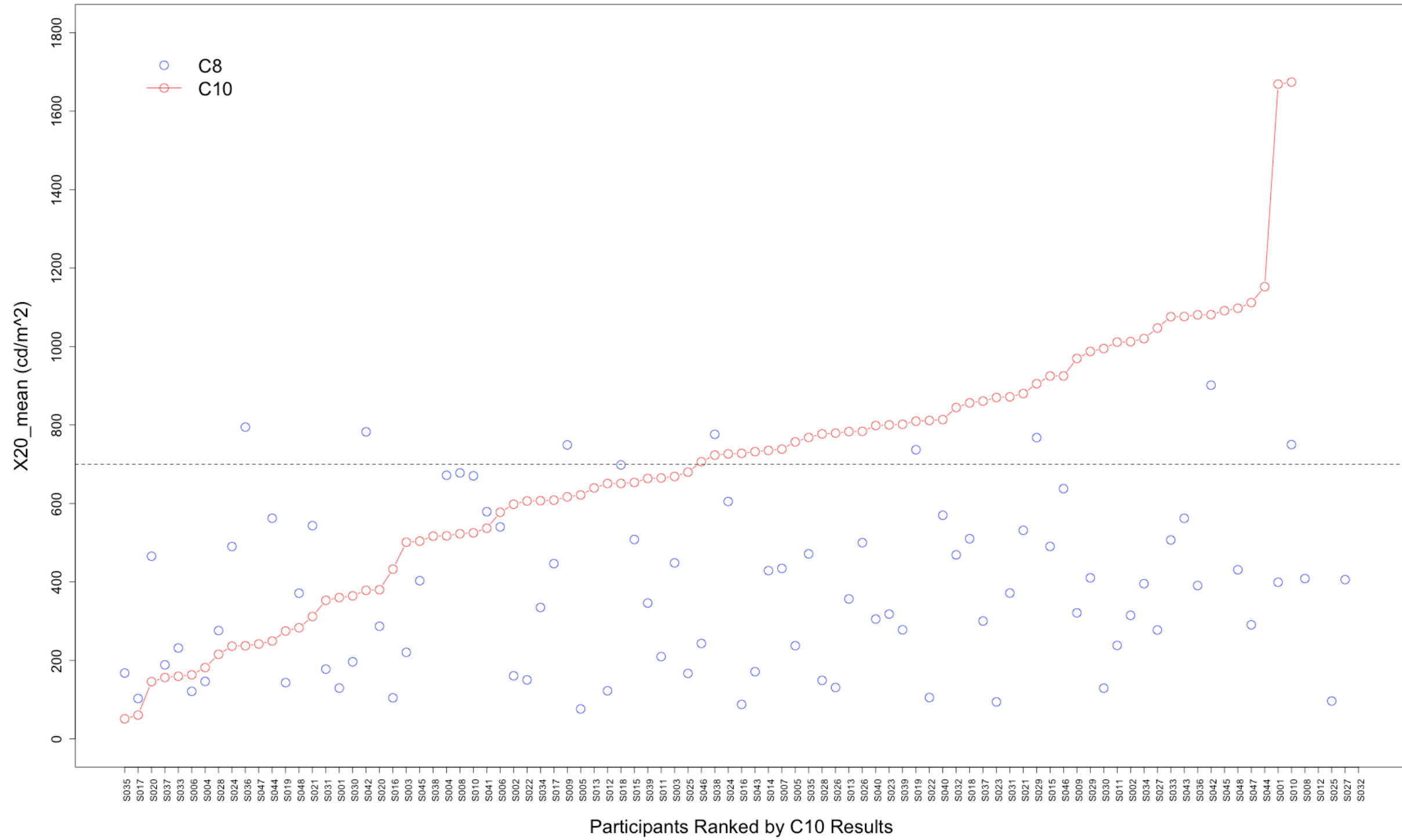


Figure 44 – Mean luminance of 40° horizontal band (X20) for C8 & C10, participants ranked by C10 results

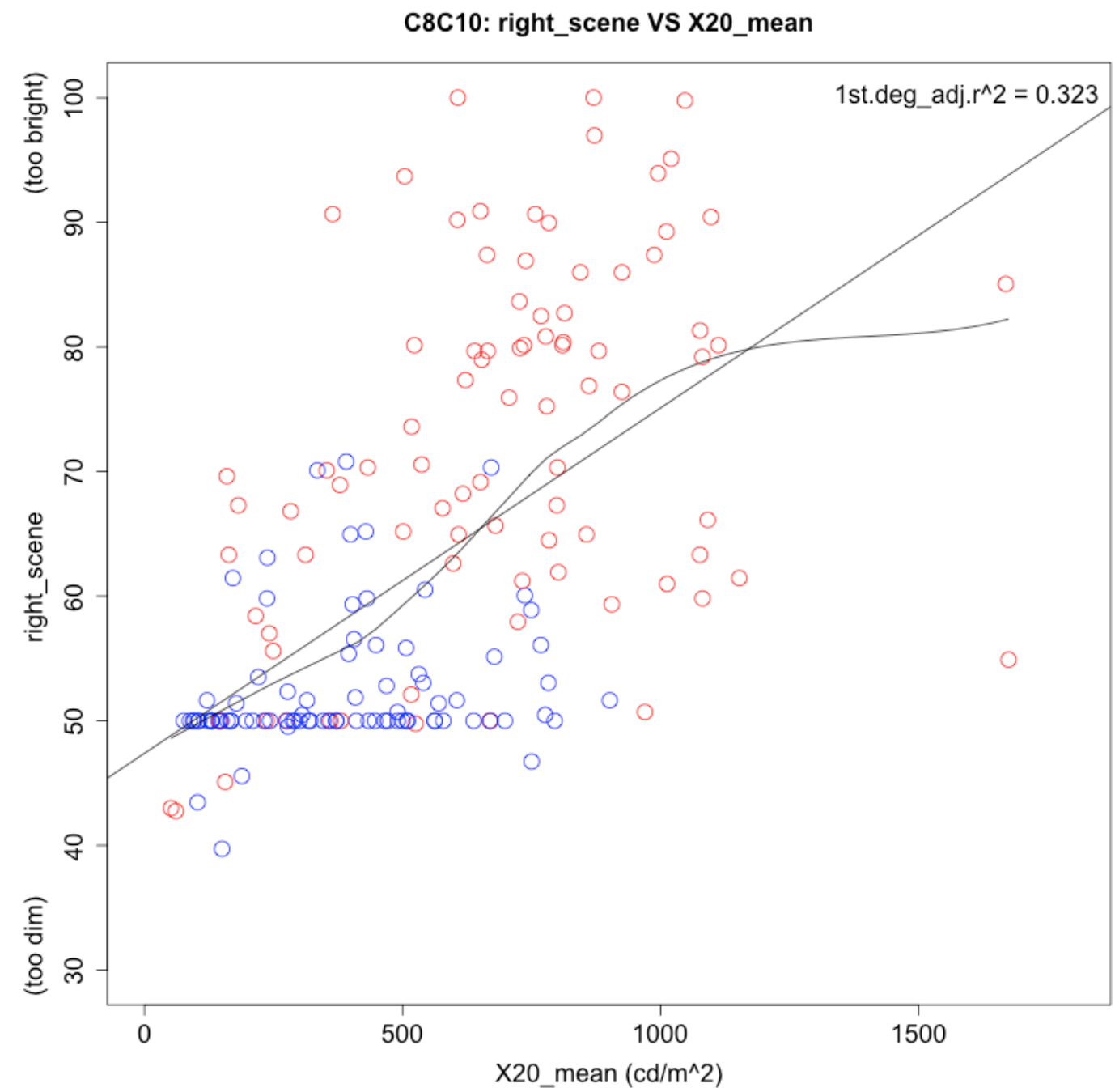
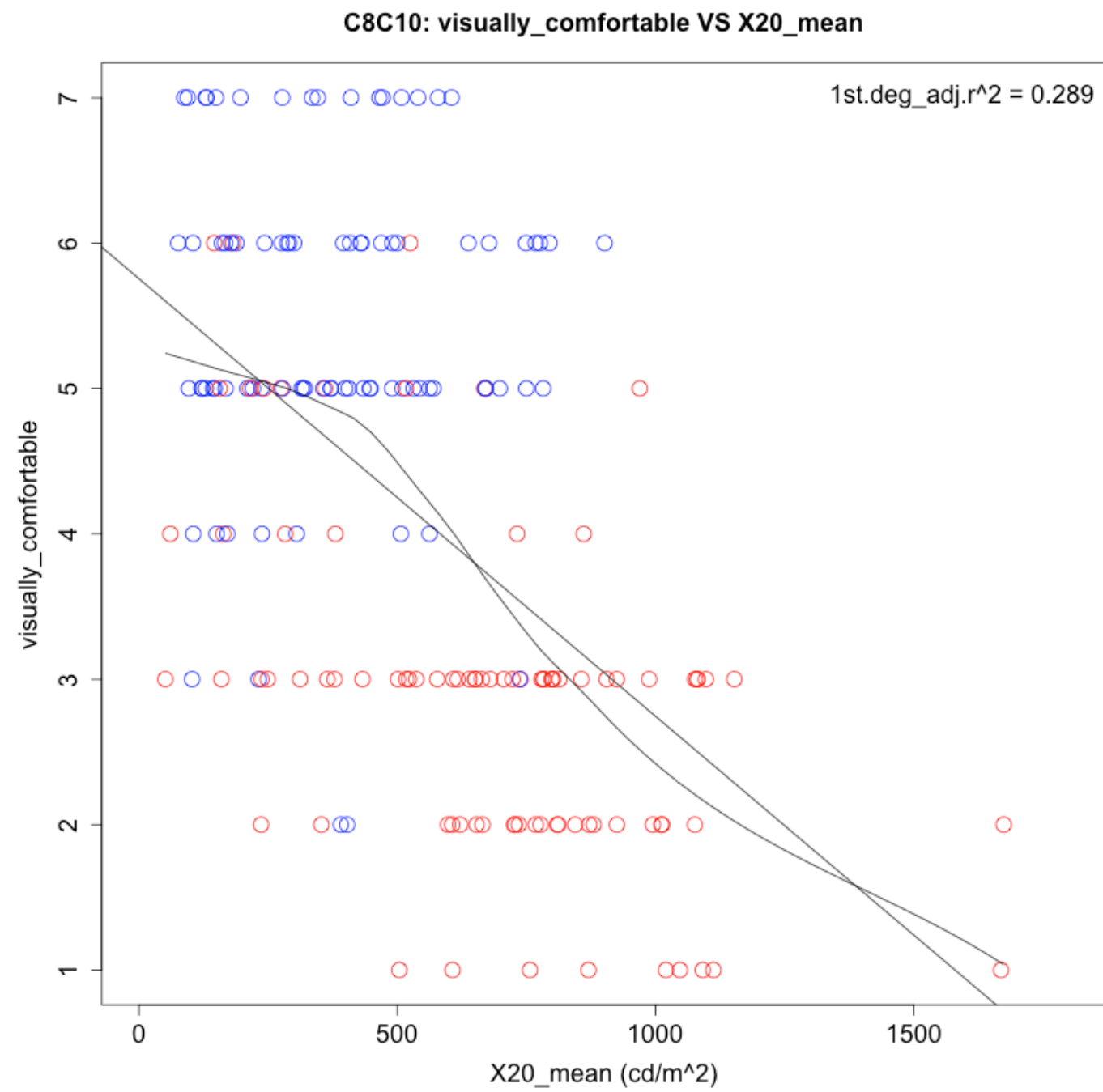


Figure 45 – Mean luminance of 40° horizontal band (X20) versus subjective ratings of QU1 (left) and right_scene (right) for C8C10

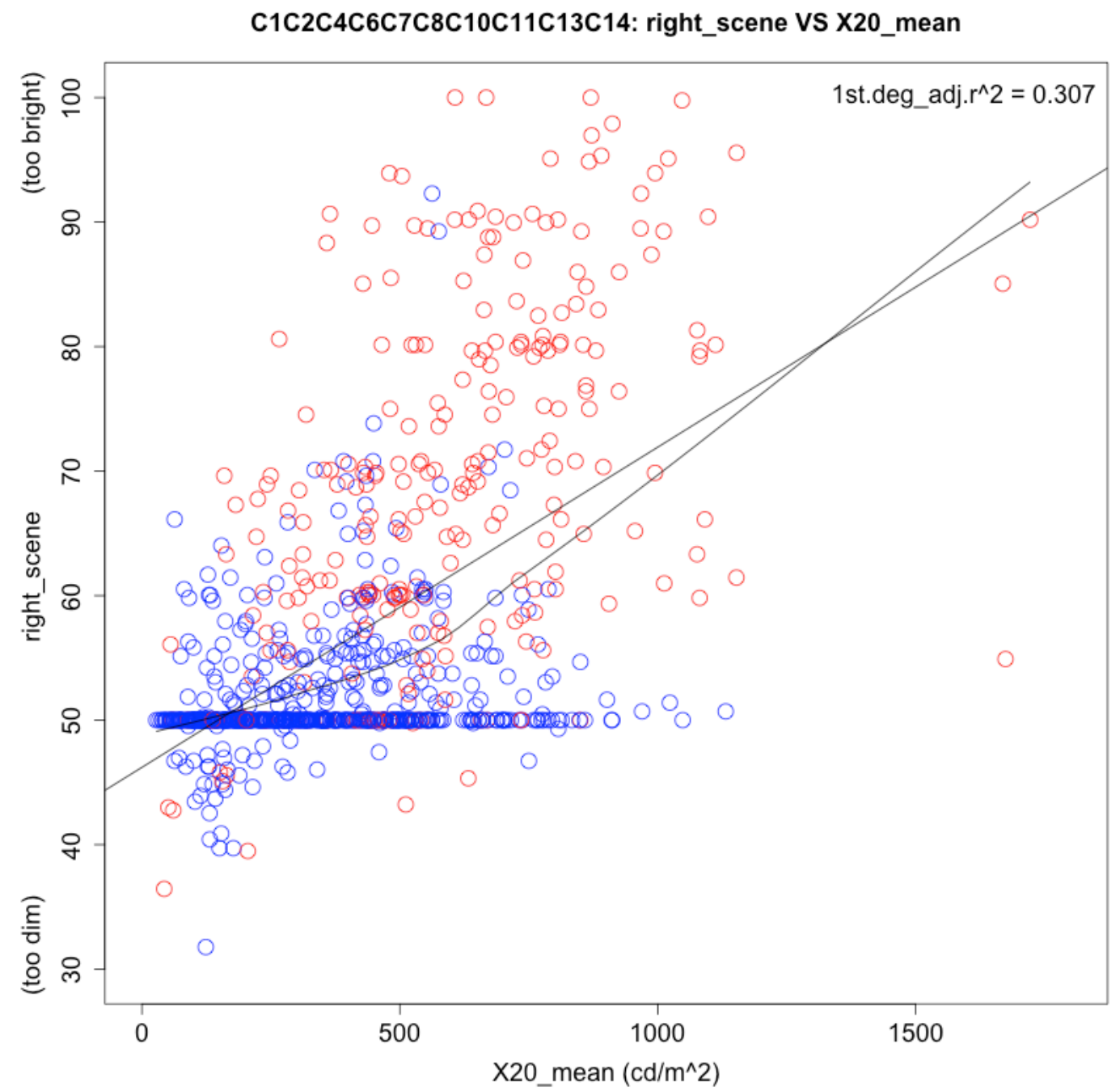
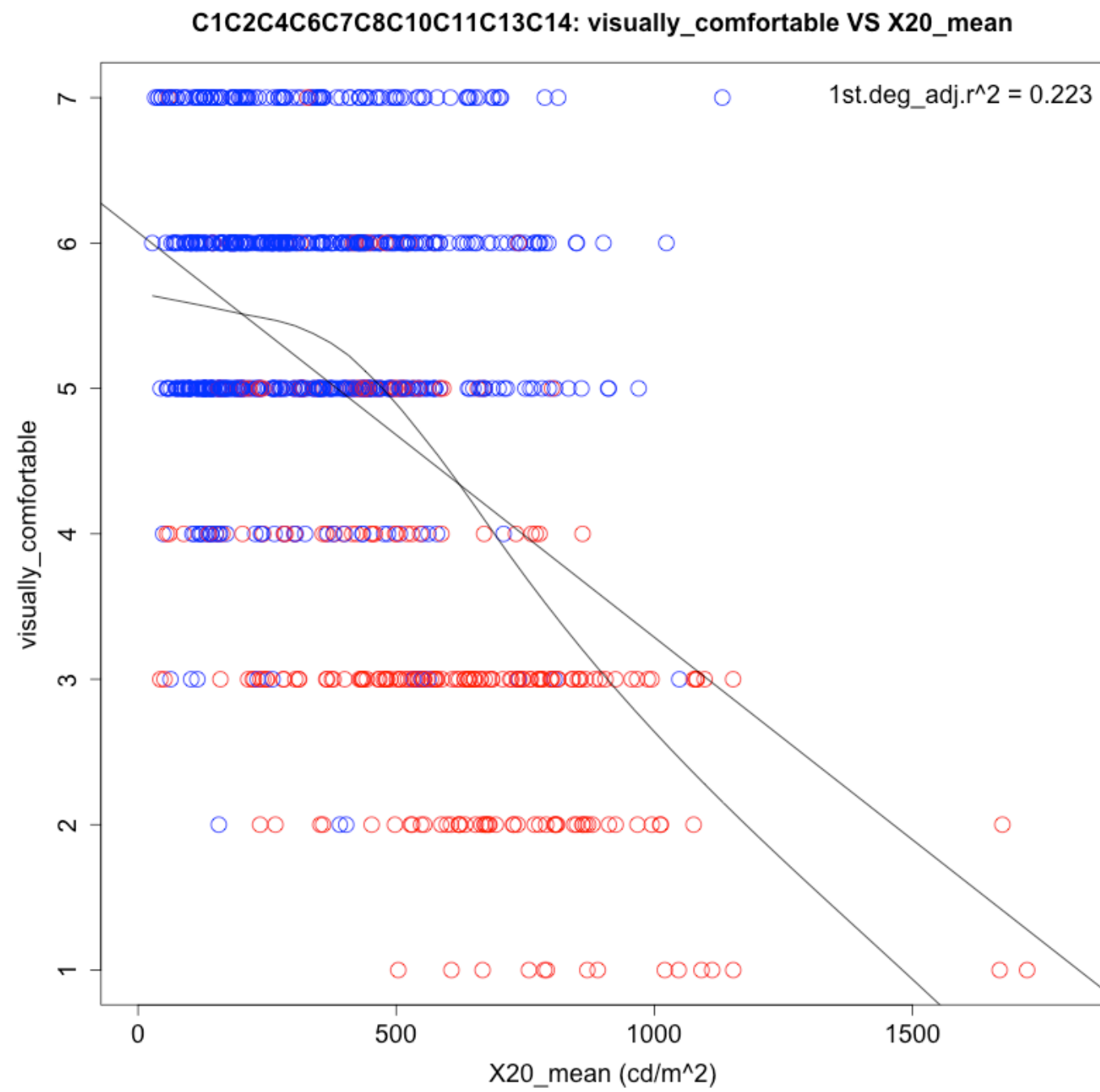


Figure 46 – Mean luminance of 40° horizontal band (X20) versus subjective ratings of QU1 (left) and right_scene (right) for the composite data set

C8 & C10: X20_mean & visually_comfortable

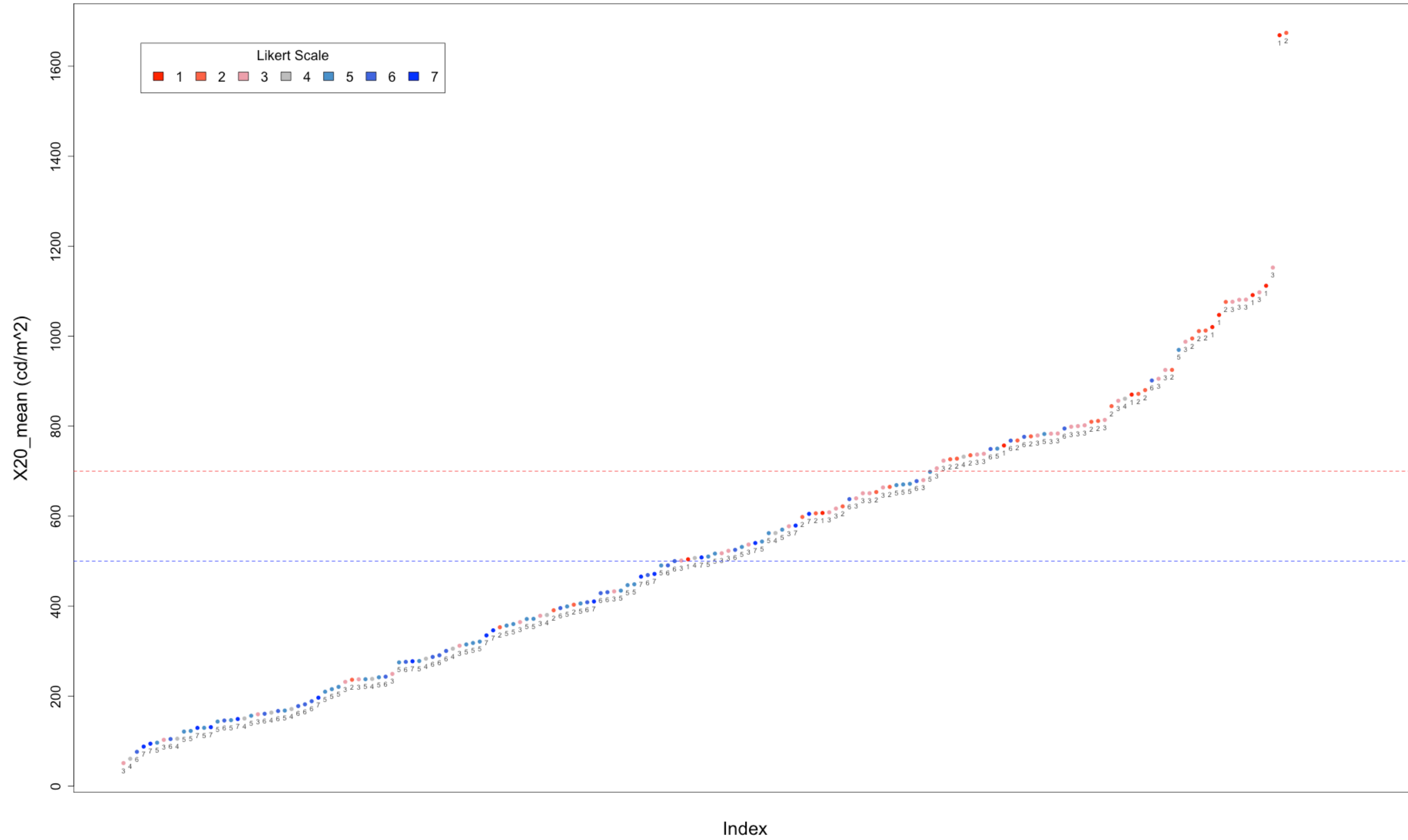


Figure 47 – Mean of luminance within the 40° horizontal band (C20) for C8 & C10, results ordered by metric and color-coded by response to QU1

Table 26 – X20_mean range and preliminary criteria

C8C10: X20_mean (cd/m²) Range						
Min.	1st Qu.	Median	Mean	3rd Qu.	Max.	σ
51	278	509	533	750	1674	311
Preliminary criteria:						
$x < 500$			Likely to be comfortable			
$500 > x < 700$			Bounded-BCD			
$x > 700$			Likely to be uncomfortable			

4.3.3 The 10th percentile luminance value of the ceiling (X14)



Figure 48 – Mask 14 (X14) encompasses the ceiling plane excluding the electric light fixture

The 10th percentile luminance value of the ceiling (X14_10th_percentile, X14 shown in Figure 48) is one of the 10 highest squared correlation coefficients for right_scene and left_scene, and light_in_scene. Figure 49 shows the results for C8C10 with participant-days results ordered by C10 results. The metric correctly differentiates C10 (MP) from C8 (JU) when C10 is greater than 225 cd/m². There are several cases where C10 scenes have values lower than other participant-day C8 cases. Figure 50 represents the ability of the metric to explain the variance in QU1 and right_scene for C8C10 and Figure 51 does the same for the composite data set. Each plot includes linear and loess polynomial fits with the $adjr^2$ value representing the first-degree linear fit. The single regression statistics can be seen in Table 27. Finally, Figure 52

takes the C8C10 data, organizes it by the metric result, and color-codes it by the response to QU1. This graphic reveals three preliminary thresholds for criteria development as described in Table 28.

Table 27 – X14_10th_percentile single regression results

C8C10: X14_10th_percentile (cd/m²)				
DV	adjR²	F-statistic:	DF	p-value
C8C10				
QU1	0.2453	57.24	172	2.23E-12
right_scene	0.3117	79.33	172	7.29E-16
Composite_data_set				
QU1	0.1988	214.6	860	2.20E-16
right_scene	0.2892	351.2	860	2.20E-16
C8C10Computer_split53				
QU1	0.3097	58.87	128	3.75E-12
right_scene	0.3476	69.73	128	9.56E-14
Composite_data_set_Computer_split53				
QU1	0.2249	201.5	690	2.20E-16
right_scene	0.3205	326.9	690	2.20E-16

C8C10: X14_10th_percentile

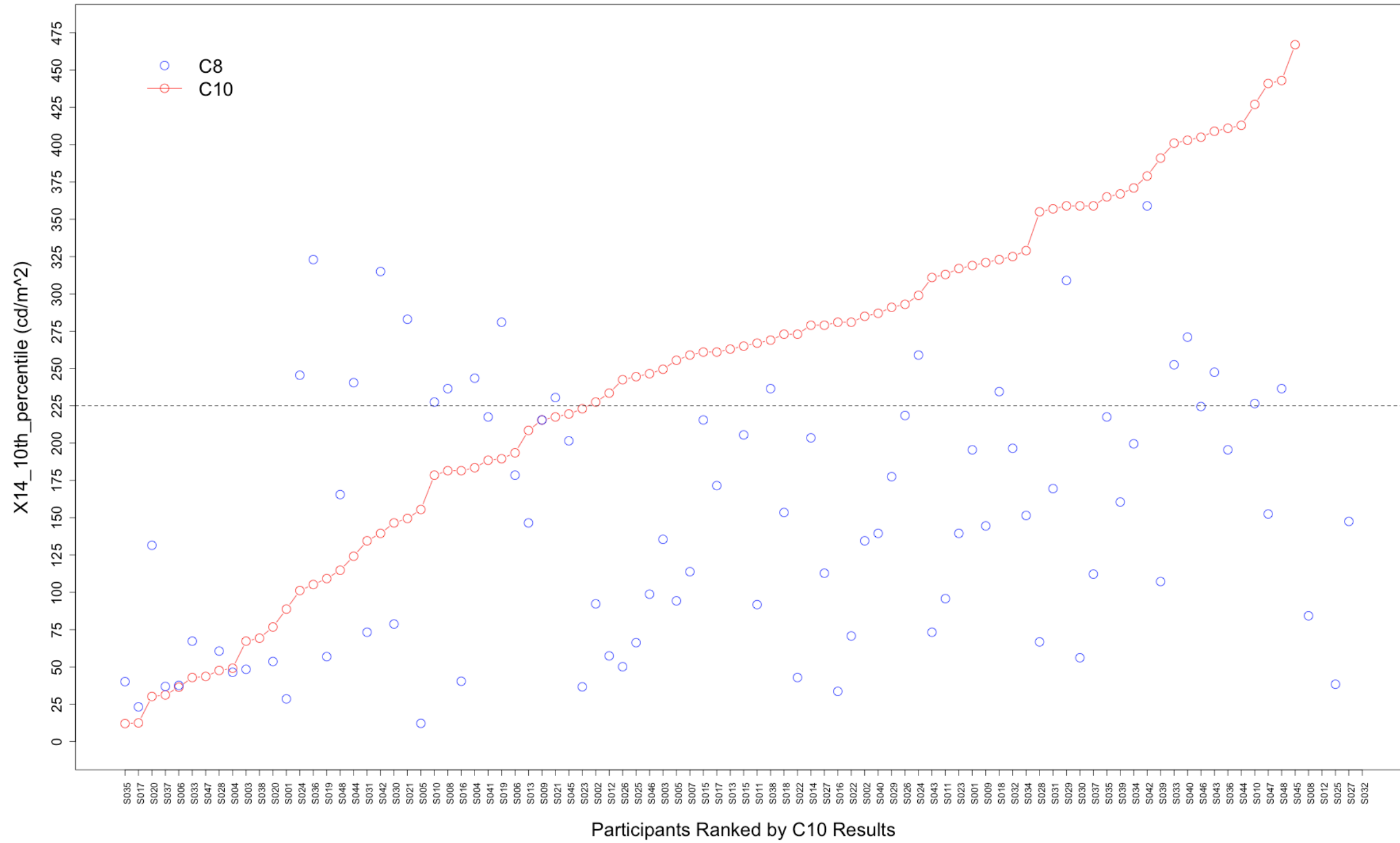


Figure 49 – 10th percentile luminance value of ceiling (X14) for C8 & C10, participants ranked by C10 results

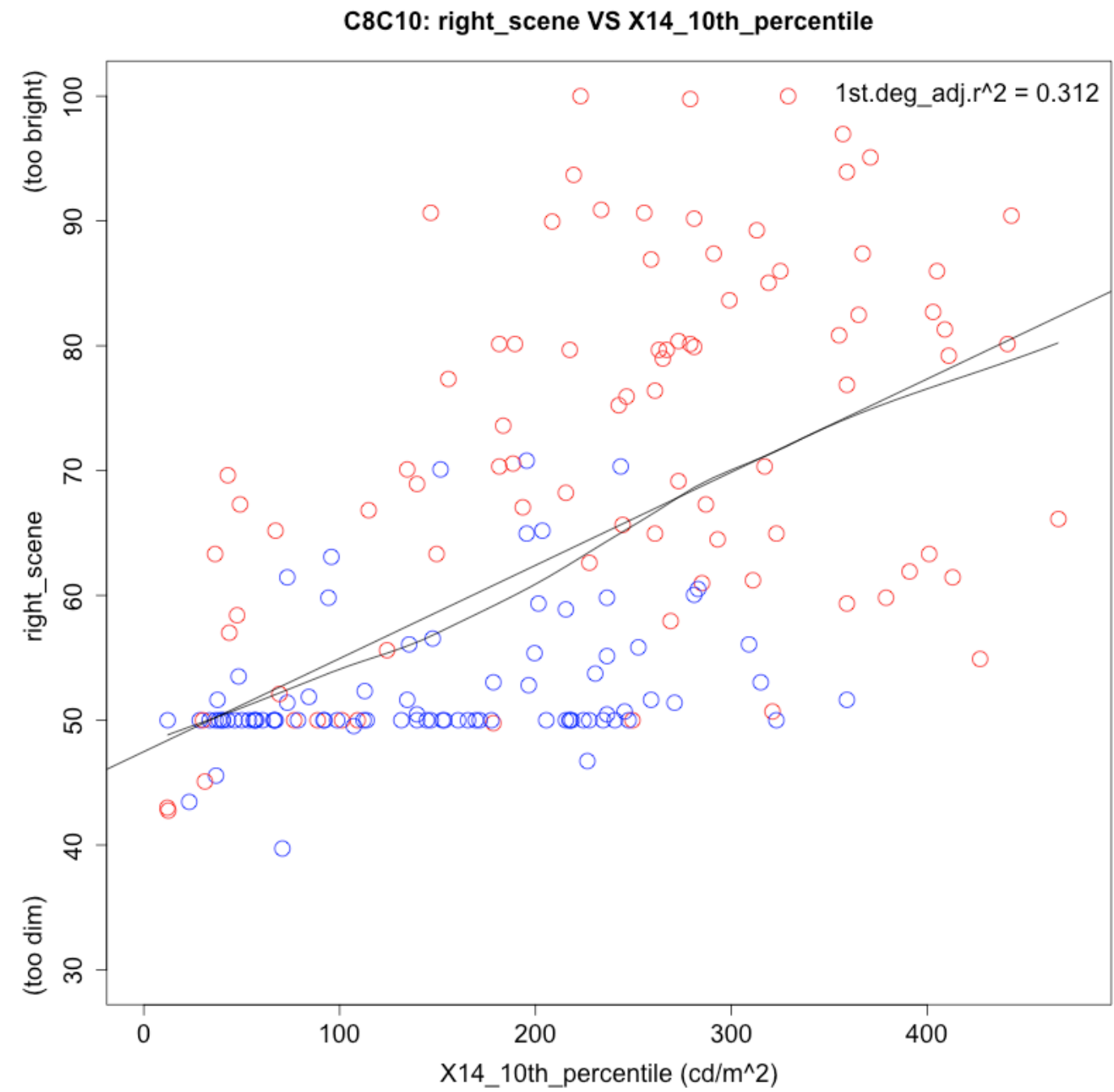
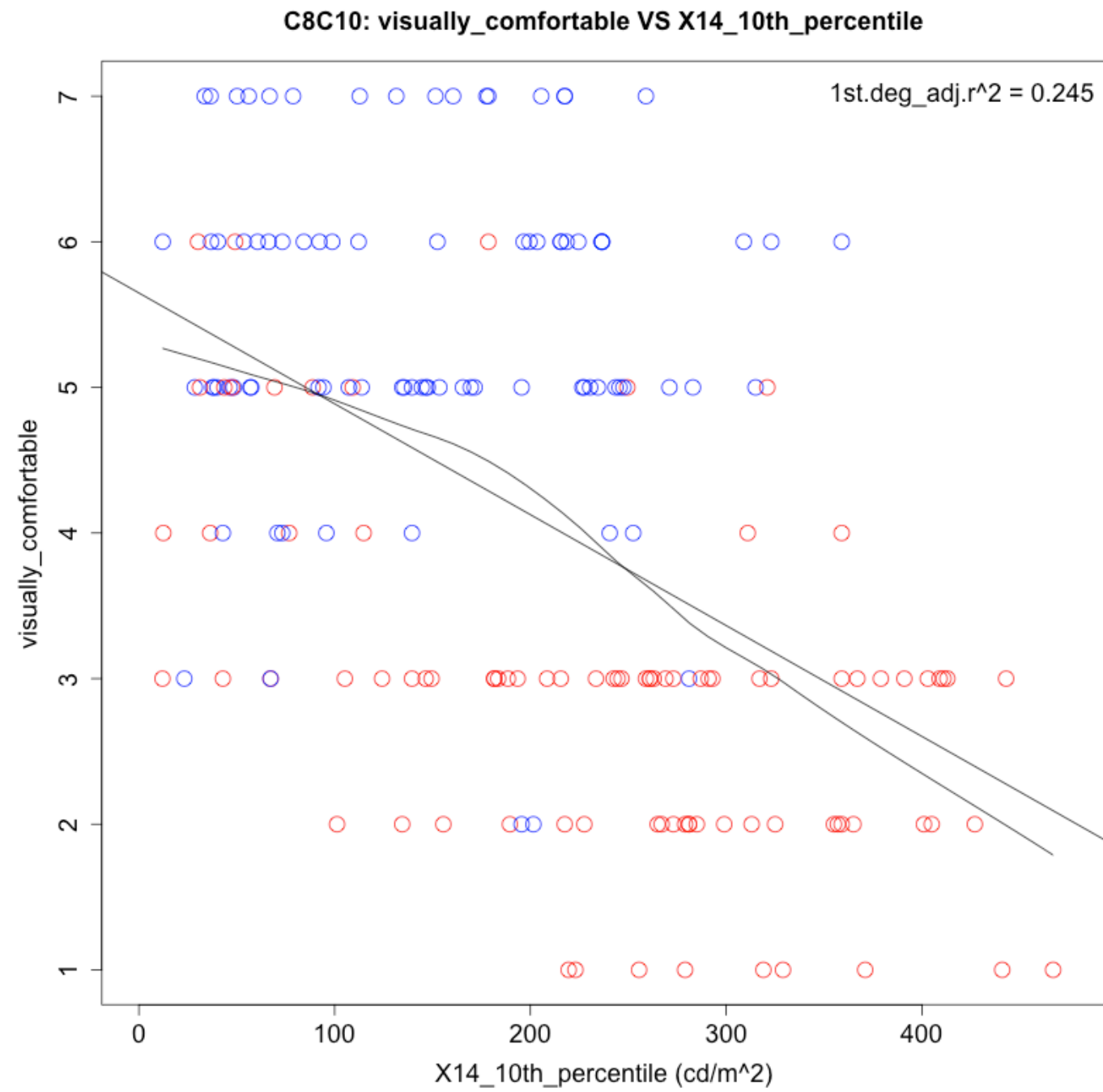


Figure 50 – 10th percentile luminance value of ceiling (X14) versus subjective ratings of QU1 (left) and right_scene (right) for C8C10

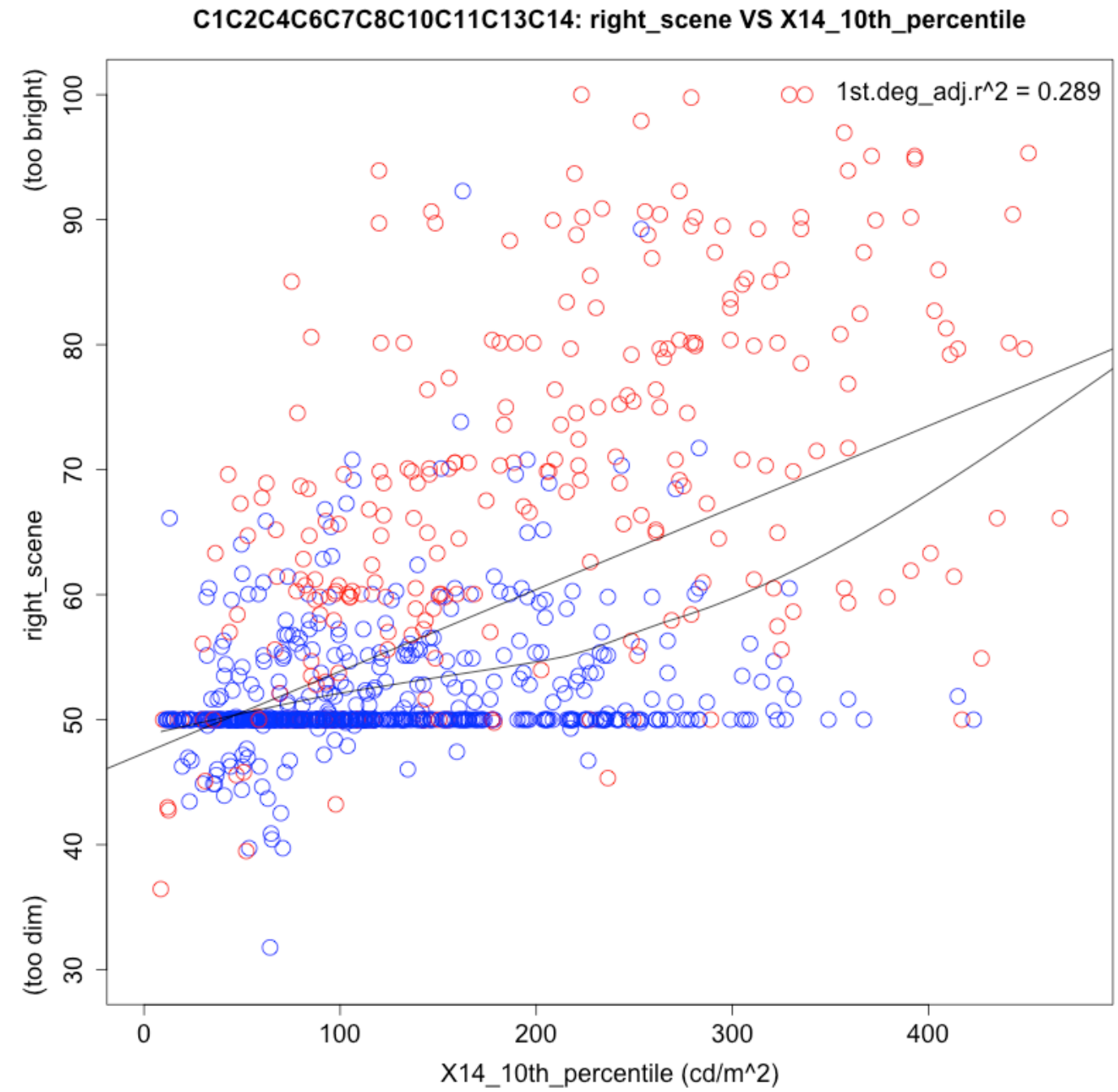
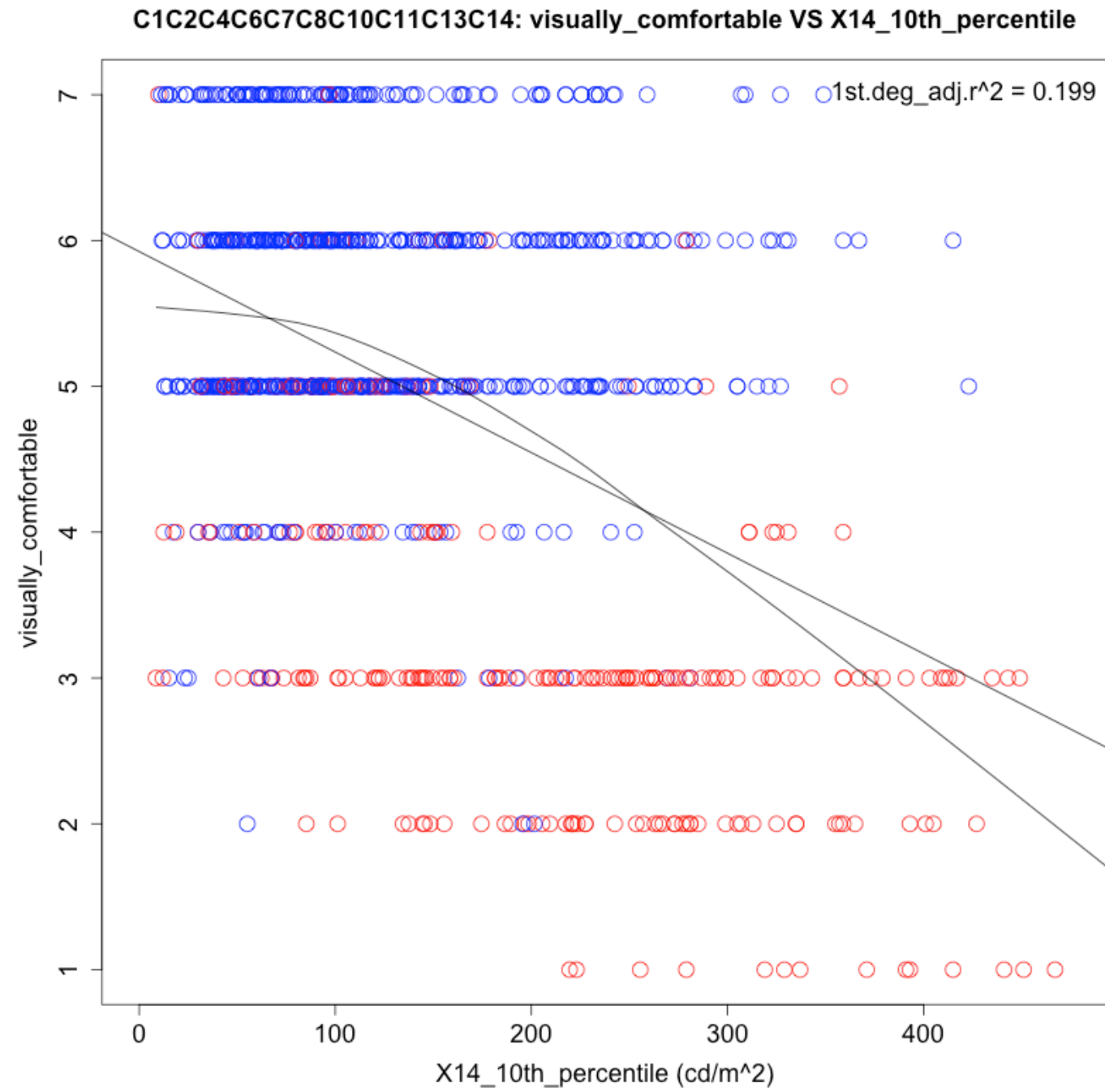


Figure 51 – 10th percentile luminance value of ceiling (X14) versus subjective ratings of QU1 (left) and right_scene (right) for the composite data set

C8 & C10: X14_10th_percentile & visually_comfortable

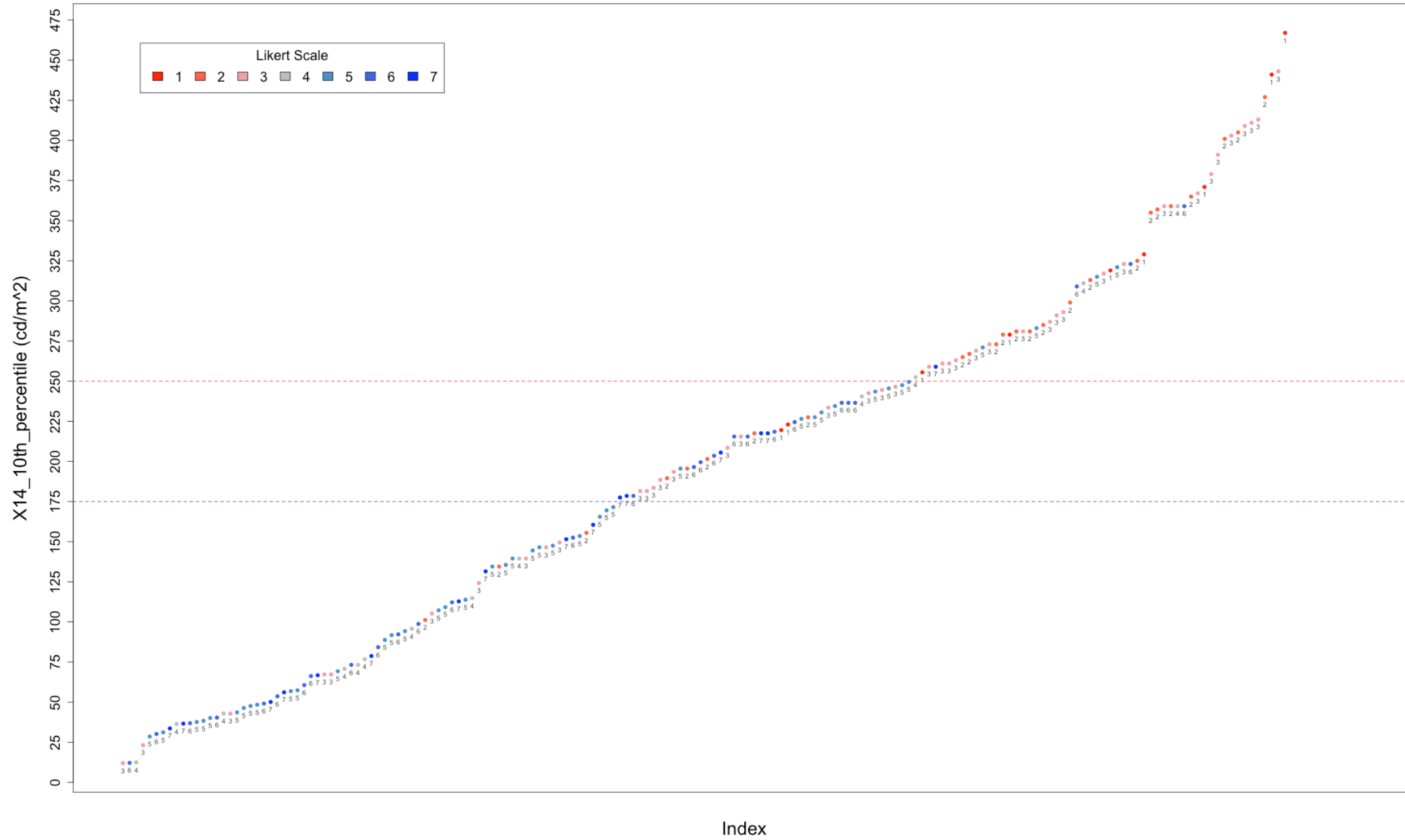


Figure 52 – 10th percentile luminance value of ceiling (X14) for C8 & C10, results ordered by metric and color-coded by response to QU1

Table 28 – X14_10th_percentile range and preliminary criteria

C8C10: X14_10th_percentile (cd/m²) Range						
Min.	1st Qu.	Median	Mean	3rd Qu.	Max.	σ
12	97	201	197	273	467	113
Preliminary criteria:						
x < 175			Likely to be comfortable			
175 > x < 250			Bounded-BCD			
x > 250			Likely to be uncomfortable			

4.3.4 Percent below 1000 cd/m² within a 40° horizontal band (X20)

The percent of the luminance values within the 40° horizontal band (Figure 43) below 1000 cd/m² (X20_percent_below_1000_cd) represents the second highest squared correlation coefficient for any metric based upon a space-independent mask. It is one of the 10 highest squared correlation coefficients for right_scene and front_scene. Figure 53 shows the results for C8C10 with participant-days results ordered by C10 results. The metric correctly differentiates C10 (MP) from C8 (JU) scenes in most cases, and in all cases where C10 had less than 89% of the scene below 1000 cd/m². There are several cases where C10 scenes have a larger percentage of the scene below 1000 cd/m² than other participant-day C8 cases. Figure 54 represents the ability of the metric to explain the variance in QU1 and right_scene for C8C10 and Figure 55 does the same for the composite data set. Each plot includes linear and loess polynomial fits with the $adjR^2$ value representing the first-degree linear fit. The single regression statistics can be seen in Table 29. Finally, Figure 56 takes the C8C10 data, organizes it by the metric result, and color-codes it by the response to QU1. This graphic reveals three preliminary thresholds for criteria development as described in Table 30.

Table 29 – X20_percent_below_1000 single regression results

C8C10: X20_percent_below_1000_cd/m²				
DV	adjR²	F-statistic:	DF	p-value
C8C10				
QU1	0.287	70.64	172	1.57E-14
right_scene	0.3512	94.63	172	2.20E-16
Composite_data_set				
QU1	0.1968	211.90	860	2.20E-16
right_scene	0.3017	373	860	2.20E-16
C8C10Computer_split53				
QU1	0.373	77.74	128	7.29E-15
right_scene	0.3948	85.16	128	7.36E-16
Composite_data_set_Computer_split53				
QU1	0.2137	188.80	690	2.20E-16
right_scene	0.3176	322.5	690	2.20E-16

C8C10: X20_percent_below_1000_cd

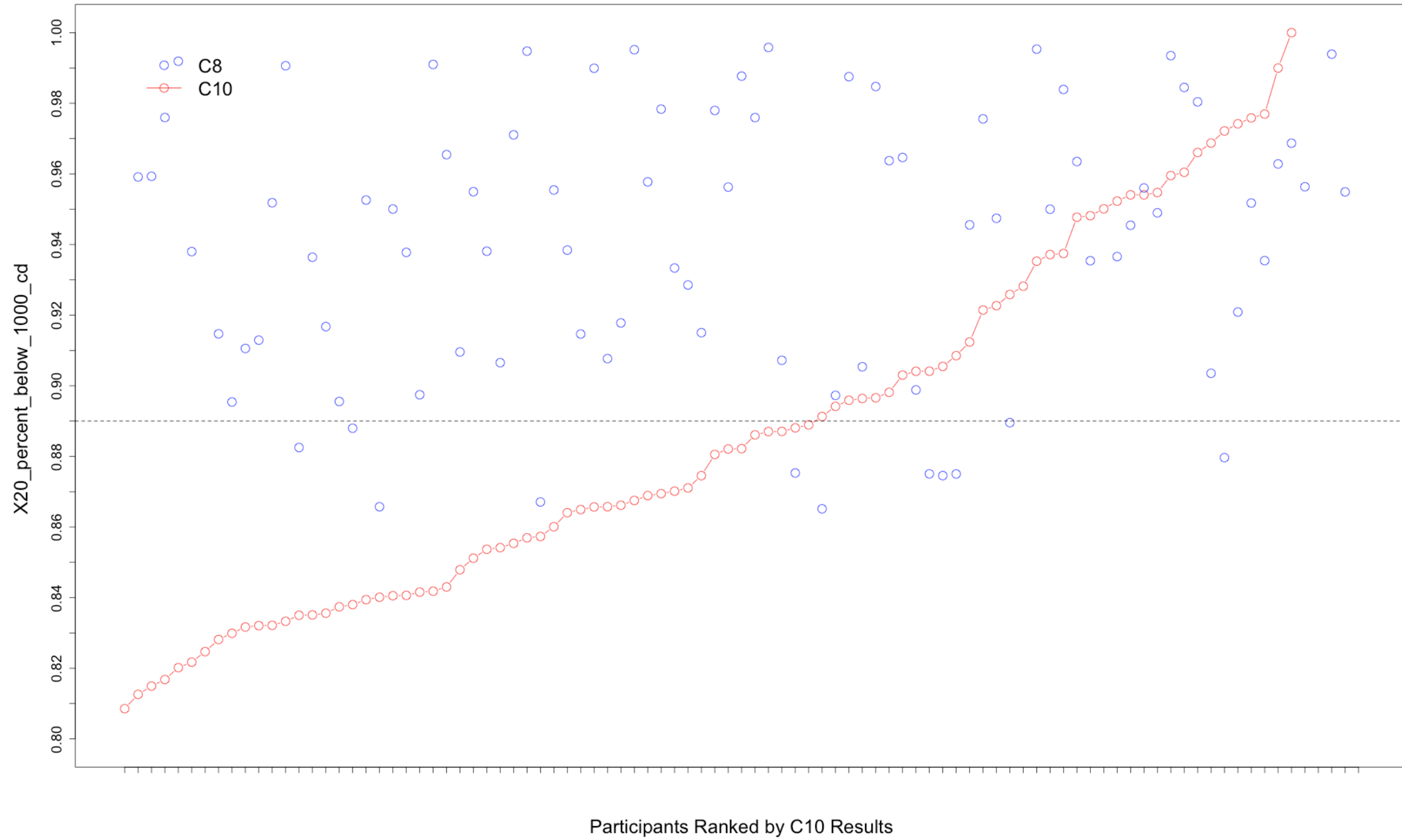


Figure 53 – Percent of pixels below 1000 cd/m² within the 40° horizontal band (X20) for C8 & C10, participants ranked by C10 results

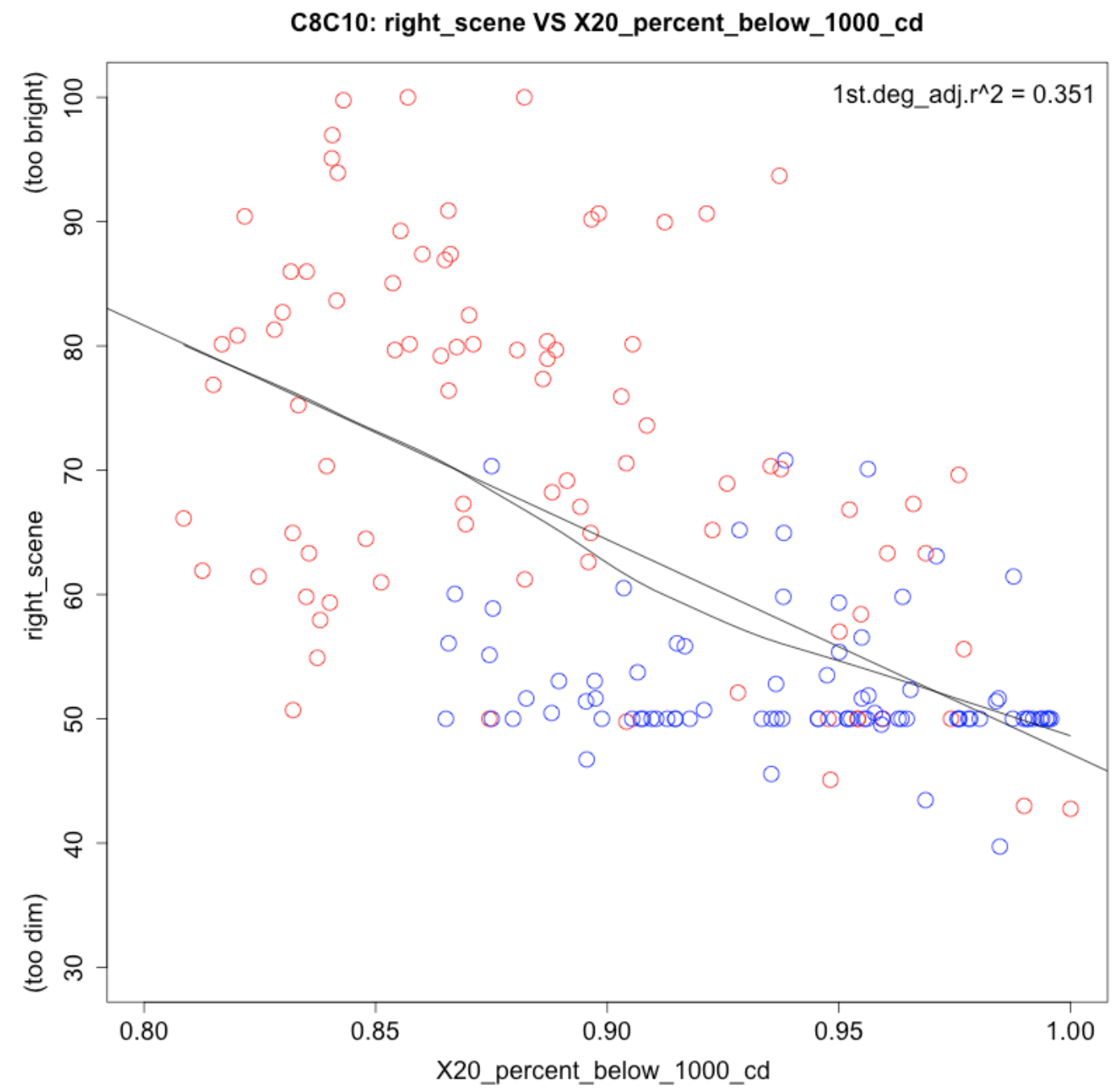
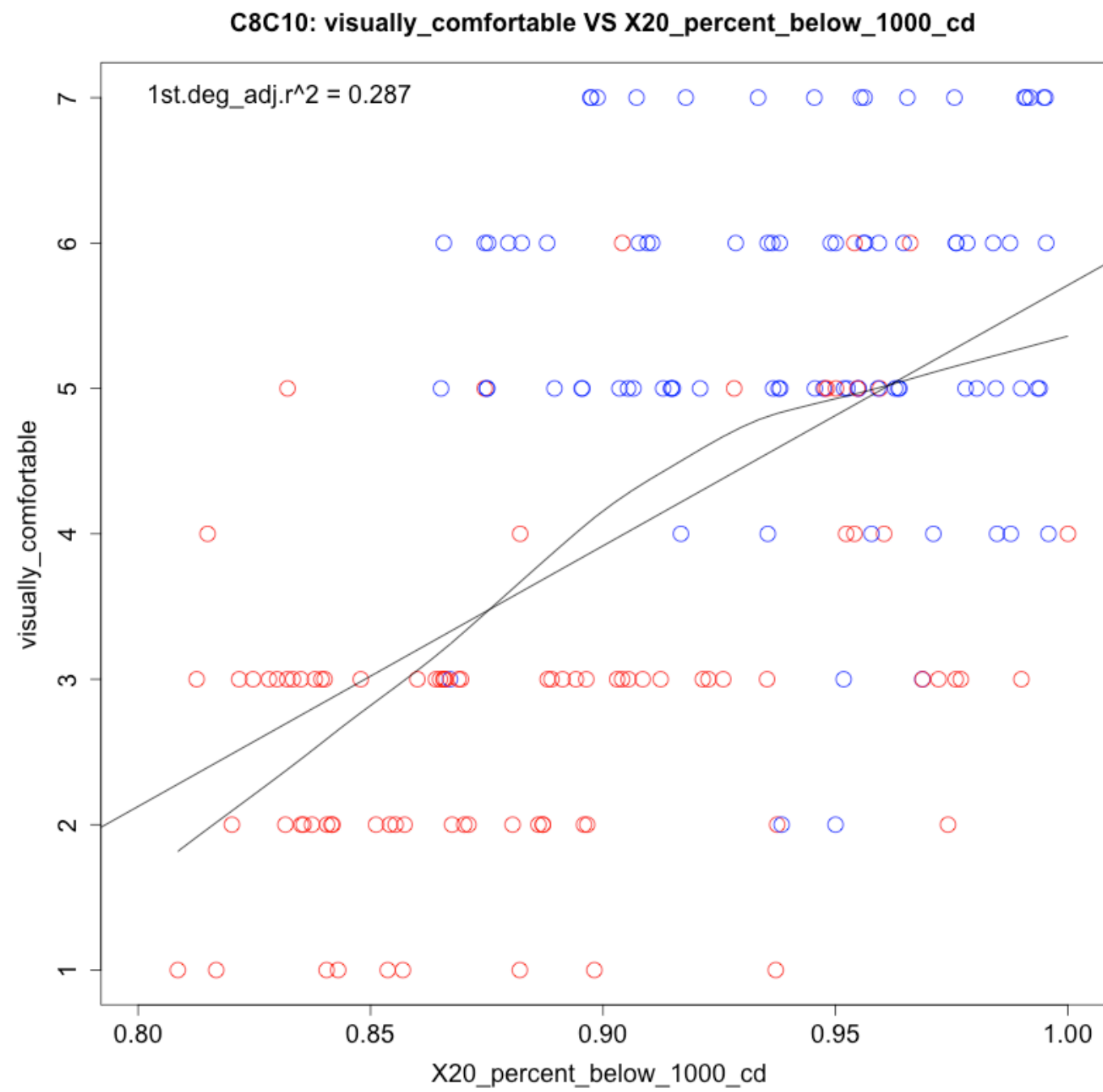


Figure 54 – Percent of pixels below 1000 cd/m² within the 40° horizontal band (X20) versus subjective ratings of QU1 (left) and right_scene (right) for C8C10

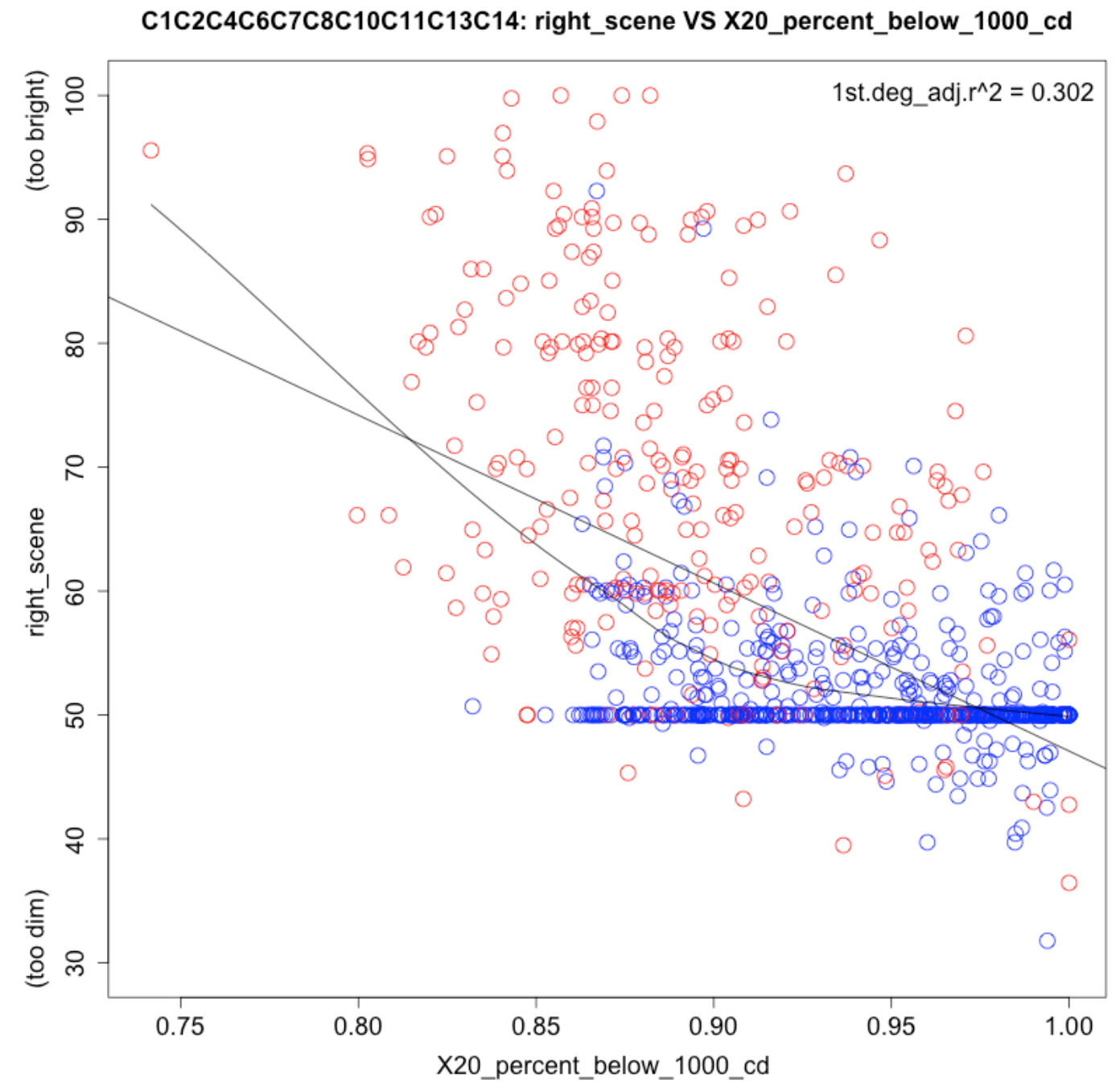
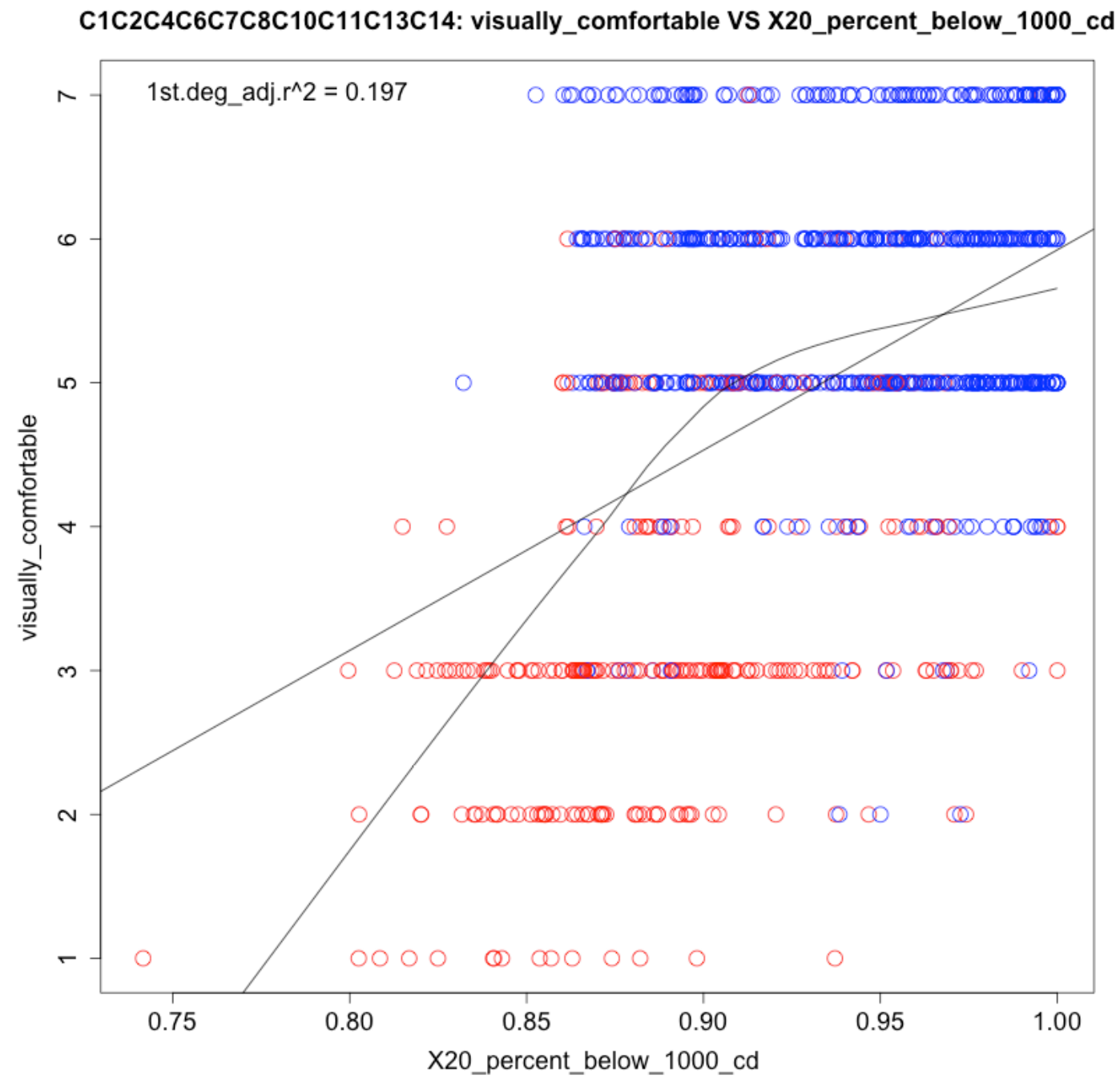


Figure 55 – Percent of pixels below 1000 cd/m² within the 40° horizontal band (X20) versus subjective ratings of QU1 (left) and right_scene (right) for the composite data set

C8 & C10: X20_percent_below_1000_cd & visually_comfortable

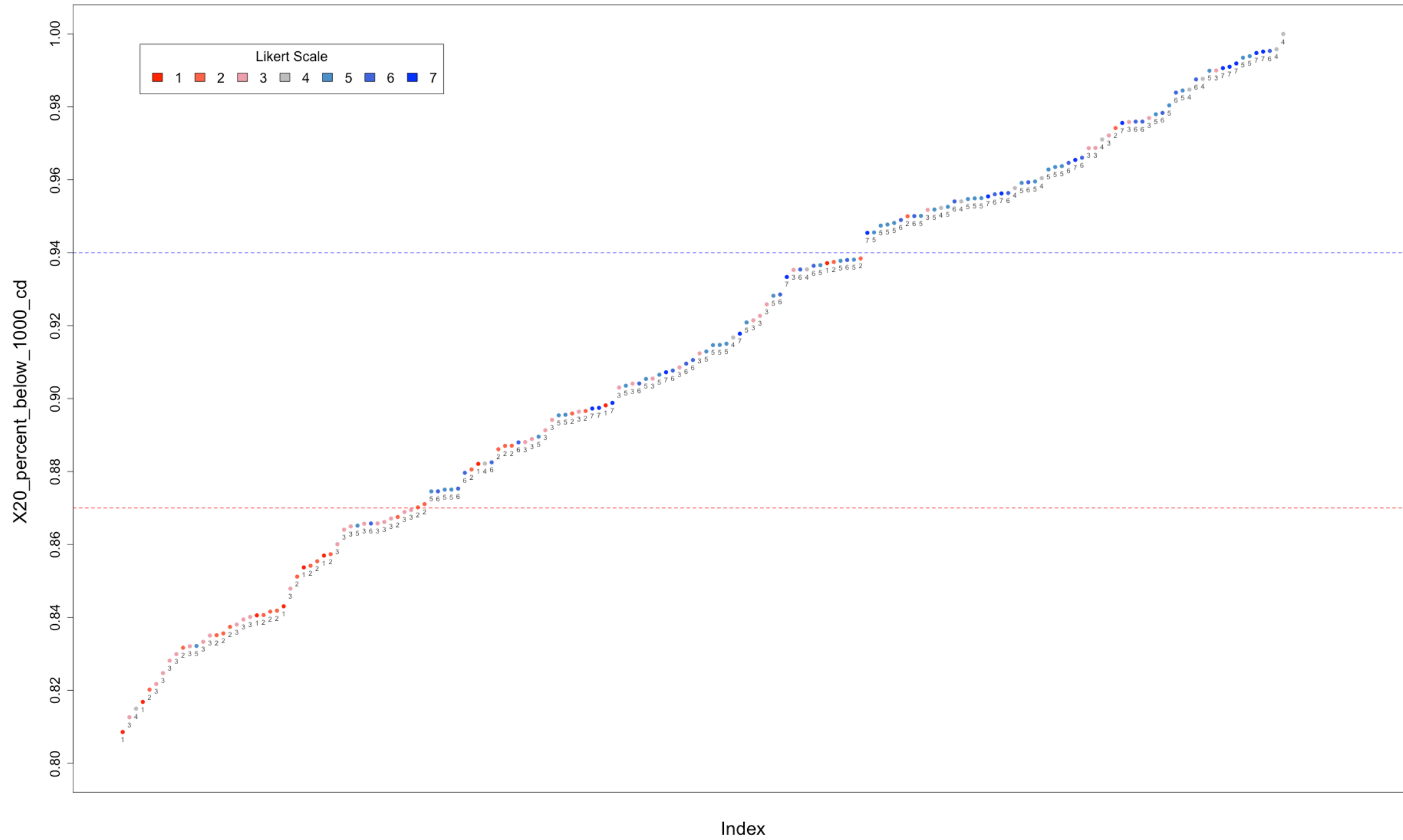


Figure 56 – Percent of pixels below 1000 cd/m² within the 40° horizontal band (X20) for C8 & C10, results ordered by metric and color-coded by response to QU1

Table 30 – X20_percent_below_1000_cd/m² range and preliminary criteria

C8C10: X20_percent_below_1000_cd/m ² Range						
Min.	1 st Qu.	Median	Mean	3 rd Qu.	Max.	σ
80.9%	87.0%	91.3%	91.3%	95.6%	100.0%	5.2%
Preliminary criteria:						
x > 94%			Likely to be comfortable			
87% > x < 94%			Bounded-BCD			
x < 87%			Likely to be uncomfortable			

4.3.5 Daylight Glare Probability using 5*mL of the circle task (using X03, X01)

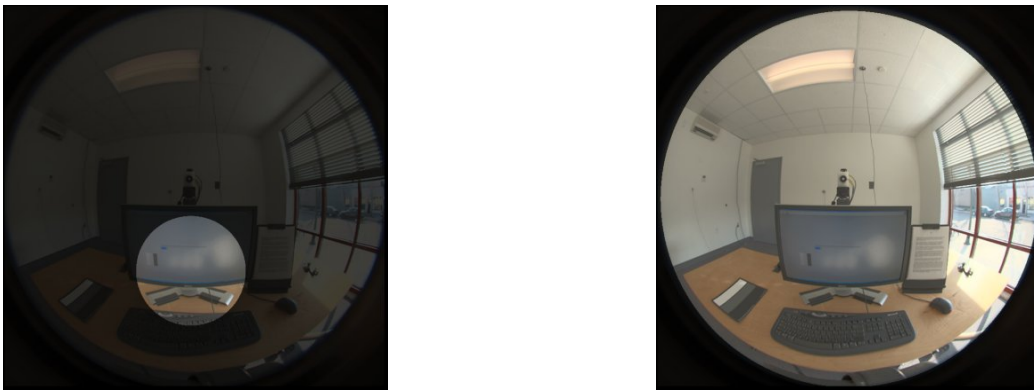


Figure 57 – Mask three (X03) encompasses a circular task about the computer monitor and keyboard (left); Mask 01 (X01) encompasses the entire 180° x 180° scene (right)

The DGP based upon 5*mL of the circle task (X03_evalglare_mL0005_dgp, X03 shown in Figure 57-left) and calculated upon the entire scene (X01, Figure 57-right) did not rank in the top 20 metrics for any subjective questionnaire items. DGP had the highest r^2 among glare indices calculated using either Evalglare or *findglare-glarendx*, with X03_evalglare_mL0003_dgp negligibly stronger than X03_evalglare_mL0005_dgp for right_scene ($r^2 = 0.2793$ versus $r^2 = 0.2783$). Several other DGP glare source identification

multipliers (for both X01 and X03) performed similarly. Figure 58 shows the results for C8C10 with participant-days results ordered by C10 results. The metric correctly differentiates C10 (MP) from C8 (JU) scenes for cases where C10 was greater than DGP of 24%. There are several cases where C10 scenes had lower DGP values than other participant-day C8 cases. Figure 59 represents the ability of the metric to explain the variance in QU1 and right_scene for C8C10 and Figure 60 does the same for the composite data set. Each plot includes linear and loess polynomial fits with the $\text{adj}r^2$ value representing the first-degree linear fit. The single regression statistics can be seen in Table 31. Finally, Figure 61 takes the C8C10 data, organizes it by the metric result, and color-codes it by the response to QU1. This graphic reveals three preliminary thresholds for criteria development as described in Table 32.

Table 31 – X03_evalglare_mL0005_dgp single regression results

C8C10: X03_evalglare_mL0005_dgp (%)				
DV	adjr^2	F-statistic:	DF	p-value
C8C10				
QU1	0.2207	50	172	3.70E-11
right_scene	0.2905	71.83	172	1.02E-14
Composite_data_set				
QU1	0.1811	191.4	860	2.20E-16
right_scene	0.2643	310.4	860	2.20E-16
C8C10Computer_split53				
QU1	0.2688	48.41	128	1.60E-10
right_scene	0.3019	56.8	128	7.76E-12
Composite_data_set Computer_split53				
QU1	0.1972	170.7	690	2.20E-16
right_scene	0.2797	269.4	690	2.20E-16

C8C10: X03_evalglare_mL0005_dgp

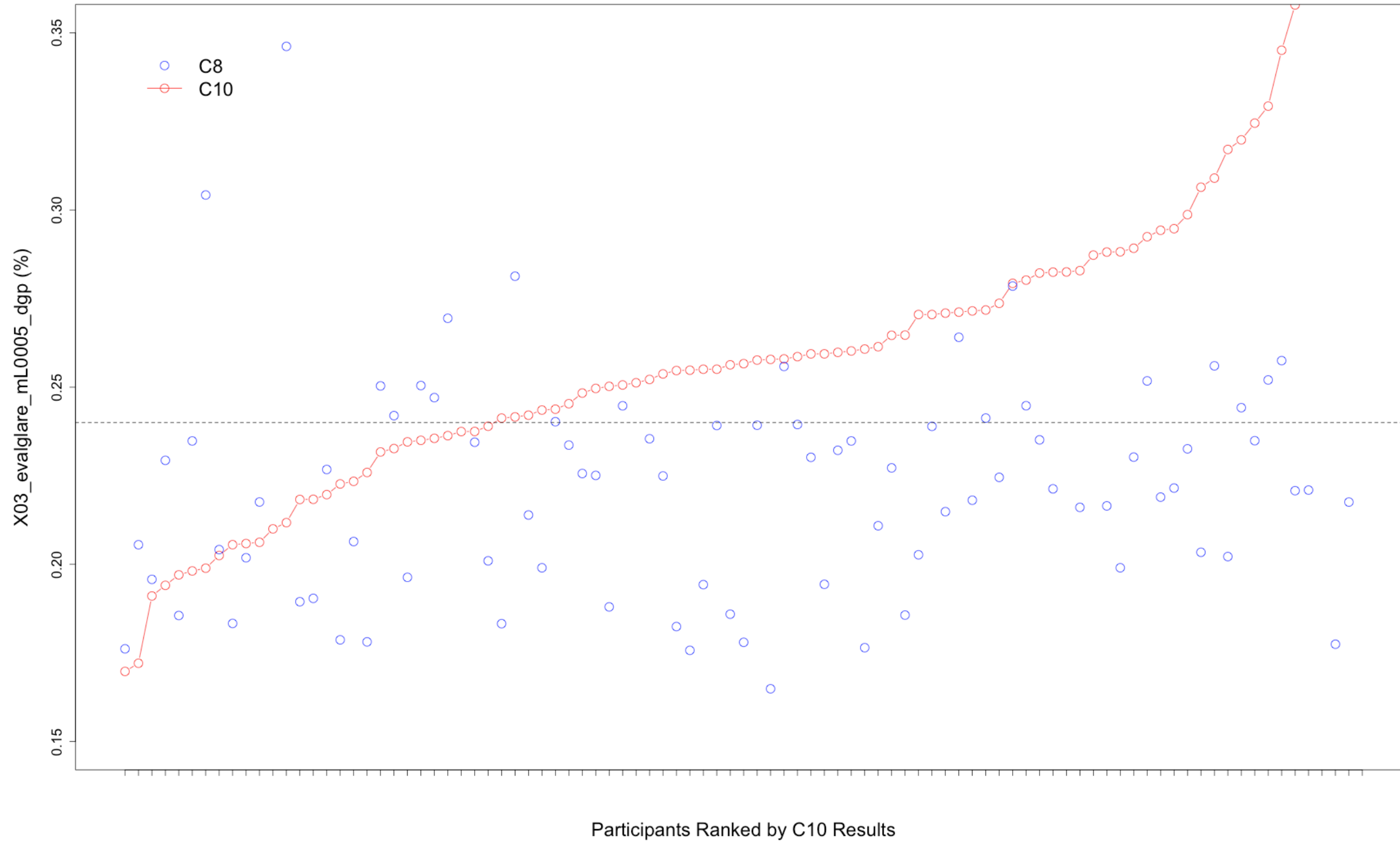


Figure 58 – DGP based upon 5*mL of the circle task (X03) using the entire scene (X01) for C8 (MP) & C10 (JU), participant-days ranked by C10 results

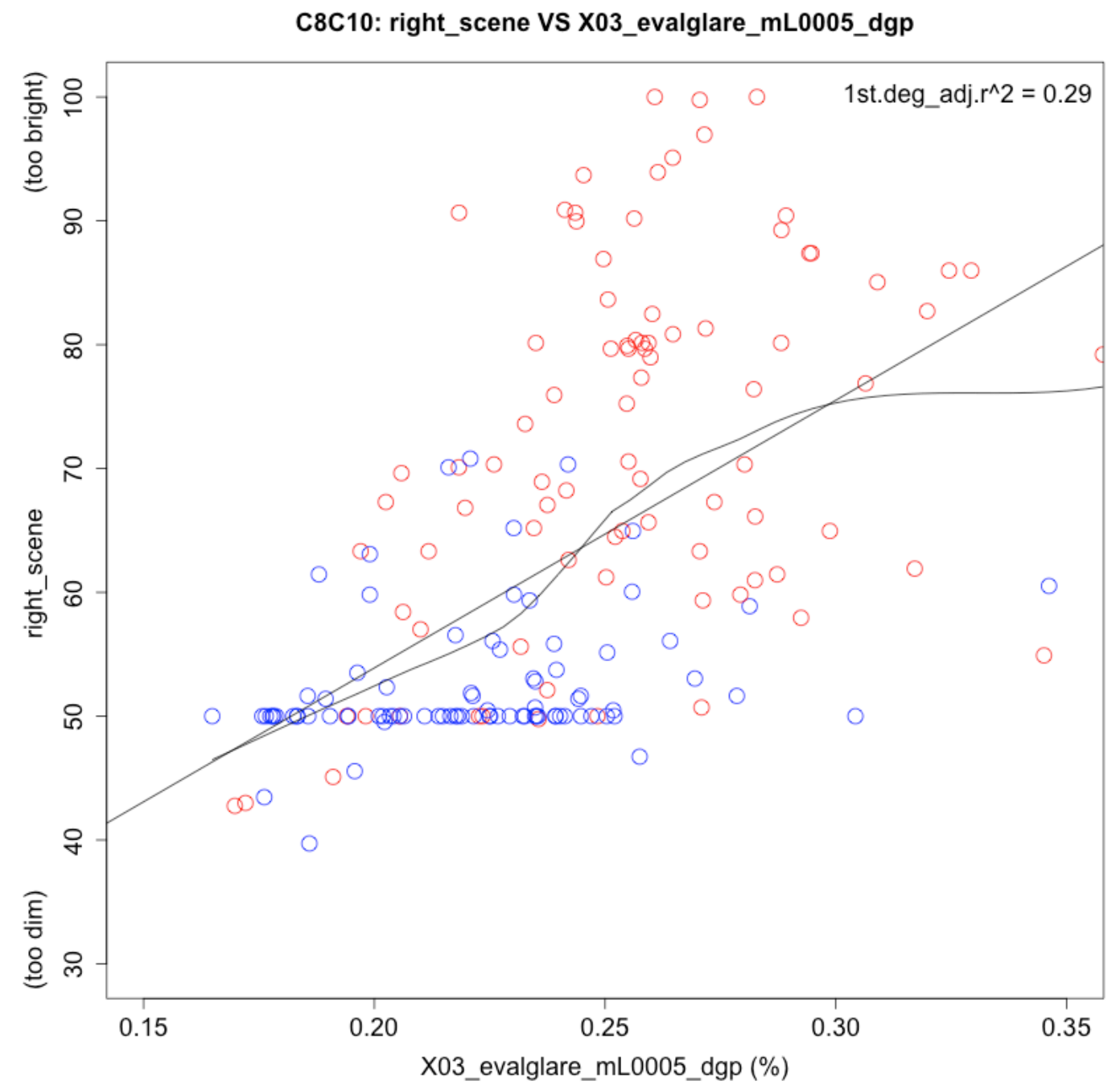
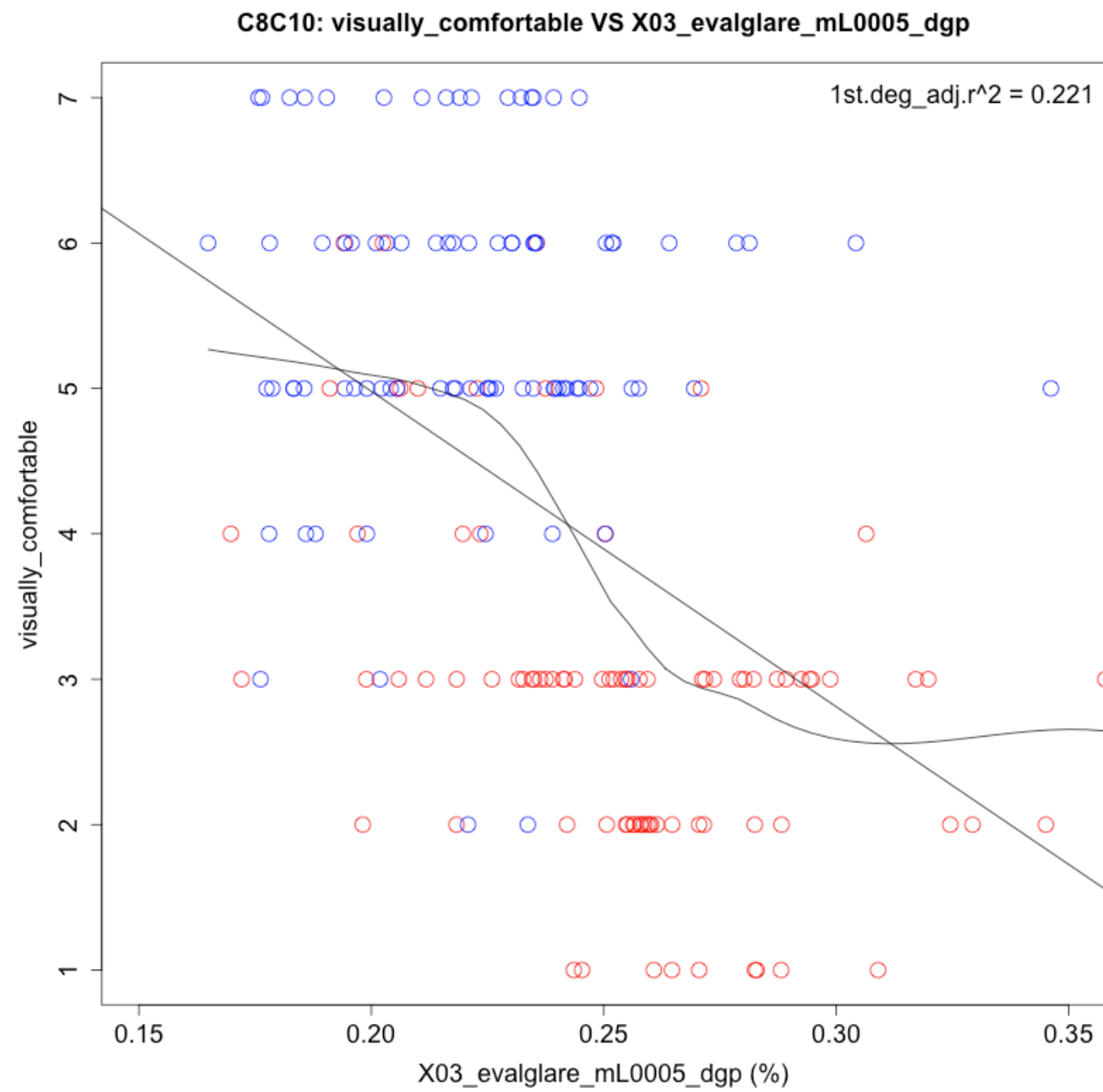


Figure 59 – DGP based upon 5*mL of the circle task (X03) using the entire scene (X01) versus subjective ratings of QU1 (left) and right_scene (right) for C8C10

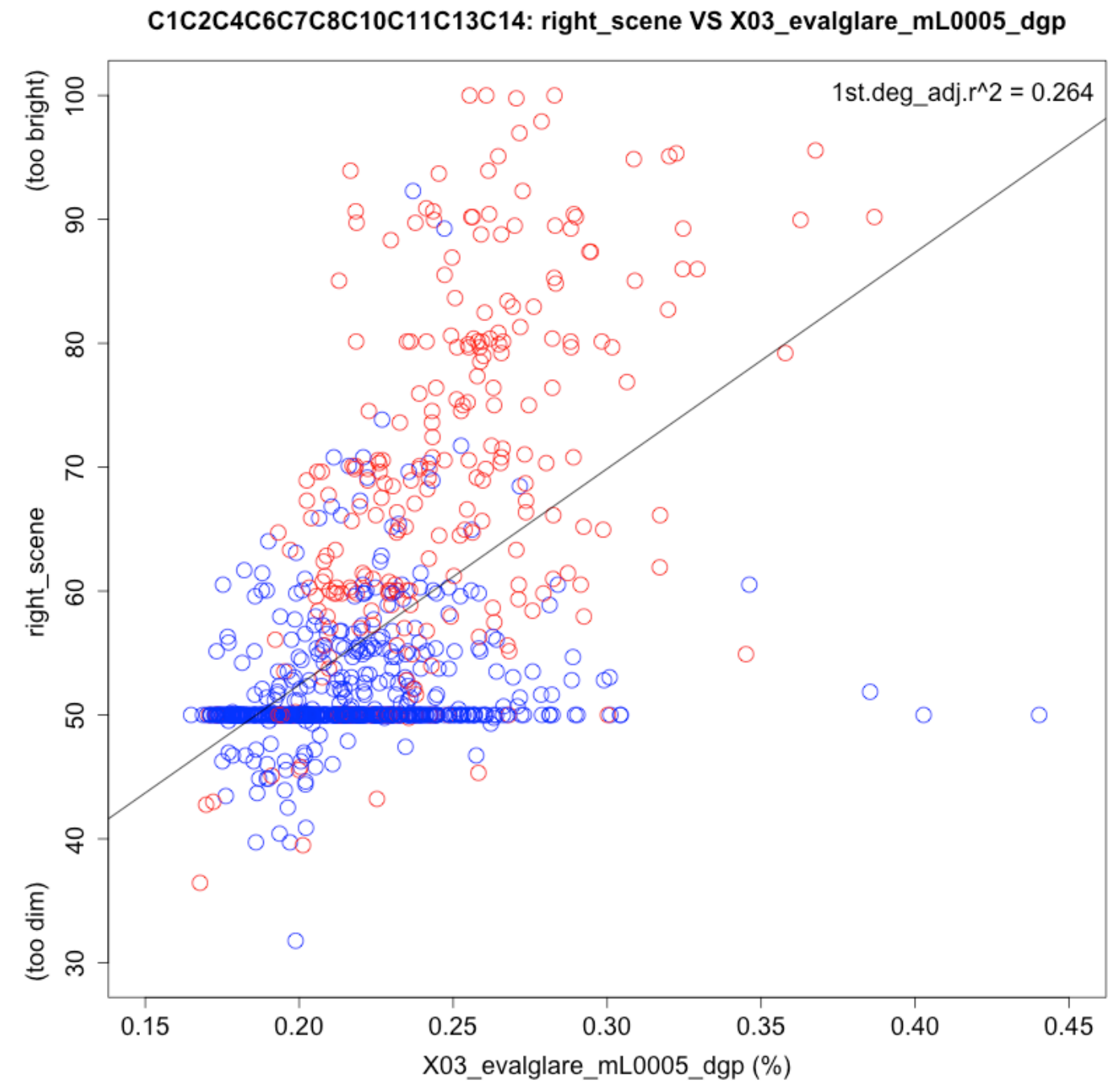
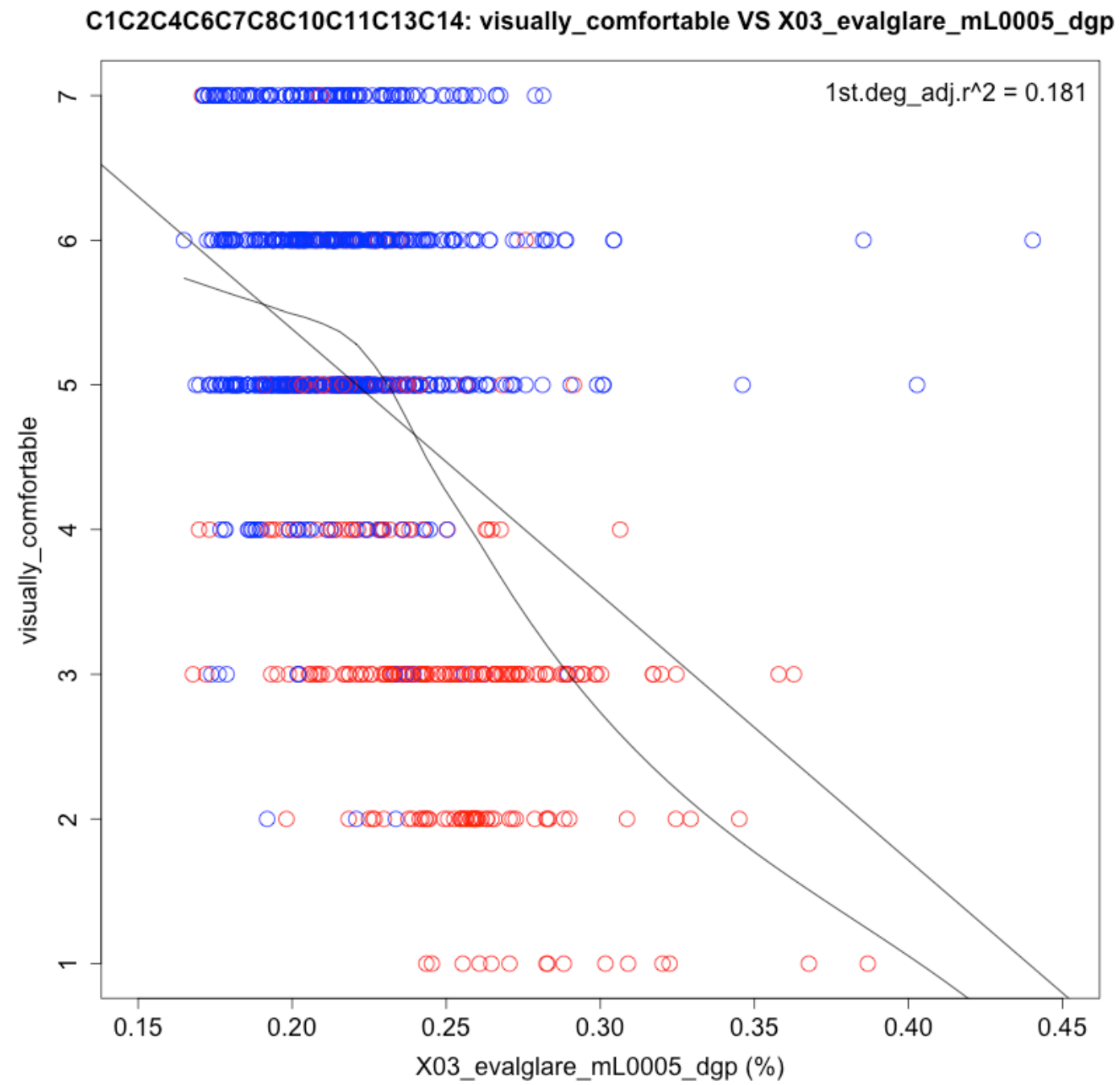


Figure 60 – DGP based upon 5*mL of the circle task (X03) using the entire scene (X01) versus subjective ratings of QU1 (left) and right_scene (right) for the composite data set

C8 & C10: X03_evalglare_mL0005_dgp & visually_comfortable

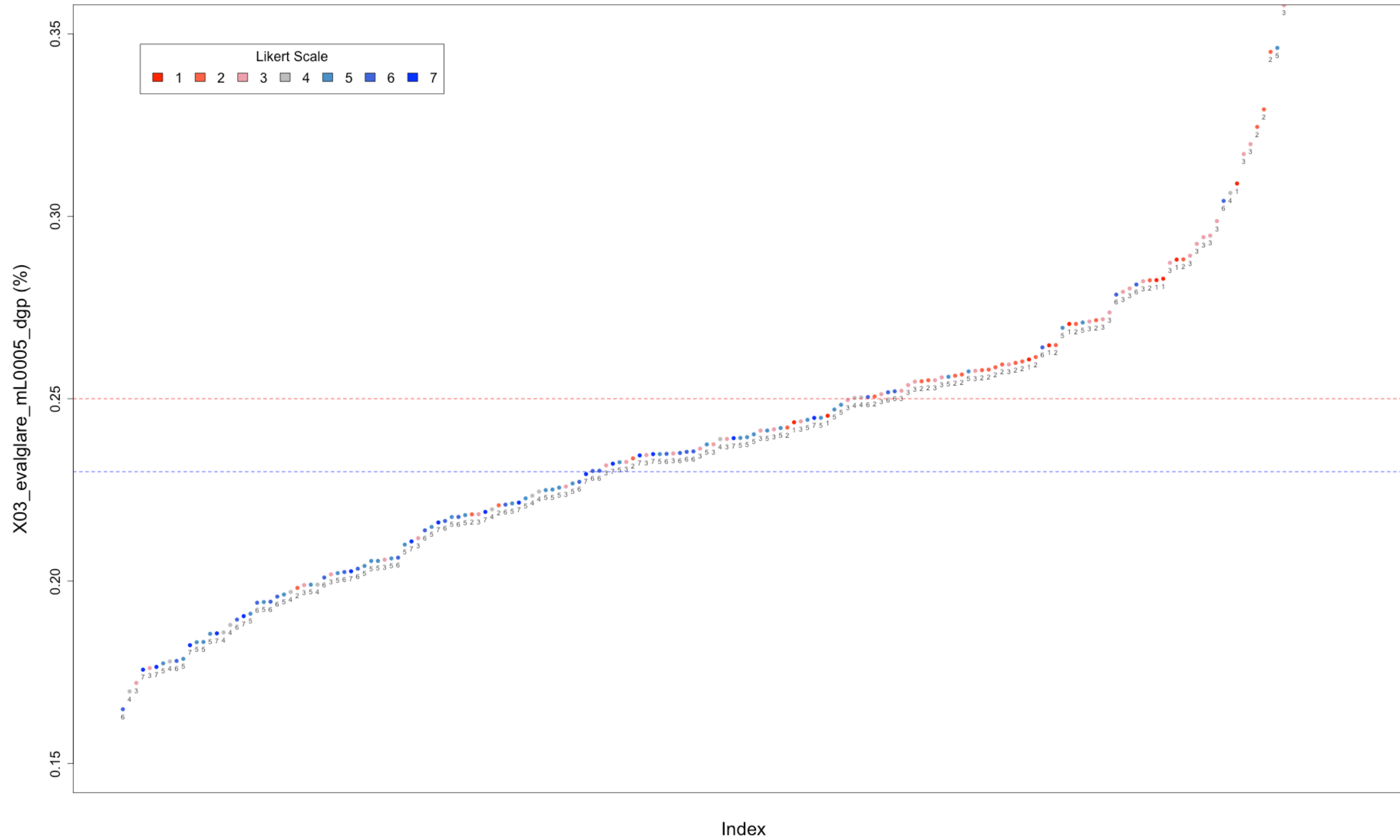


Figure 61 – DGP based upon 5*mL of the circle task (X03) using the entire scene (X01) for C8 & C10, results ordered by metric and color-coded by response to QU1

Table 32 – X03_evalglare_mL0005_dgp range and preliminary criteria

C8C10: X03_evalglare_mL0005_dgp (%) Range						
Min.	1st Qu.	Median	Mean	3rd Qu.	Max.	σ
16.5%	21.1%	23.7%	23.8%	25.9%	35.8%	3.8%
Preliminary criteria:						
$x < 23\%$			Likely to be comfortable			
$23\% > x < 25\%$			Bounded-BCD			
$x > 25\%$			Likely to be uncomfortable			

4.3.6 Standard deviation of luminance within a 40° horizontal band (X20)

The standard deviation of the luminance within the 40° horizontal band (X20_standard_deviation, X20 shown in Figure 43) did not rank in the top 20 metrics for any subjective questionnaire items. Figure 62 shows the results for C8C10 with participant-days results ordered by C10 results. The metric correctly differentiates C10 (MP) from C8 (JU) scenes for cases where $C10 \sigma > 1750 \text{ cd/m}^2$. There are several cases where C10 scenes had lower σ values than other participant-day C8 cases. Figure 63 represents the ability of the metric to explain the variance in QU1 and right_scene for C8C10 and Figure 64 does the same for the composite data set. Each plot includes linear and loess polynomial fits with the $\text{adj}r^2$ value representing the first-degree linear fit. The single regression statistics can be seen in Table 33. Finally, Figure 65 takes the C8C10 data, organizes it by the metric result, and color-codes it by the response to QU1. This graphic reveals three preliminary thresholds for criteria development as described in Table 34.

Table 33 – X20_standard_deviation single regression

C8C10: X20_standard_deviation (cd/m²)				
DV	adjR²	F-statistic:	DF	p-value
C8C10				
QU1	0.2237	50.8600	172	2.63E-11
right_scene	0.2415	56.0800	172	3.48E-12
Composite_data_set				
QU1	0.1882	200.7000	860	2.20E-16
right_scene	0.2533	293.1000	860	2.20E-16
C8C10Computer_split53				
QU1	0.273	49.4300	128	1.10E-10
right_scene	0.2736	49.5900	128	1.03E-10
Composite_data_set_Computer_split53				
QU1	0.2095	184.1000	690	2.20E-16
right_scene	0.2794	269.0000	690	2.20E-16

C8C10: X20_standard_deviation

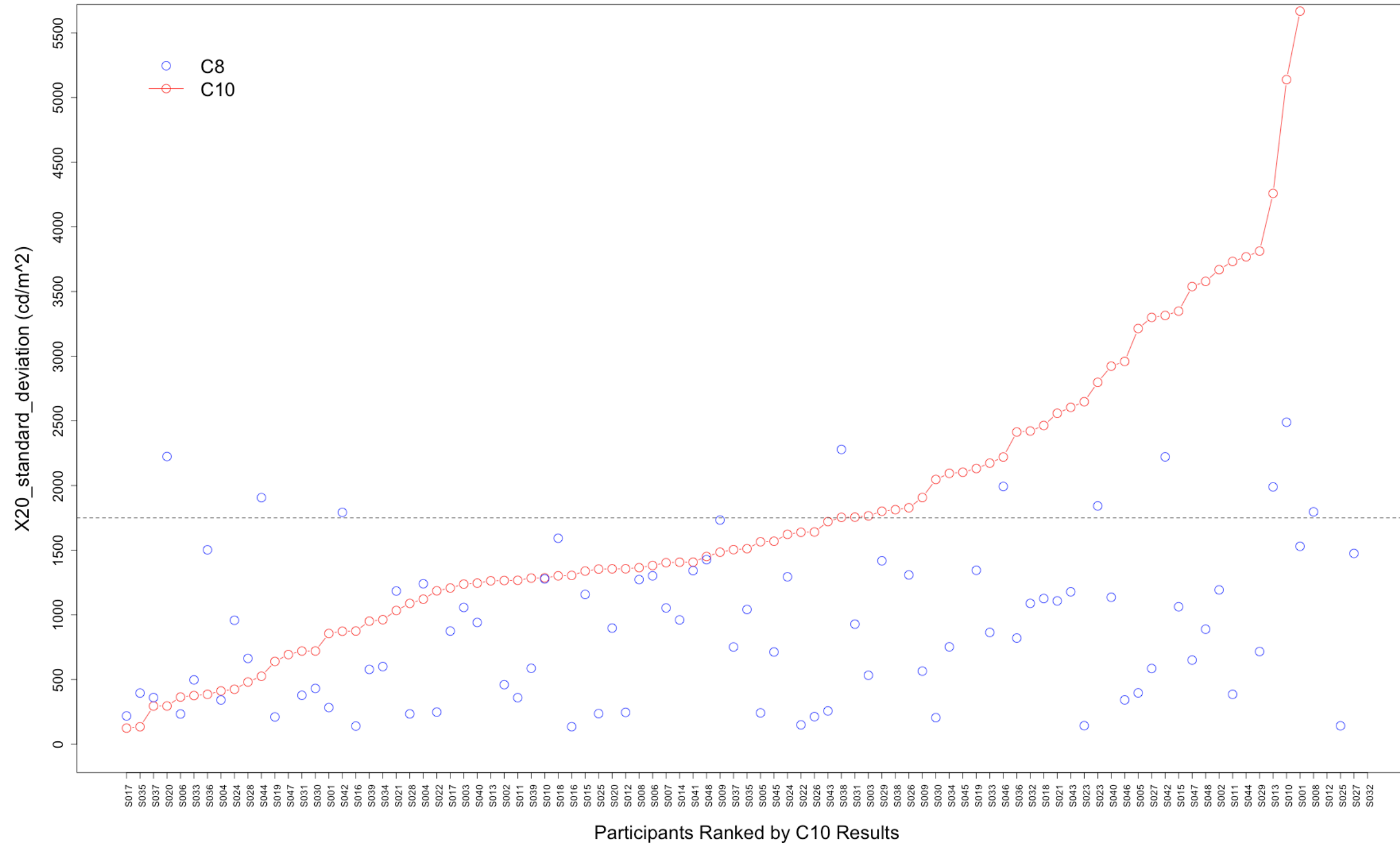


Figure 62 – Standard deviation of luminance within the 40° horizontal band (X20) for C8 & C10, participants ranked by C10 results

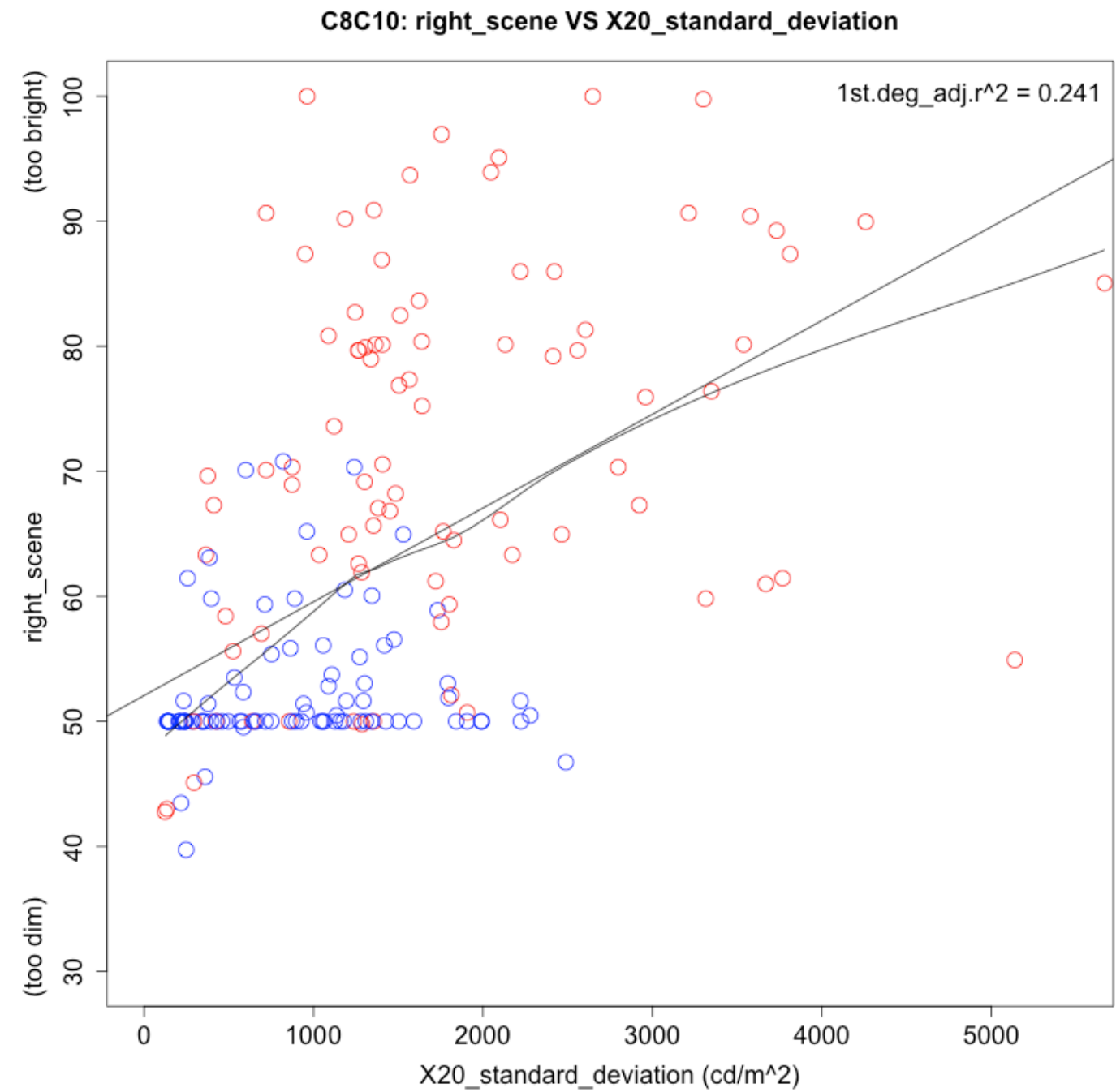
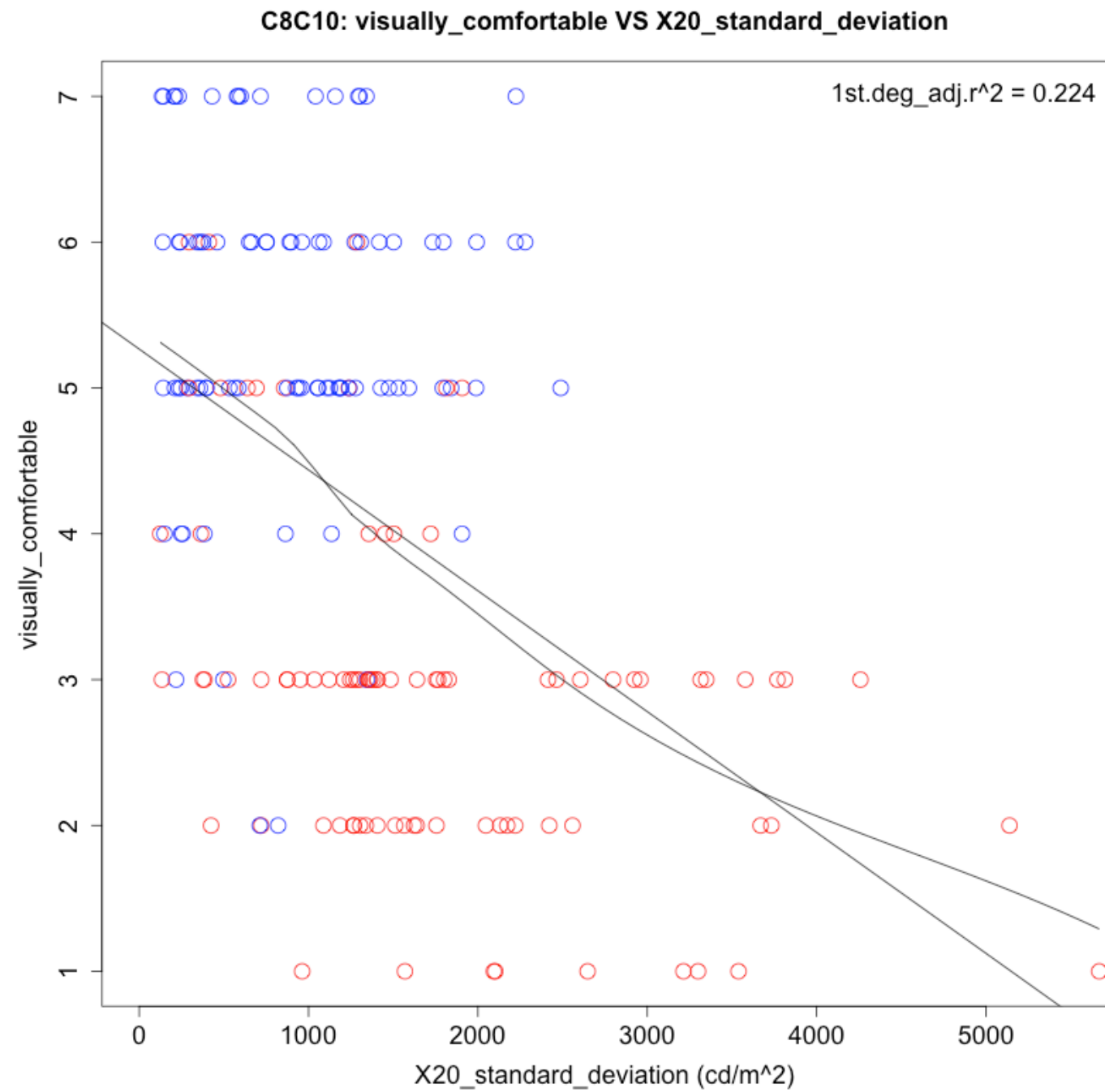


Figure 63 – Standard deviation of luminance within the 40° horizontal band (X20) versus subjective ratings of QU1 (left) and right_scene (right) for C8C10

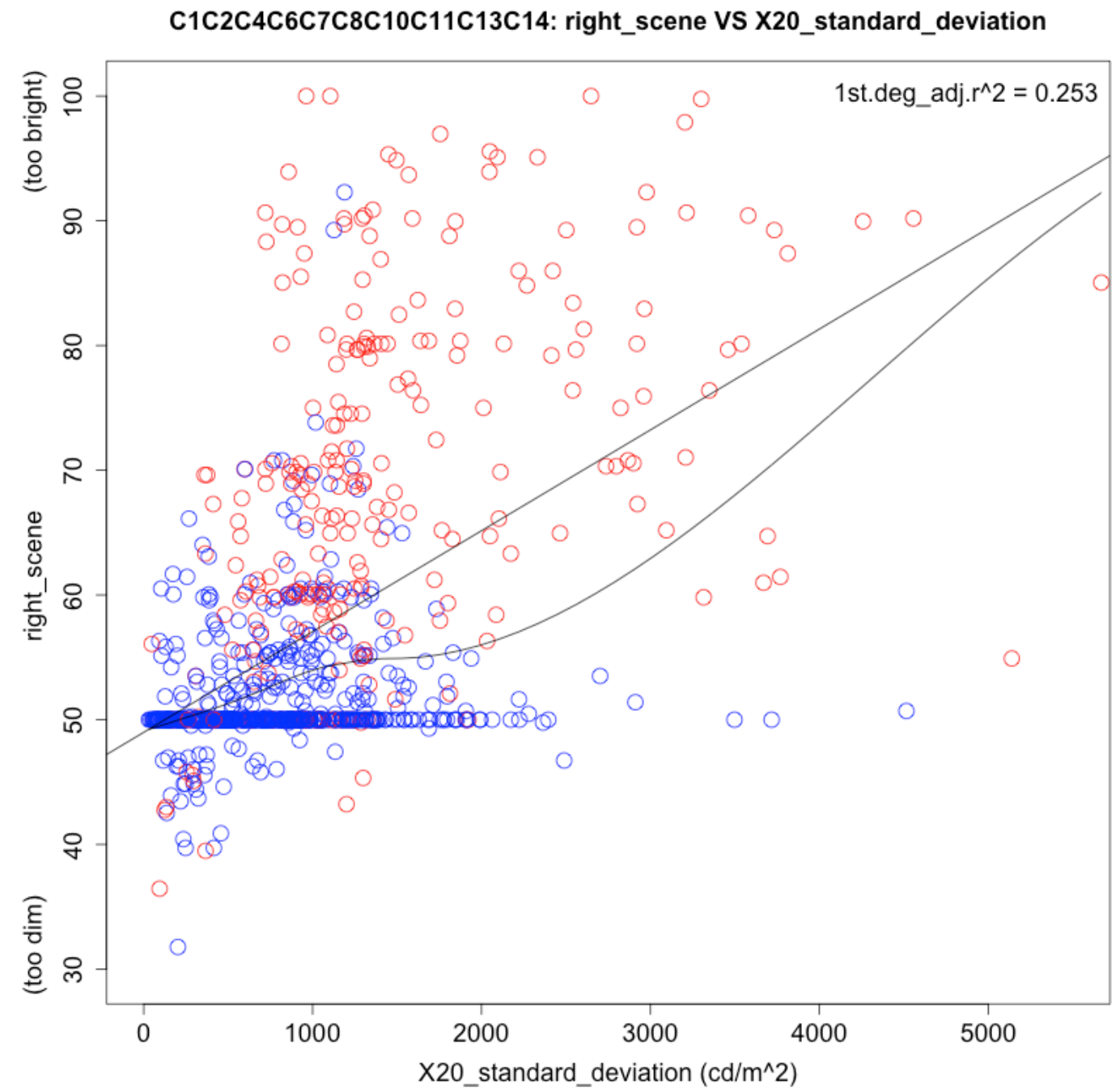
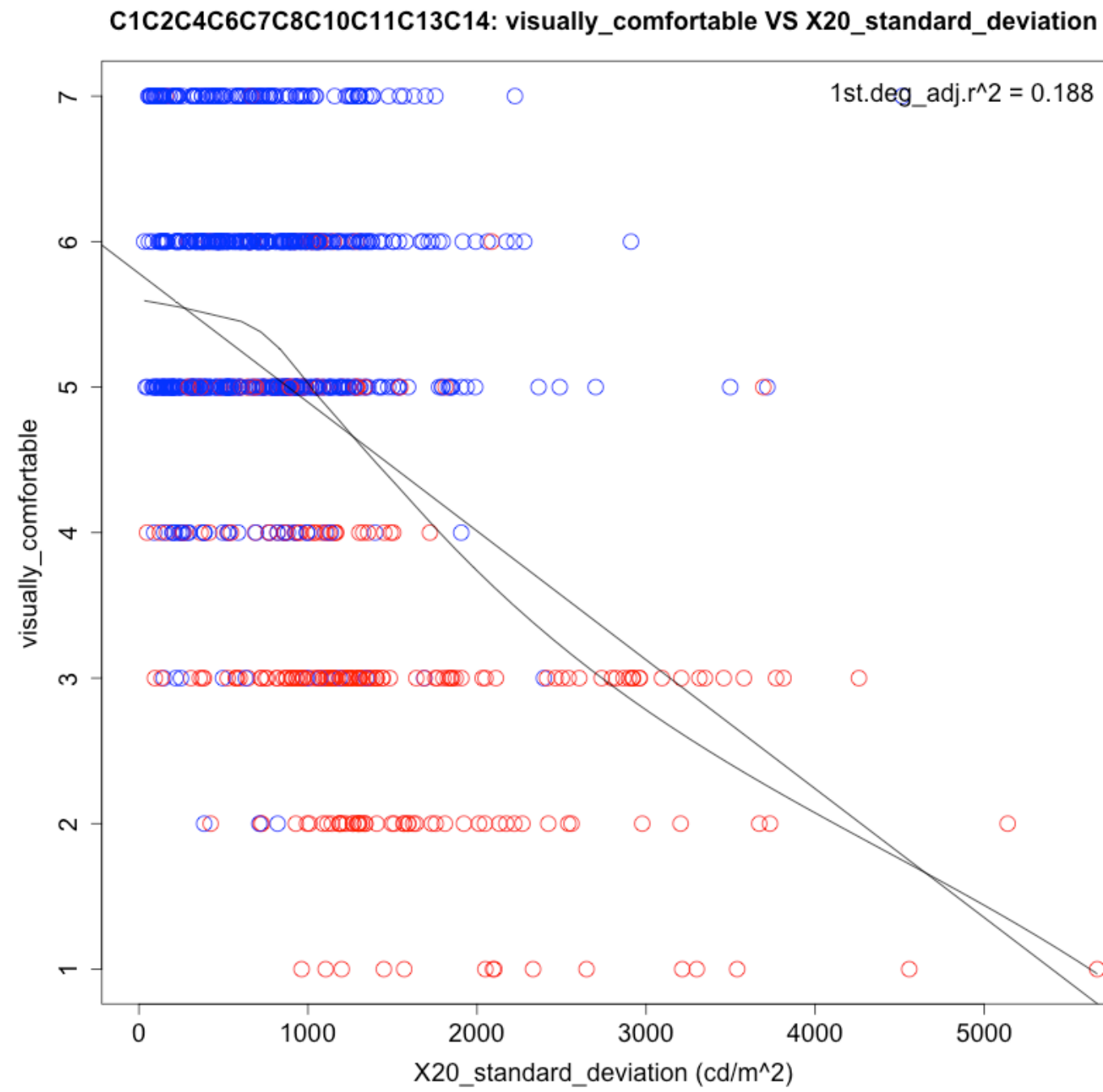


Figure 64 – Standard deviation of luminance within the 40° horizontal band (X20) versus subjective ratings of QU1 (left) and right_scene (right) for the composite data set

C8 & C10: X20_standard_deviation & visually_comfortable

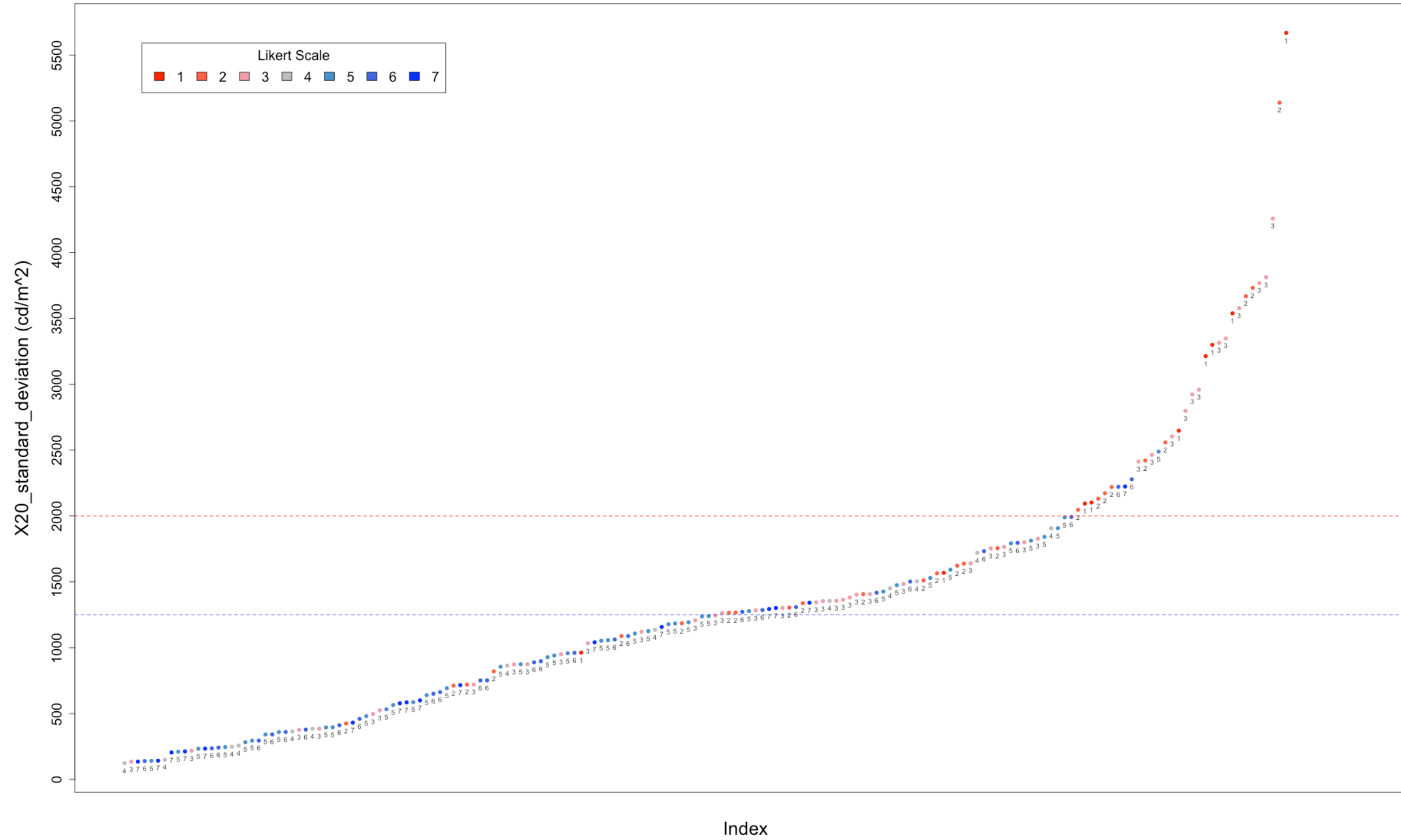


Figure 65 – Standard deviation of luminance within the 40° horizontal band (X20) for C8 & C10, results ordered by metric and color-coded by response to QU1

Table 34 – X20_standard_deviation range and preliminary criteria

C8C10: X20_standard_deviation (cd/m²) Range						
Min.	1st Qu.	Median	Mean	3rd Qu.	Max.	σ
31	442	847	961	1229	5668	760
Preliminary criteria:						
x < 1250			Likely to be comfortable			
1250 > x < 2000			Bounded-BCD			
x > 2000			Likely to be uncomfortable			

4.3.7 Standard deviation of luminance within the entire scene (X01)

The standard deviation of the luminance within the entire scene (X01_standard_deviation, X01 shown in Figure 57-right) did not rank in the top 20 metrics for any subjective questionnaire items. Figure 66 shows the results for C8C10 with participant-days results ordered by C10 results. The metric correctly differentiates C10 (MP) from C8 (JU) scenes for cases where C10 $\sigma > 1250$ cd/m². There are several cases where C10 scenes had lower σ values than other participant-day C8 cases. Figure 67 represents the ability of the metric to explain the variance in QU1 and right_scene for C8C10 and Figure 68 does the same for the composite data set. Each plot includes linear and loess polynomial fits with the $adjr^2$ value representing the first-degree linear fit. The single regression statistics can be seen in Table 35. Finally, Figure 69 takes the C8C10 data, organizes it by the metric result, and color-codes it by the response to QU1. This graphic reveals three preliminary thresholds for criteria development as described in Table 36.

Table 35 – X20_standard_deviation single regression results

C8C10: X01_standard_deviation (cd/m²)				
DV	adjR²	F-statistic:	DF	p-value
C8C10				
QU1	0.2545	60.0500	172	7.67E-13
right_scene	0.3351	88.1800	172	2.20E-16
Composite_data_set				
QU1	0.1846	195.9000	860	2.20E-16
right_scene	0.2599	303.3000	860	2.20E-16
C8C10Computer_split53				
QU1	0.2765	50.3000	128	7.98E-11
right_scene	0.3317	65.0300	128	4.55E-13
Composite_data_set_Computer_split53				
QU1	0.2005	174.3000	690	2.20E-16
right_scene	0.2745	262.4000	690	2.20E-16

C8C10: X01_standard_deviation

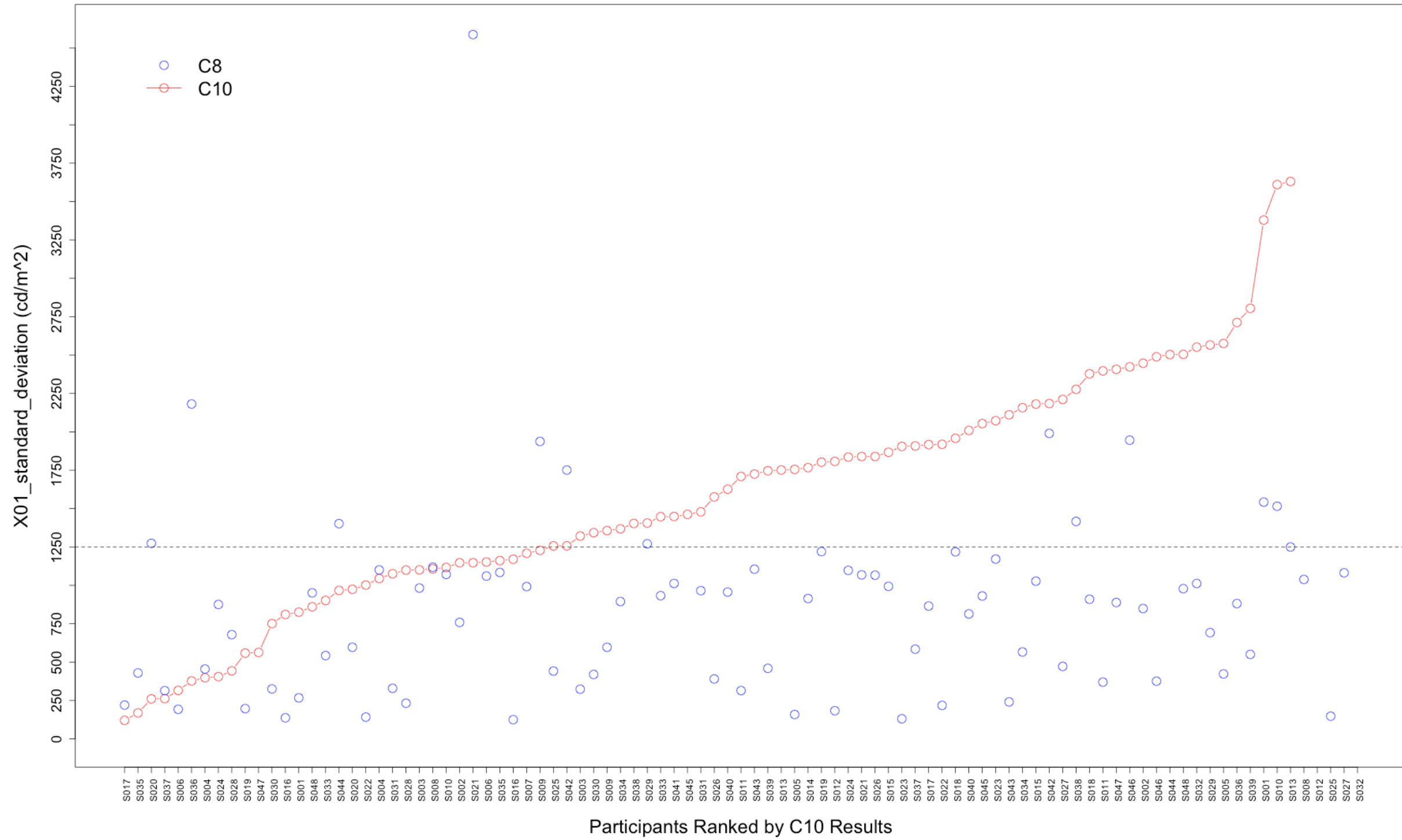


Figure 66 – Standard deviation of scene luminance (X01) for C8 (MP) & C10 (JU), participant-days ranked by C10 results

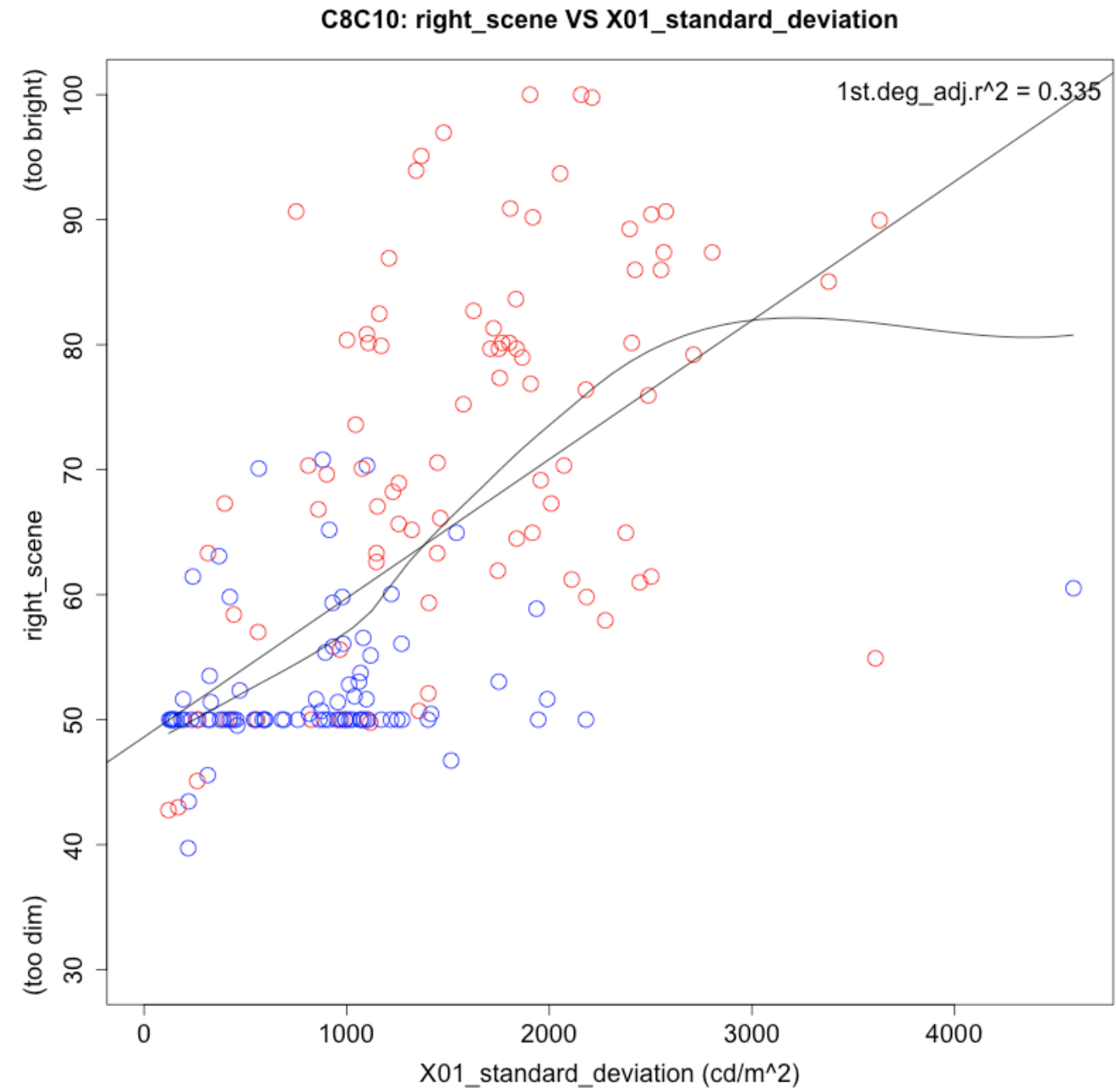
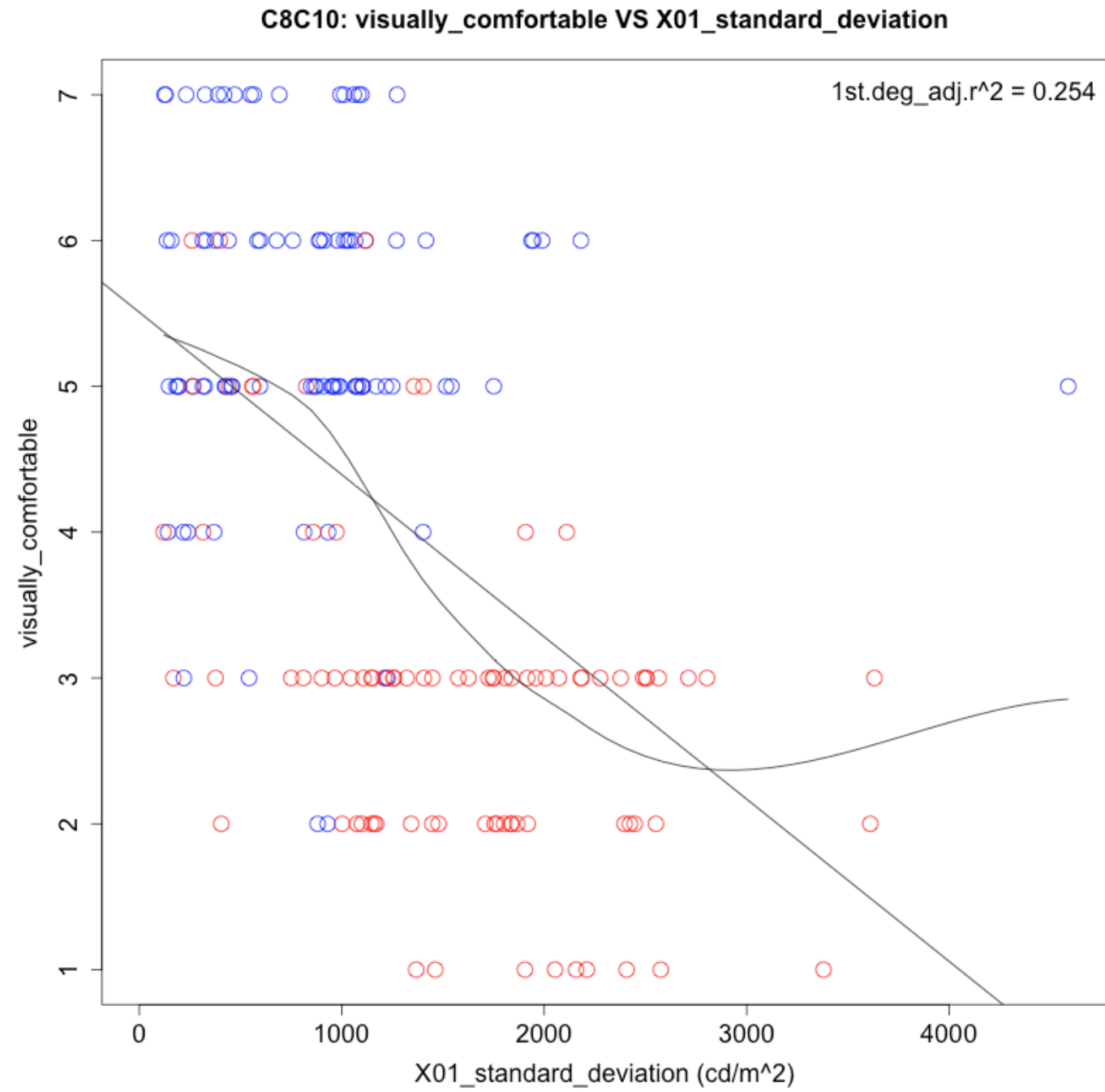


Figure 67 – Standard deviation of scene luminance (X01) versus subjective ratings of QU1 (left) and right_scene (right) for C8C10

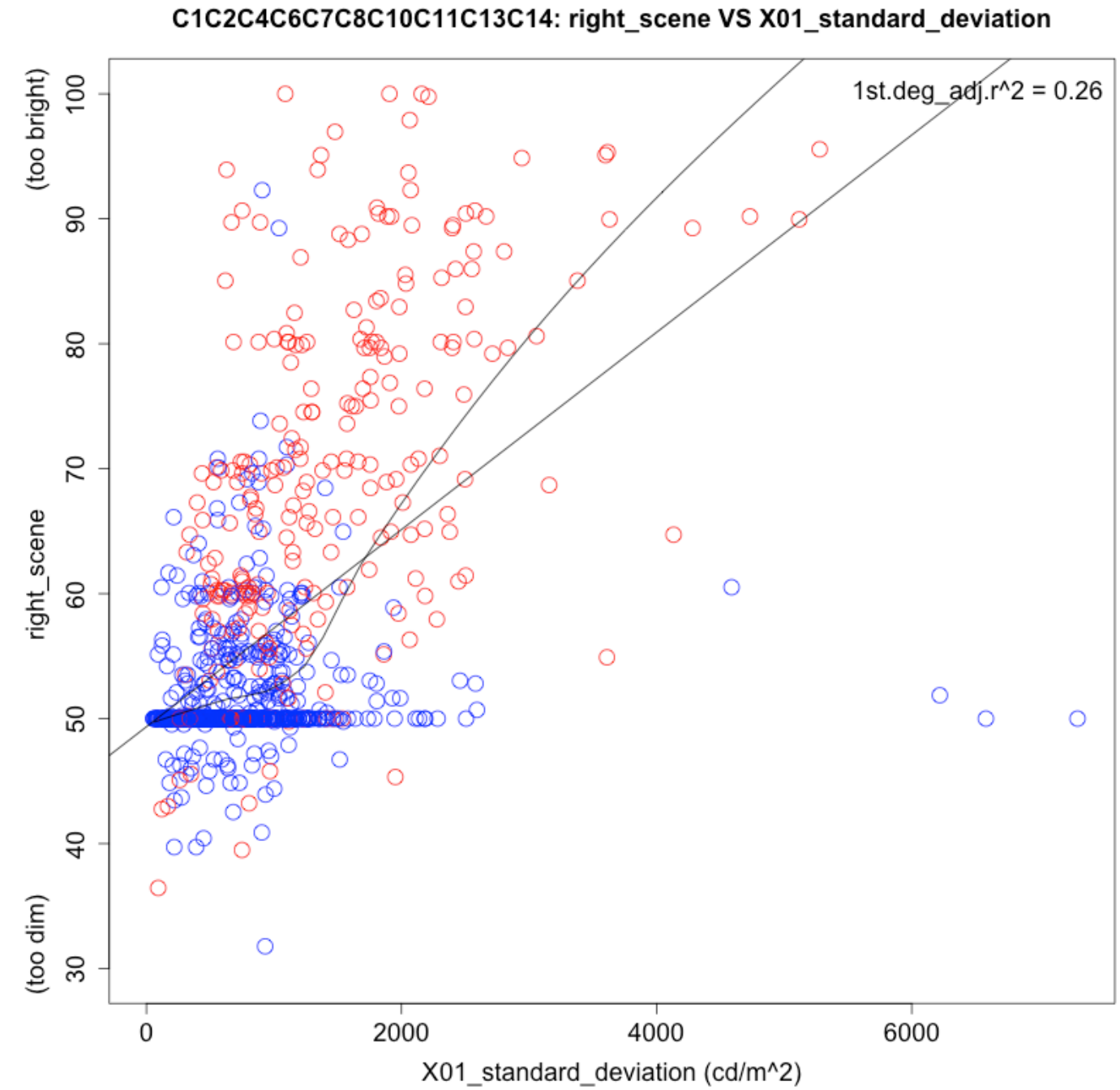
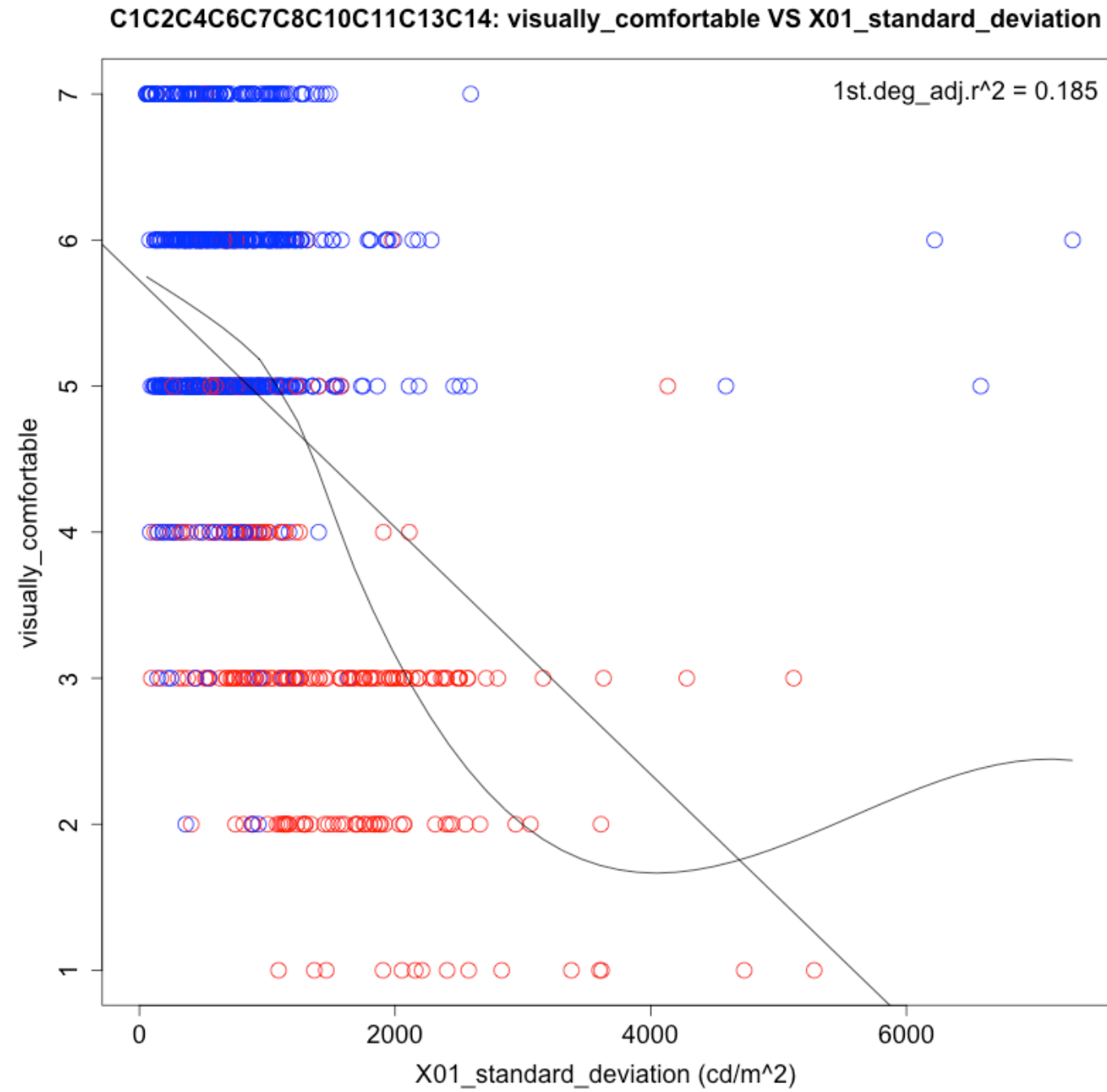


Figure 68 – Standard deviation of scene luminance (X01) versus subjective ratings of QU1 (left) and right_scene (right) for the composite data set

C8 & C10: X01_standard_deviation & visually_comfortable

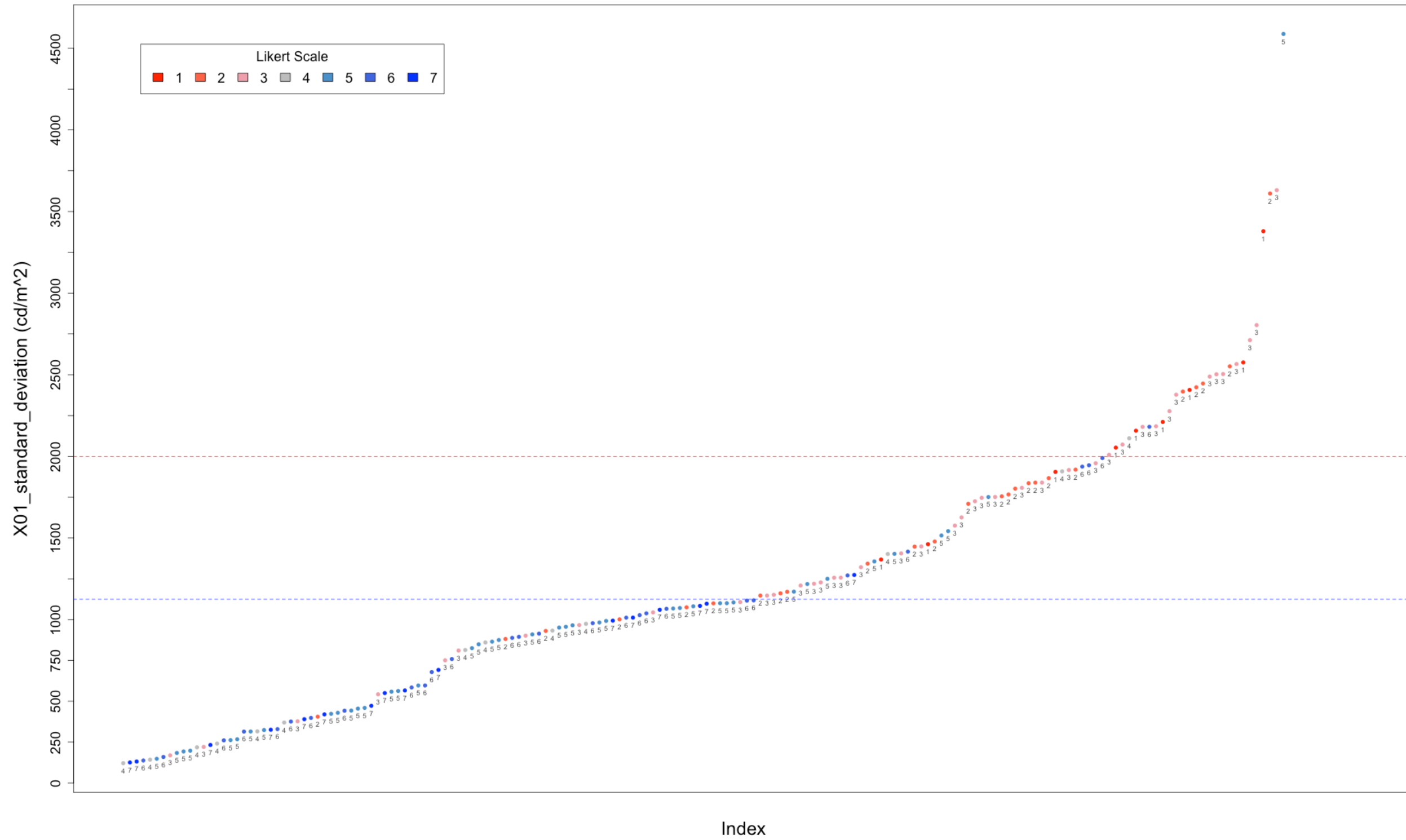


Figure 69 – Standard deviation of scene luminance (X01) for C8 & C10, results ordered by metric and color-coded by response to QU1

Table 36 – X01_standard_deviation range and preliminary criteria

C8C10: X01_standard_deviation (cd/m ²) Range						
Min.	1 st Qu.	Median	Mean	3 rd Qu.	Max.	σ
54	459	780	945	1139	7300	785
Preliminary criteria:						
$x < 1250$			Likely to be comfortable			
$1250 > x < 2000$			Bounded-BCD			
$x > 2000$			Likely to be uncomfortable			

4.3.8 E_v at the top of the monitor in viewing direction

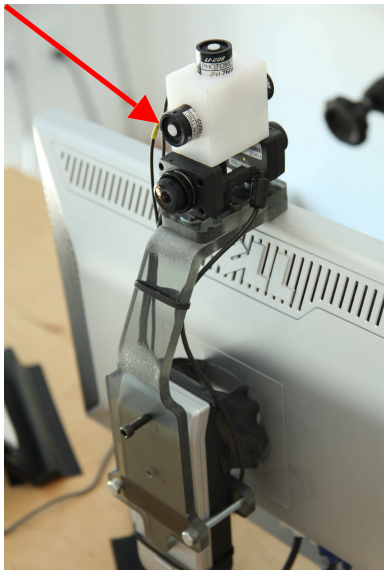


Figure 70 – E_v measured in the participants' viewing direction at the top of monitor

E_v measured in the participants' viewing direction from the top of the monitor

(MD_daq02_illuminance_topFF406, shown in Figure 70) represents the illuminance-based measure with the highest squared correlation coefficient for right_scene. This metric did not rank in the top 20 for right_scene but it did for all Likert questions. Figure 71 shows the results for C8C10 with participant-days results ordered by C10 results. The metric correctly differentiates C10 (MP) from C8 (JU) scenes for most cases, especially where C10 $E_v > 1600$ lux.

There are several cases where C10 scenes had lower E_v values than other participant-day C8 cases. Figure 72 represents the ability of the metric to explain the variance in QU1 and right_scene for C8C10 and Figure 73 does the same for the composite data set. Each plot includes linear and loess polynomial fits with the $\text{adj}r^2$ value representing the first-degree linear fit. The single regression statistics can be seen in Table 37. Finally, Figure 74 takes the C8C10 data, organizes it by the metric result, and color-codes it by the response to QU1. This graphic reveals three preliminary thresholds for criteria development as described in Table 38.

Table 37 – MD_daq02_illumiance_topFF406 single regression results

C8C10: MD_daq02_illumiance_topFF406 (lux)				
DV	$\text{adj}r^2$	F-statistic:	DF	p-value
C8C10				
QU1	0.1418	28.93	168	2.48E-07
right_scene	0.1436	29.33	168	2.09E-07
Composite_data_set				
QU1	0.1546	152.60	828	2.20E-16
right_scene	0.2073	217.70	828	2.20E-16
C8C10Computer_split53				
QU1	0.3043	56.55	126	9.00E-12
right_scene	0.2741	283.00	126	1.37E-10
Composite_data_set_Computer_split53				
QU1	0.2378	209.10	666	2.20E-16
right_scene	0.2971	283.00	666	2.20E-16

C8C10: MD_daq02_illuminance_topFF406

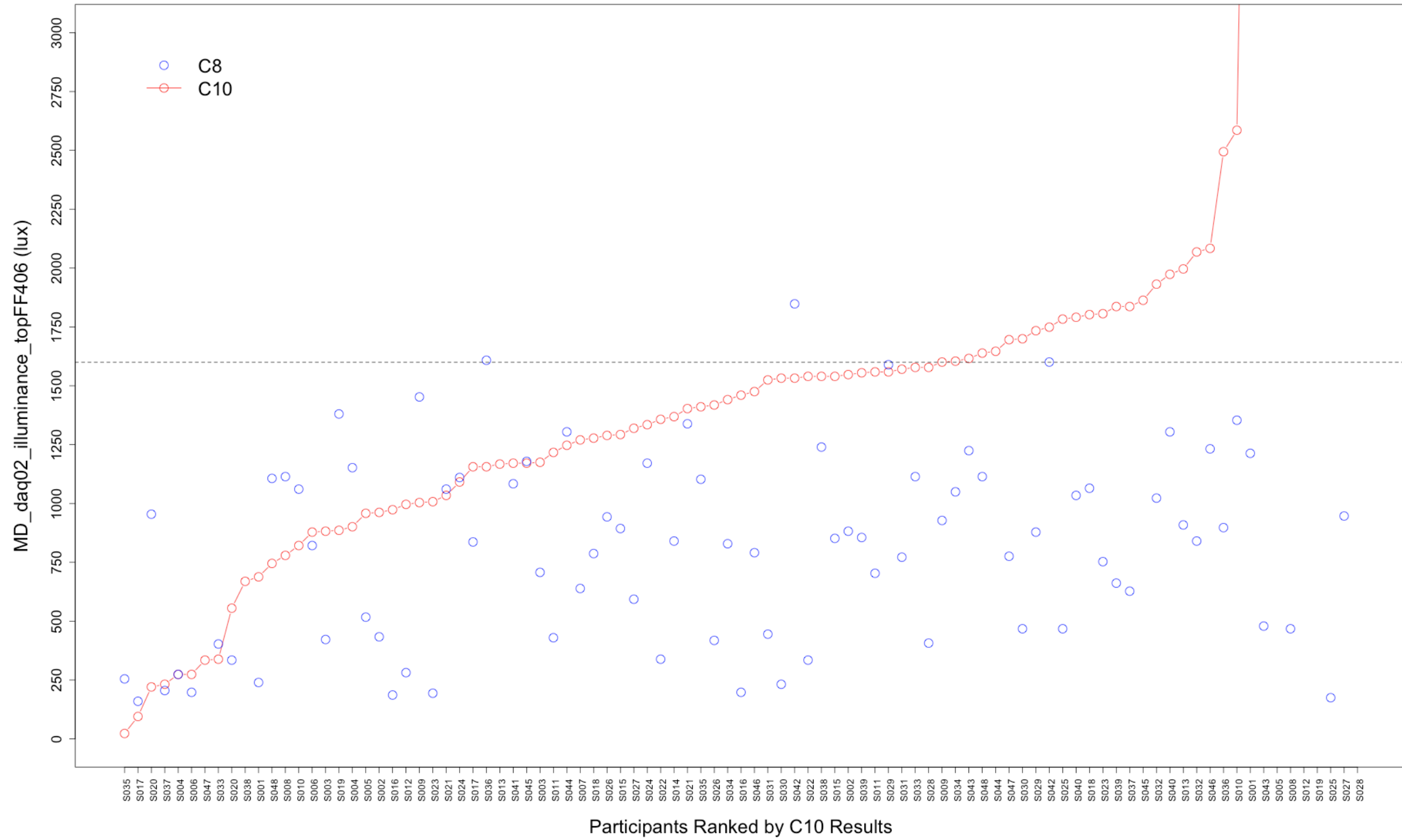


Figure 71 – E_v (at top of monitor in participants' viewing direction) for C8 (MP) & C10 (JU), participant-days ranked by C10 results

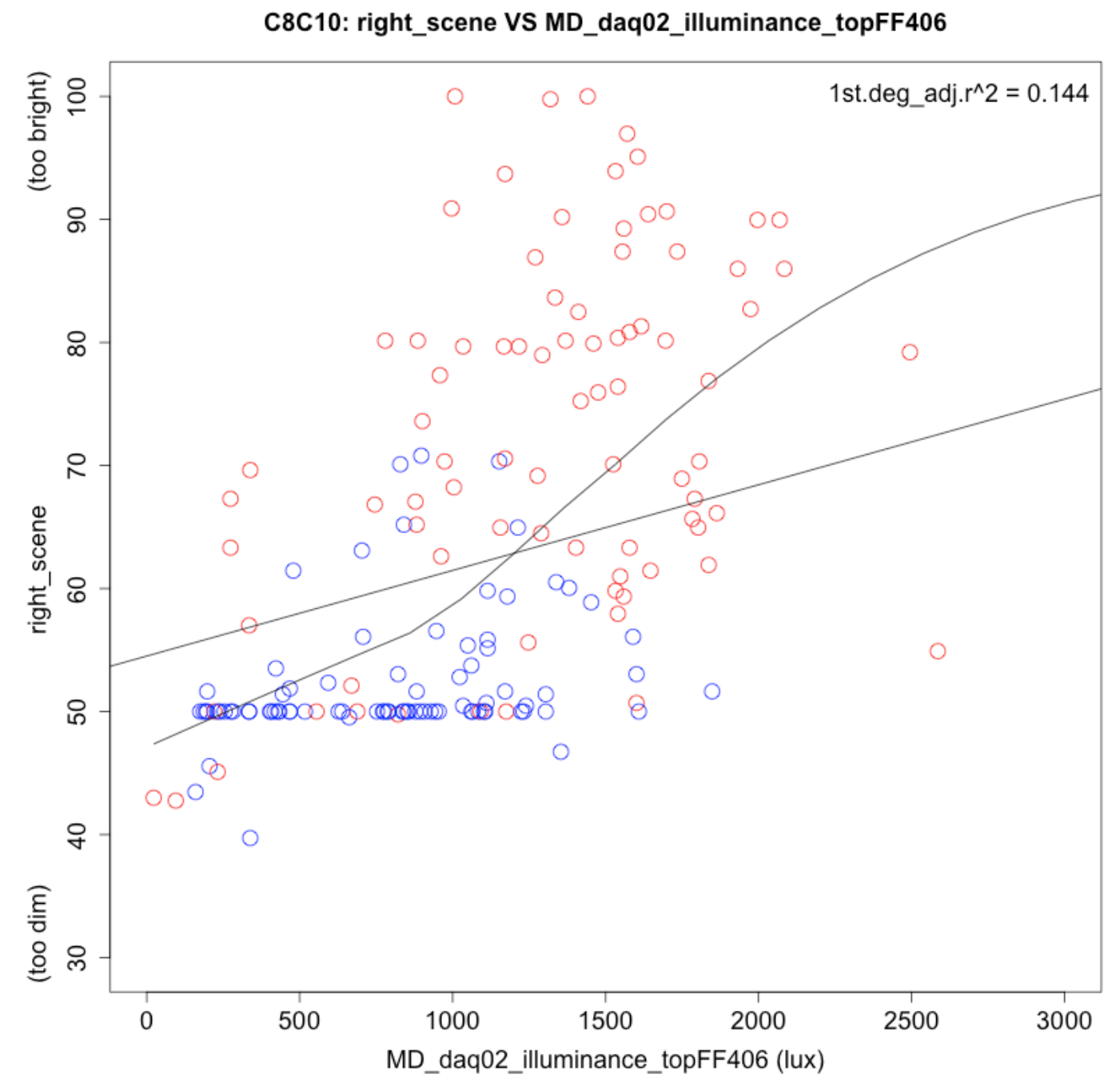
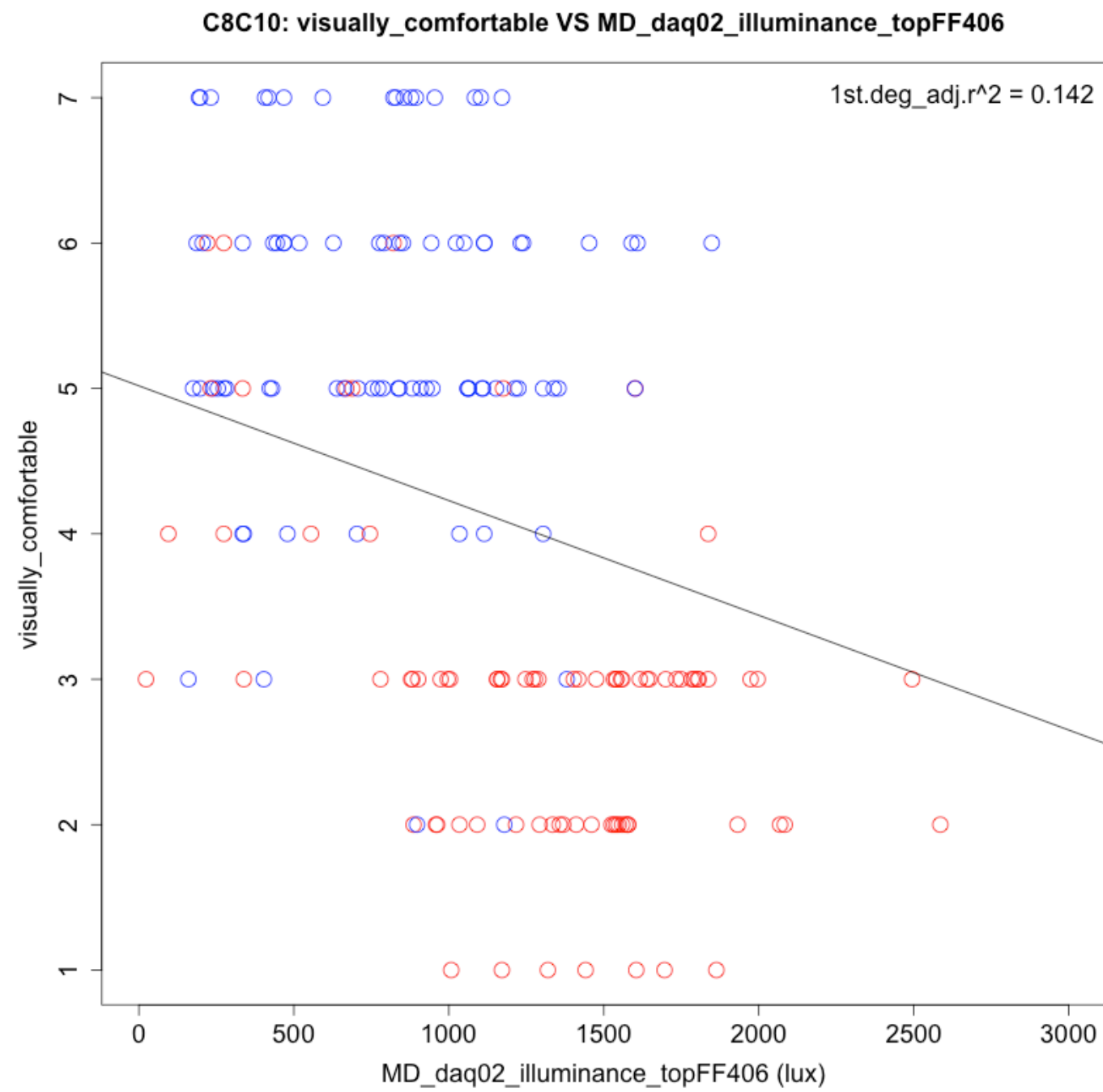
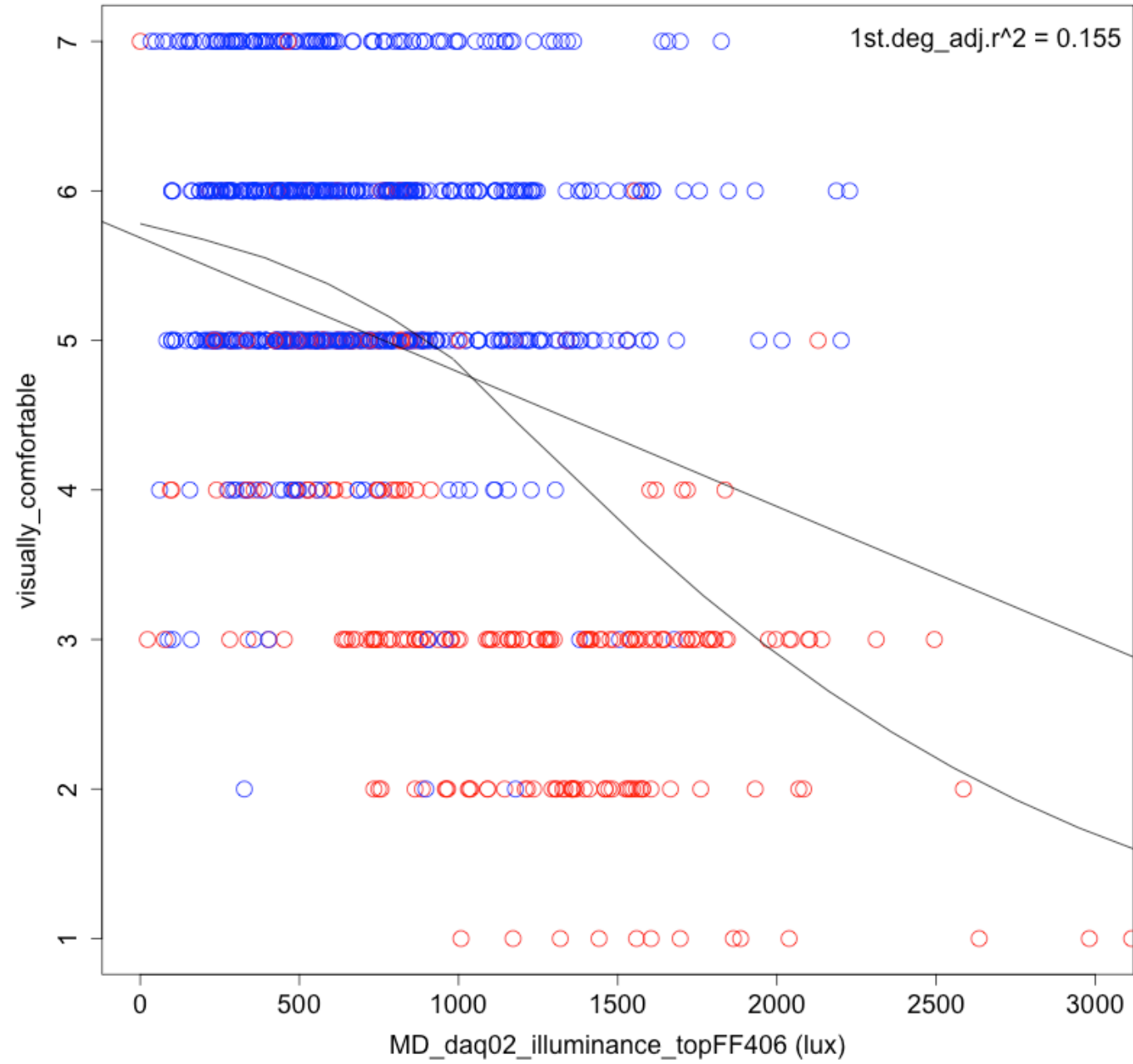


Figure 72 – E_v (at top of monitor in participants' viewing direction) versus subjective ratings of QU1 (left) and right_scene (right) for C8C10

C1C2C4C6C7C8C10C11C13C14: visually_comfortable VS MD_daq02_illuminance_topFF4



C1C2C4C6C7C8C10C11C13C14: right_scene VS MD_daq02_illuminance_topFF406

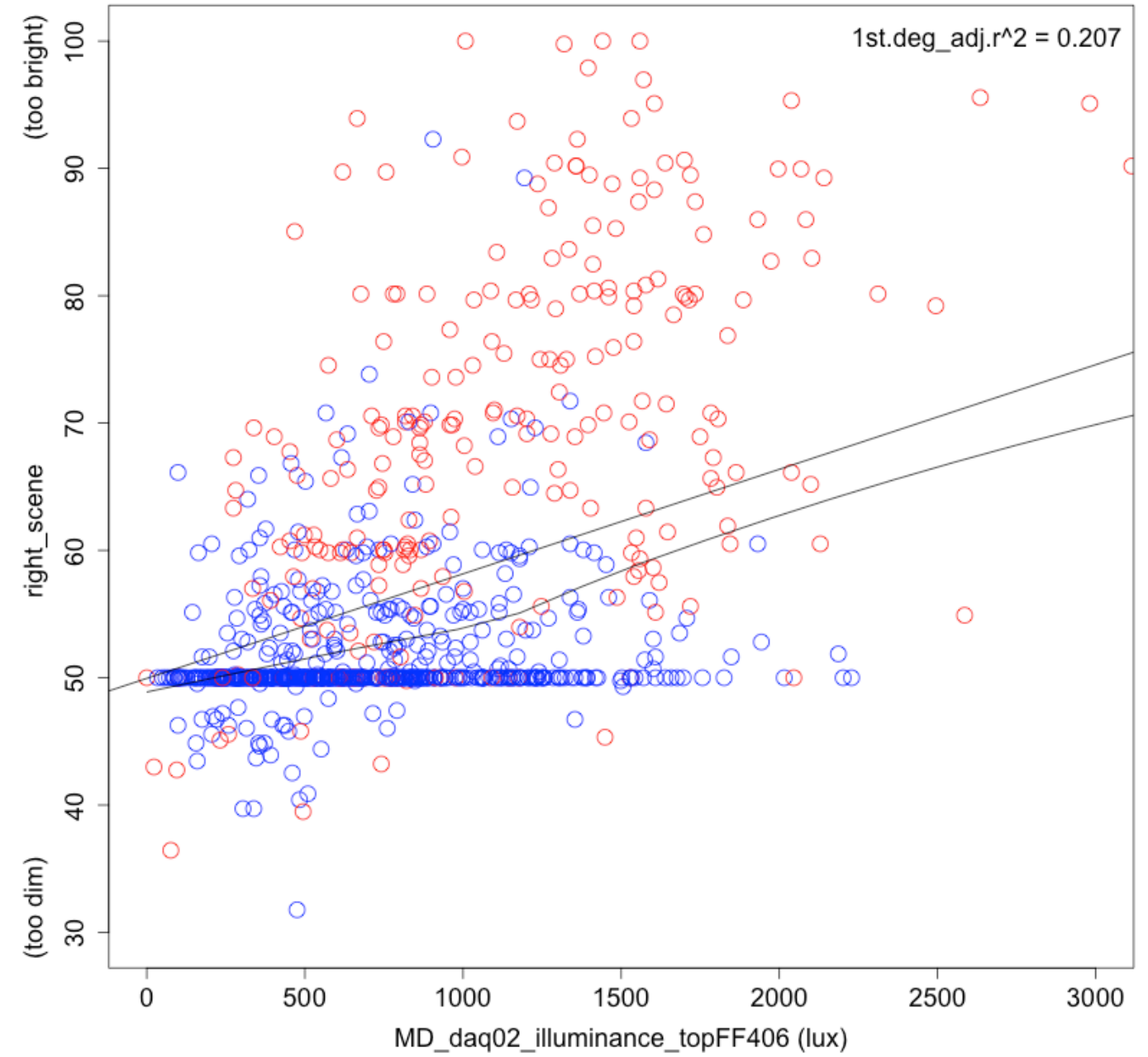


Figure 73 – E_v (at top of monitor in participants' viewing direction) versus subjective ratings of QU1 (left) and right_scene (right) for the composite data set

C8 & C10: MD_daq02_illuminance_topFF406 & visually_comfortable

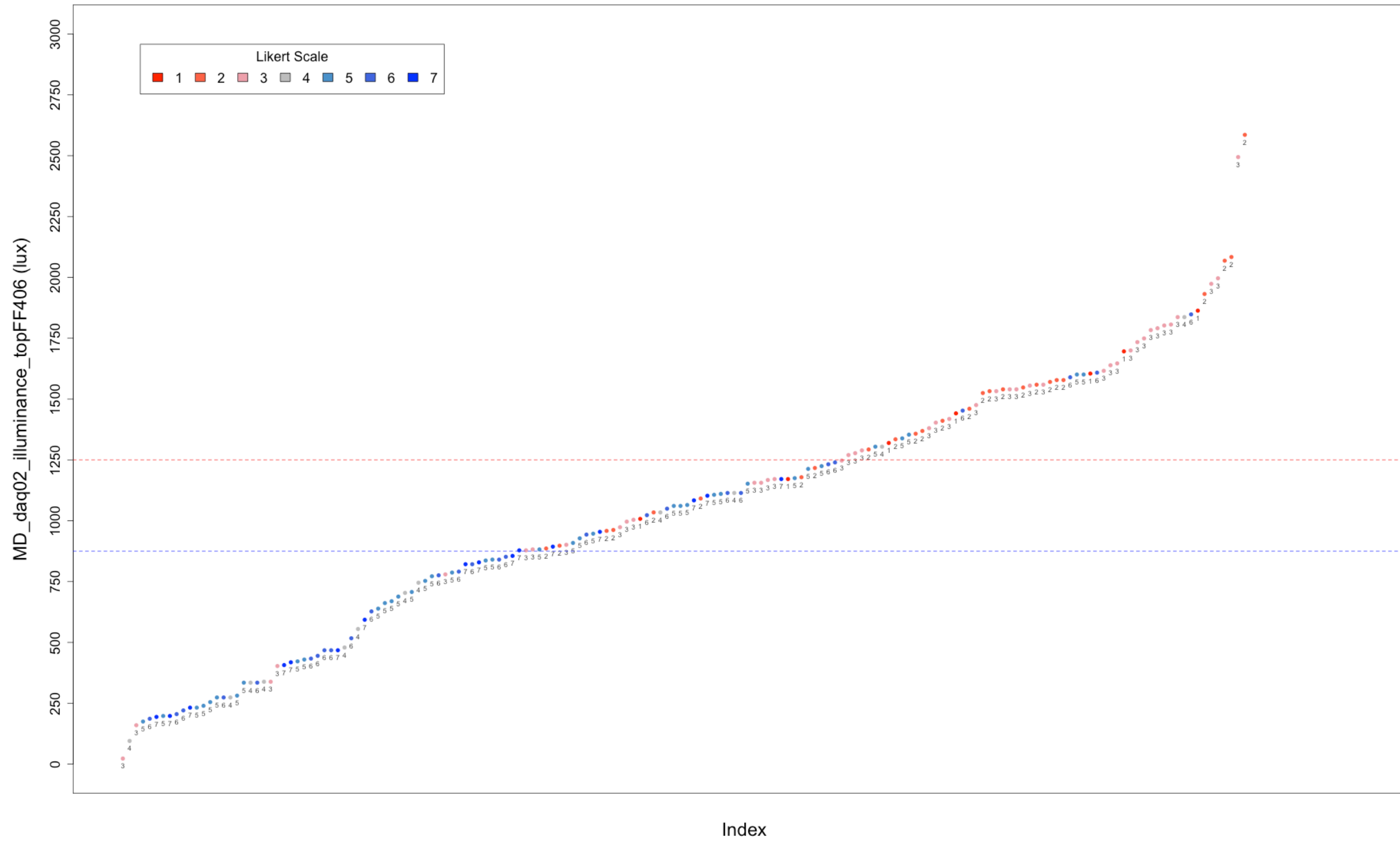


Figure 74 – E_v (at top of monitor in participants' viewing direction) for C8 & C10, results ordered by metric and color-coded by response to QU1

Table 38 – E_v (at top of monitor in participants’ viewing direction) range and preliminary criteria

C8C10: MD_daq02_illuminance_topFF406 (lux) Range						
Min.	1st Qu.	Median	Mean	3rd Qu.	Max.	σ
23	434	726	824	1145	5757	540
Preliminary criteria:						
$x < 875$			Likely to be comfortable			
$875 > x < 1250$			Bounded-BCD			
$x > 1250$			Likely to be uncomfortable			

4.3.9 Percent of scene above 2000 cd/m² (X01)

The percent of the scene above 2000 cd/m² (X01_percent_above_2000_cd, X01 shown in Figure 57-right) did not rank in the top 20 metrics for any subjective questionnaire items.

Figure 75 shows the results for C8C10 with participant-days results ordered by C10 results. The metric correctly differentiates C10 (MP) from C8 (JU) scenes for cases where C10 percent above 2000 cd/m² > 5%. There are several cases where C10 scenes had lower results than other participant-day C8 cases. Figure 76 represents the ability of the metric to explain the variance in QU1 and right_scene for C8C10 and Figure 77 does the same for the composite data set. Each plot includes linear and loess polynomial fits with the adjr2 value representing the first-degree linear fit. The single regression statistics can be seen in Table 39. Finally, Figure 78 takes the C8C10 data, organizes it by the metric result, and color-codes it by the response to QU1. This graphic reveals three preliminary thresholds for criteria development as described in Table 40.

Table 39 – X01_percent_above_2000_cd single regression results

C8C10: X01_percent_above_2000_cd (%)				
DV	adjR²	F-statistic:	DF	p-value
C8C10				
QU1	0.1904	41.69	172	1.05E-09
right_scene	0.2485	58.19	172	1.55E-12
Composite_data_set				
QU1	0.14	141.20	860	2.20E-16
right_scene	0.209	228.50	860	2.20E-16
C8C10Computer_split53				
QU1	0.2353	40.70	128	2.97E-09
right_scene	0.252	44.47	128	6.99E-10
Composite_data_set_Computer_split53				
QU1	0.1503	123.30	690	2.20E-16
right_scene	0.2127	187.60	690	2.20E-16

C8C10: X01_percent_above_2000_cd

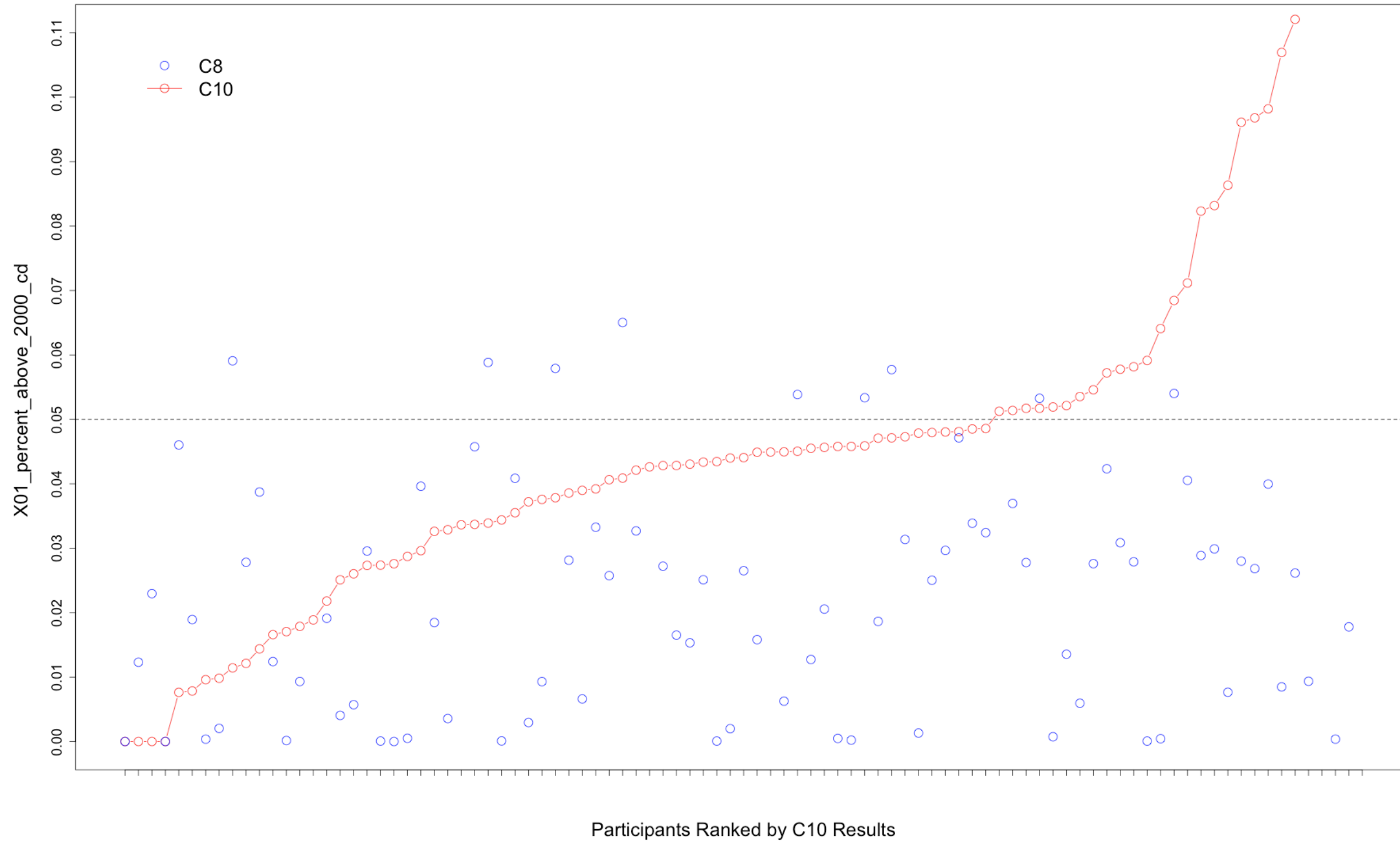


Figure 75 – Percent of scene above 2000 cd/m² (X01) for C8 (MP) & C10 (JU), participant-days ranked by C10 results

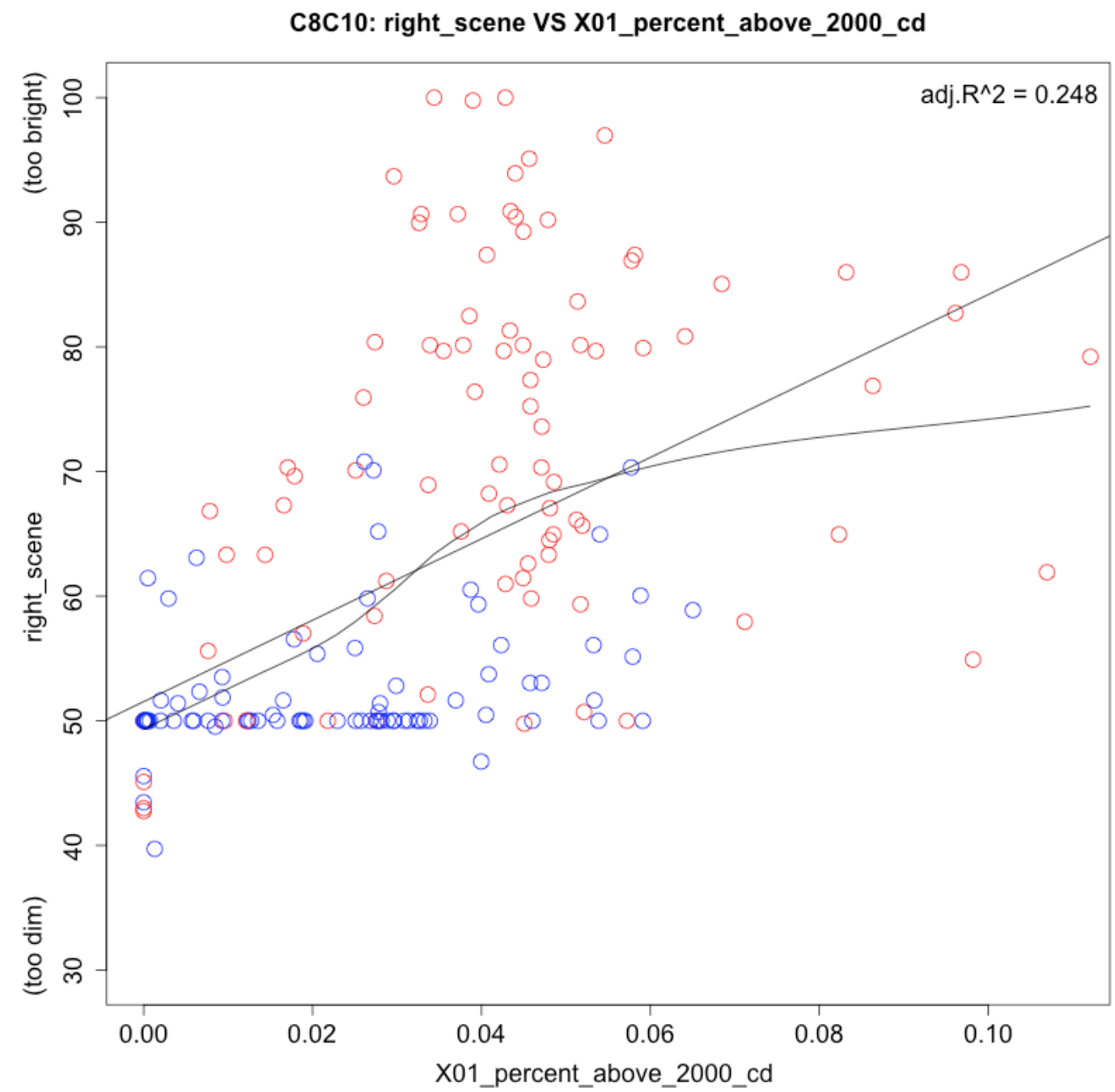
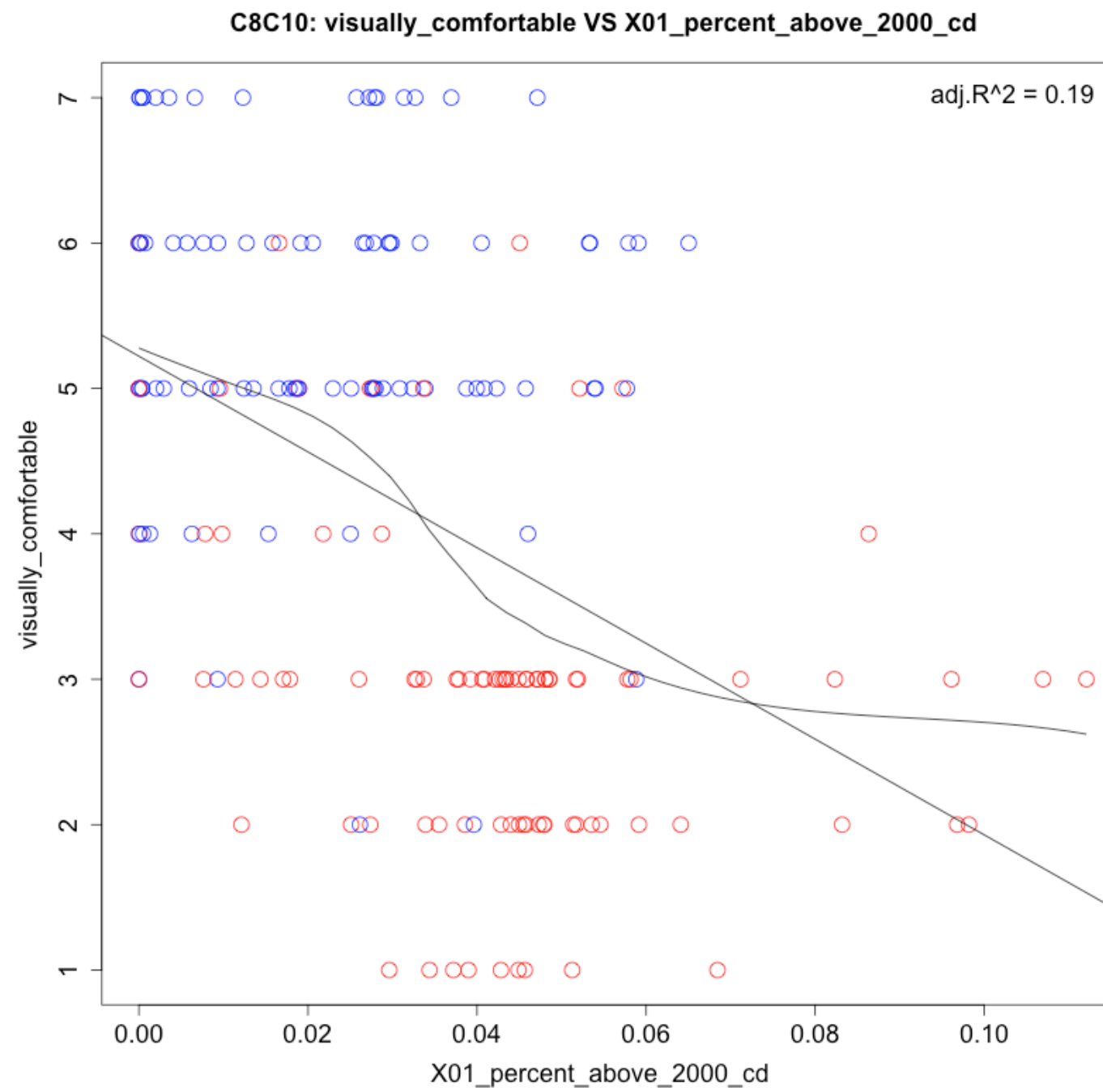


Figure 76 – Percent of scene above 2000 cd/m² (X01) versus subjective ratings of QU1 (left) and right_scene (right) for C8C10

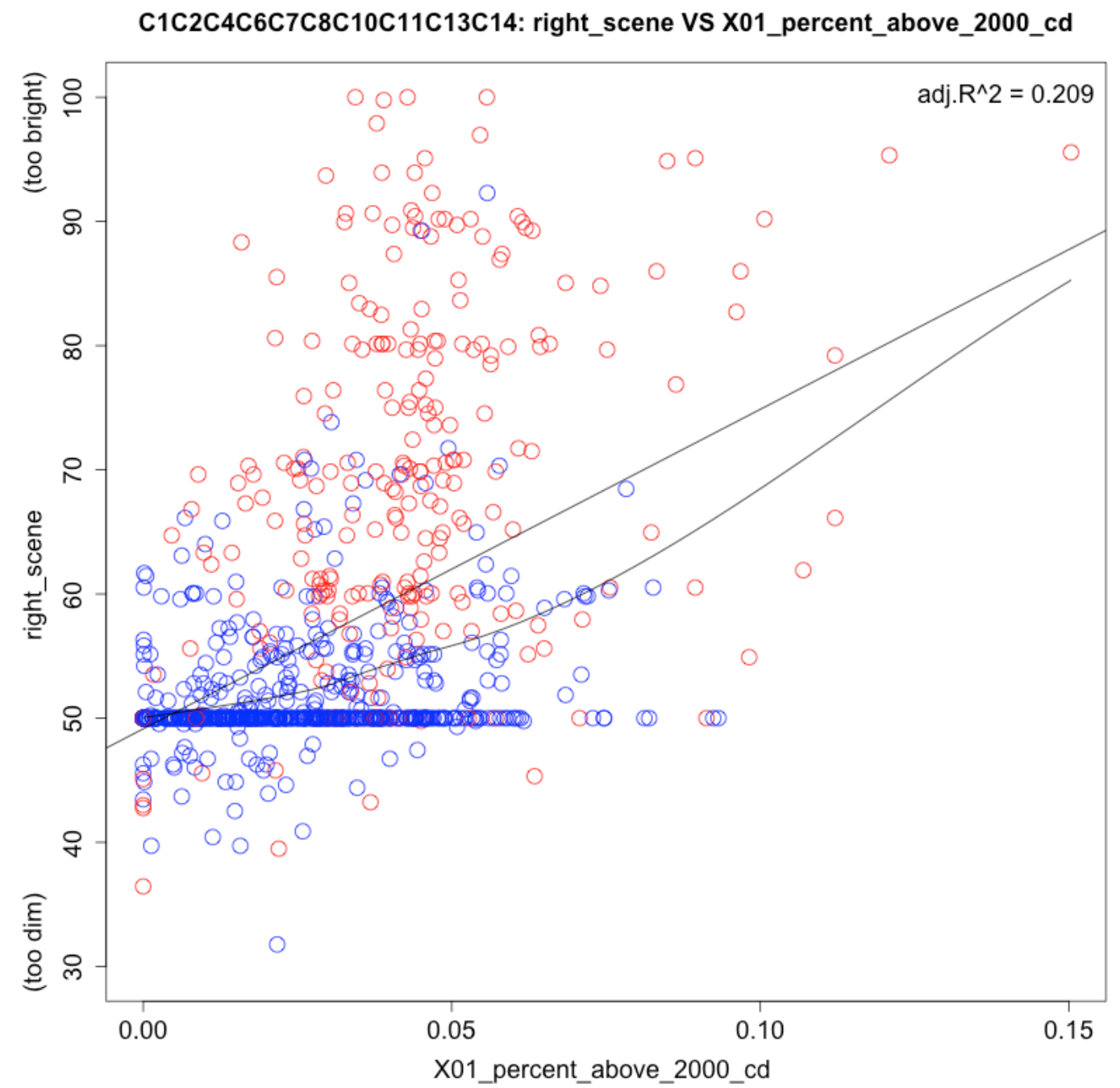
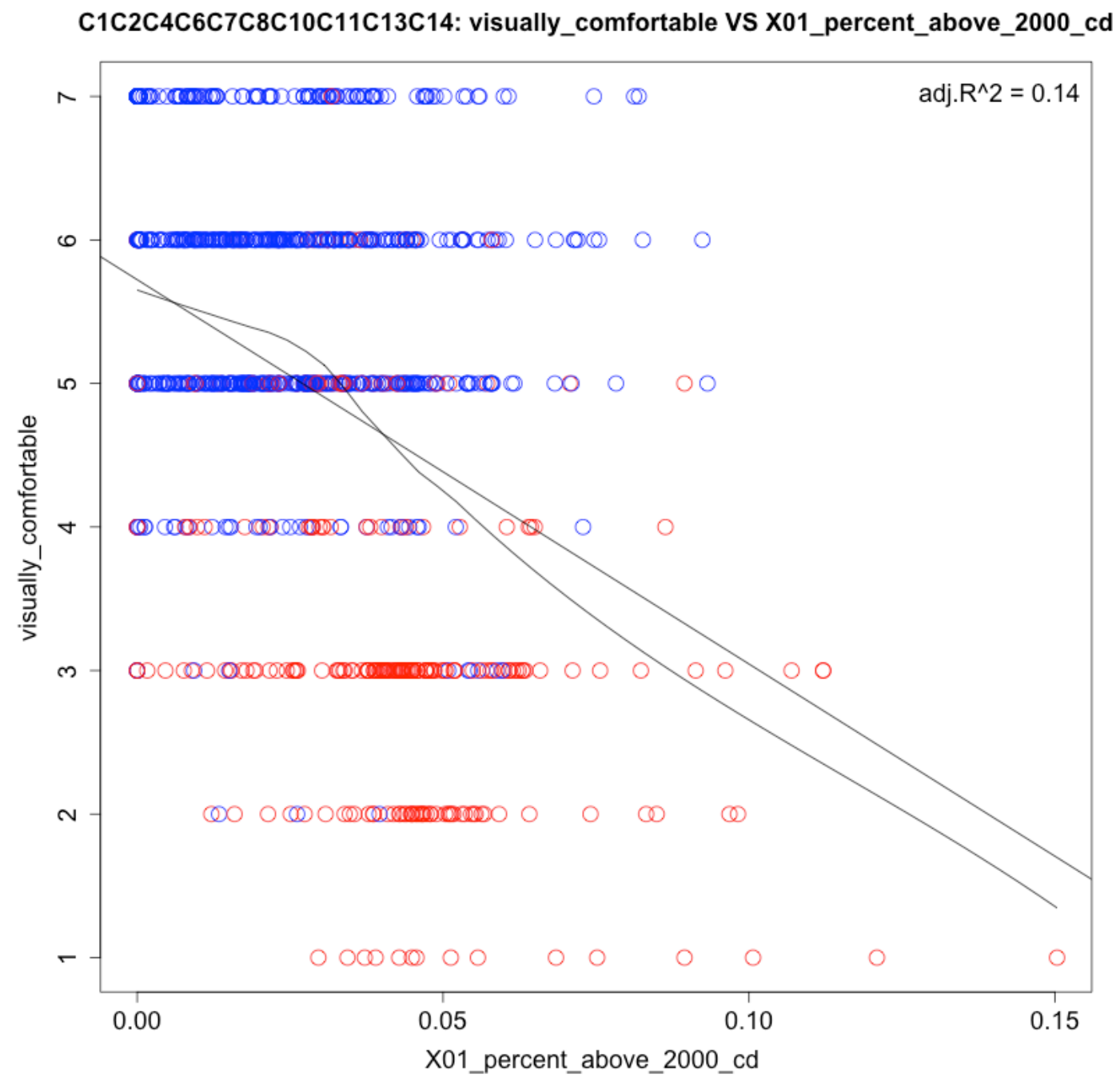


Figure 77 – Percent of scene above 2000 cd/m² (X01) versus subjective ratings of QU1 (left) and right_scene (right) for the composite data set

C8 & C10: X01_percent_above_2000_cd & visually_comfortable

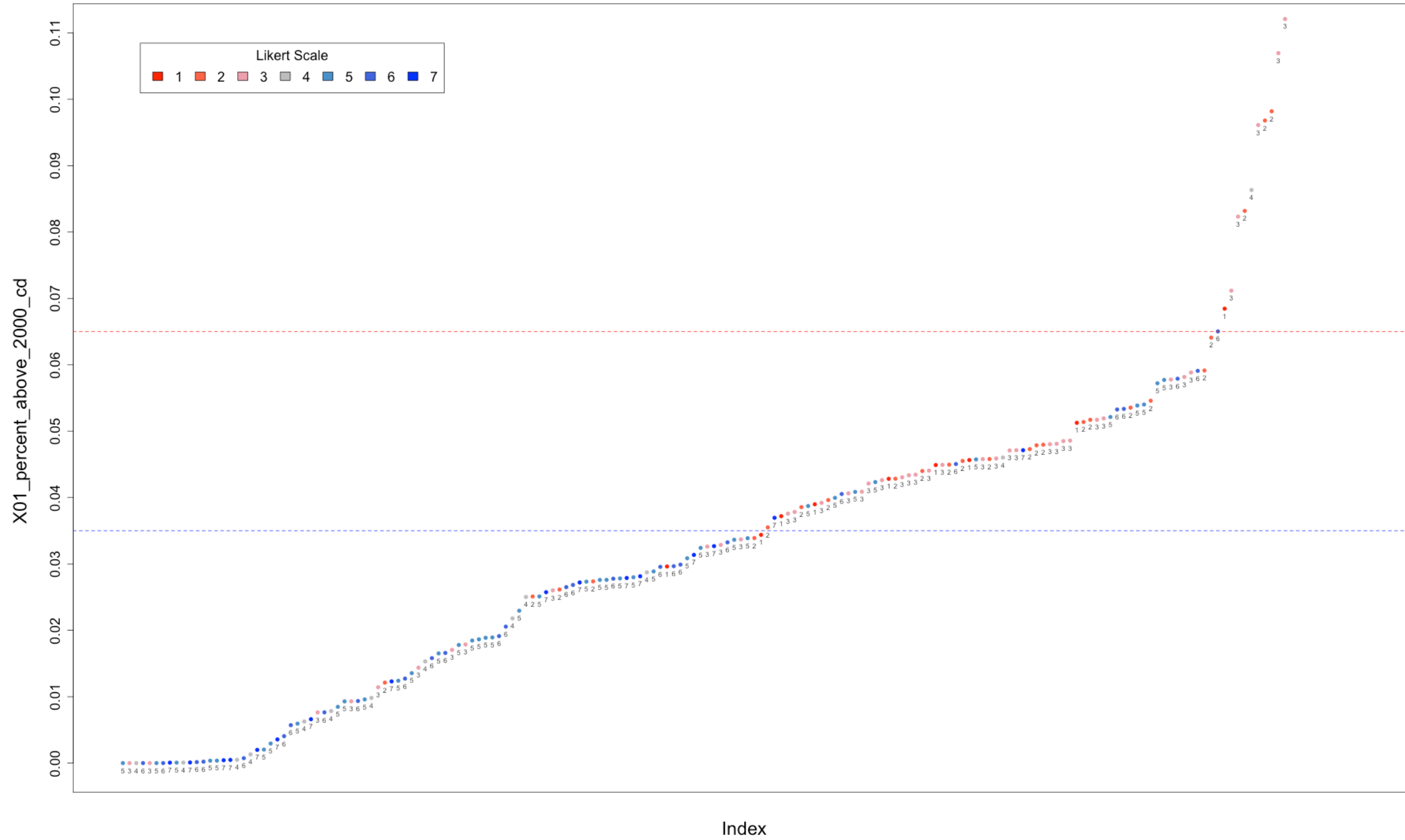


Figure 78 – Percent of scene above 2000 cd/m² (X01) for C8 & C10, results ordered by metric and color-coded by response to QU1

Table 40 – X01_percent_above_2000_cd range and preliminary criteria

C8C10: X01_percent_above_2000_cd (%) Range						
Min.	1st Qu.	Median	Mean	3rd Qu.	Max.	σ
0.00%	1.38%	3.25%	3.26%	4.59%	11.21%	2.32%
Preliminary criteria:						
$x < 3.5\%$			Likely to be comfortable			
$3.5\% > x < 6.5\%$			Bounded-BCD			
$x > 6.5\%$			Likely to be uncomfortable			

4.3.10 Luminance ratio of daylight source (X08) to task (X03)

The ratio of the mean luminance values between the daylight source (X08_mean, X08 shown in Figure 38) and the task (X03_mean, X03 shown in Figure 57) did not rank in the top 20 metrics for any subjective questionnaire items. This metric (X08_mean_to_03_mean) can be interpreted to resemble the IESNA recommend luminance ratio criteria of 1:10 (now 1:20) between the task and remote light surfaces (see Section 2.3.2.1). It did not have squared correlation coefficients higher than 0.1 for any questionnaire items except for right_scene ($r^2=0.1454$). Figure 79 shows the results for C8C10 with participant-days results ordered by C10 results. The metric does not consistently differentiate C10 (MP) from C8 (JU) scenes. Nearly all C10 scenes fall within the range of other participant-day C8 scenes. Figure 80 represents the ability of the metric to explain the variance in QU1 and right_scene for C8C10 and Figure 81 does the same for the composite data set. Each plot includes linear and loess polynomial fits with the adjr2 value representing the first-degree linear fit. The single regression statistics can be seen in Table 41. Finally, Figure 82 takes the C8C10 data, organizes it by the metric result, and color-codes it by the response to QU1. This graphic reveals one weak threshold of the borderline between comfort and discomfort that can be identified and this is described in Table 42.

Table 41 – X08_mean_to_03_mean single regression results

C8C10: X08_mean_to_03_mean				
DV	adj²r²	F-statistic:	DF	p-value
C8C10				
QU1	0.09584	19.3400	172	1.91E-05
right_scene	0.164	34.9400	172	1.79E-08
Composite_data_set				
QU1	0.09929	95.9200	860	2.20E-16
right_scene	0.1600	165.0000	860	2.20E-16
C8C10Computer_split53				
QU1	0.101	15.5000	128	1.35E-04
right_scene	0.1444	22.7700	128	4.89E-06
Composite_data_set Computer_split53				
QU1	0.0901	69.4200	690	4.29E-16
right_scene	0.1442	117.4000	690	2.20E-16

C8C10: X08_mean_to_03_mean

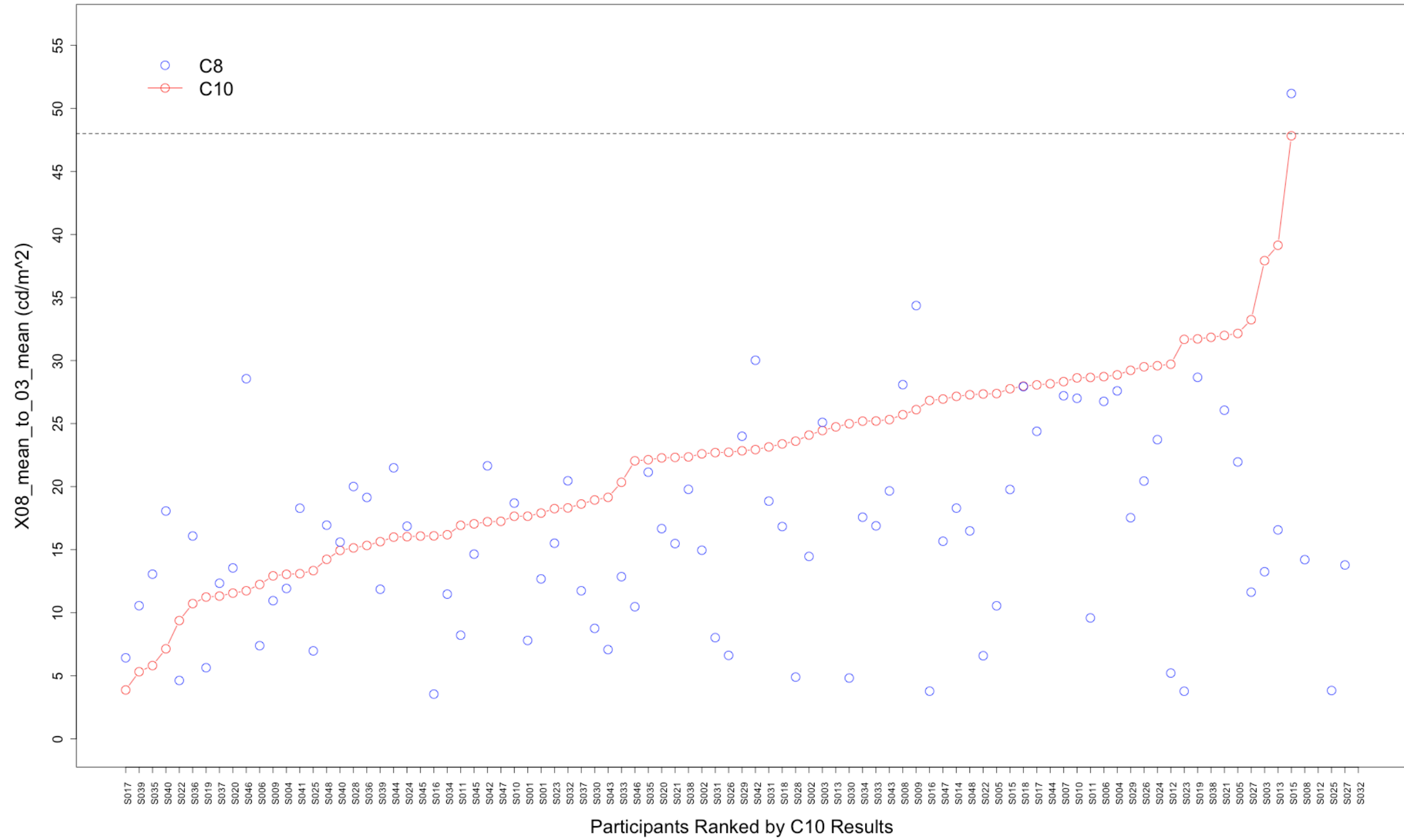


Figure 79 – Ratio of mean luminance between task (X03) and window (X08) for C8 (MP) & C10 (JU), participant-days ranked by C10 results

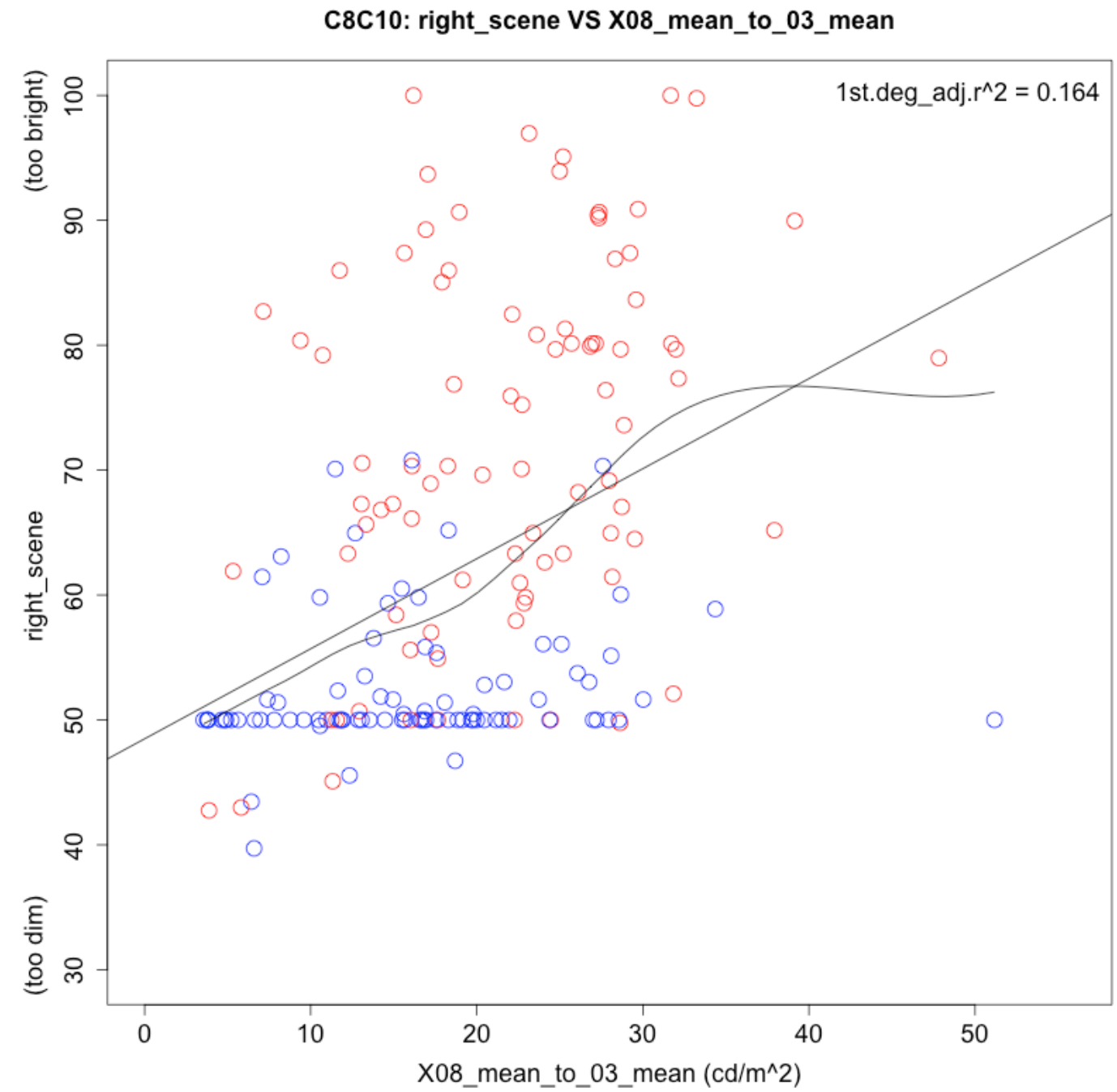
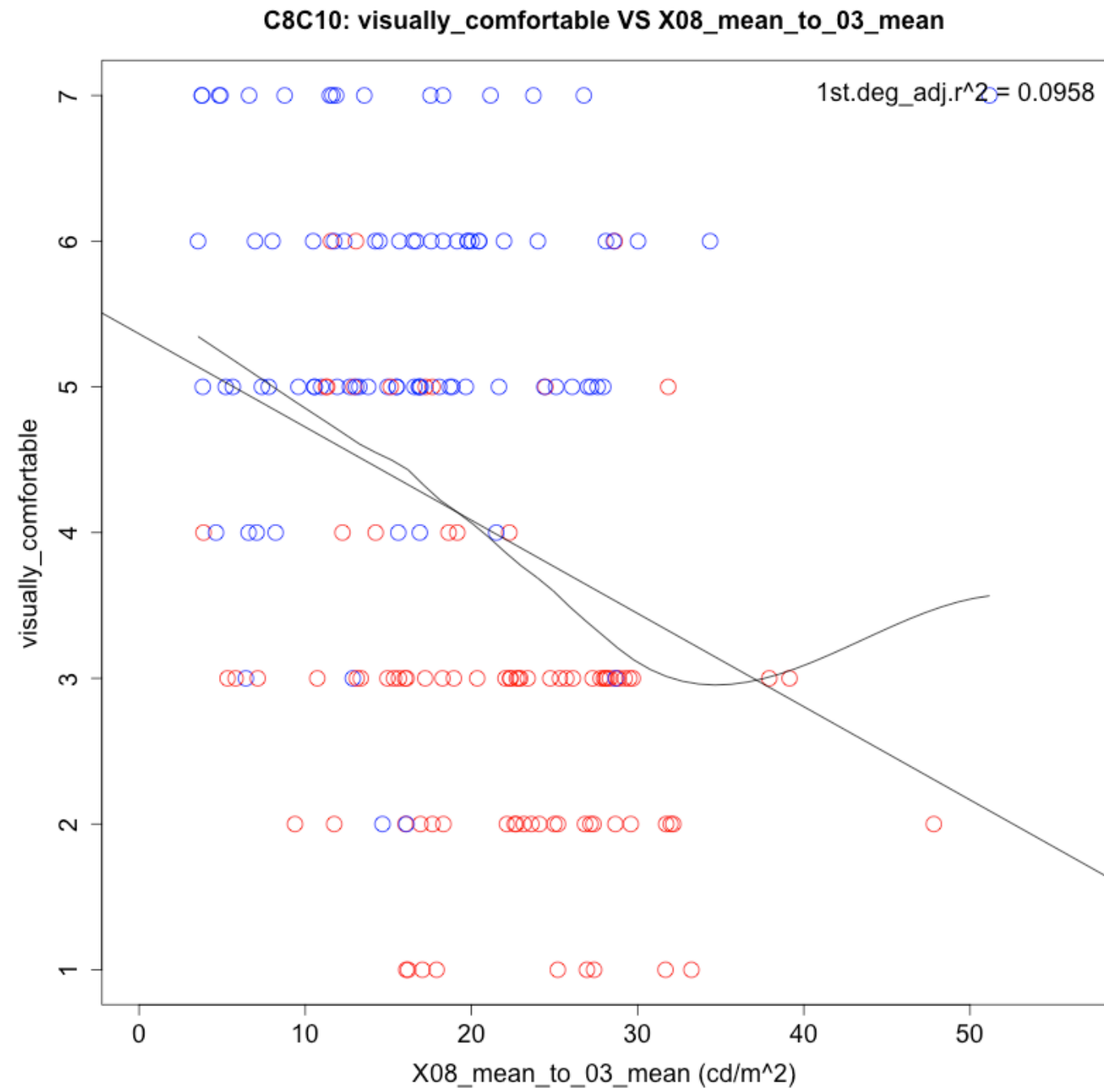


Figure 80 – Ratio of mean luminance between task (X03) and window (X08) versus subjective ratings of QU1 (left) and right_scene (right) for C8C10

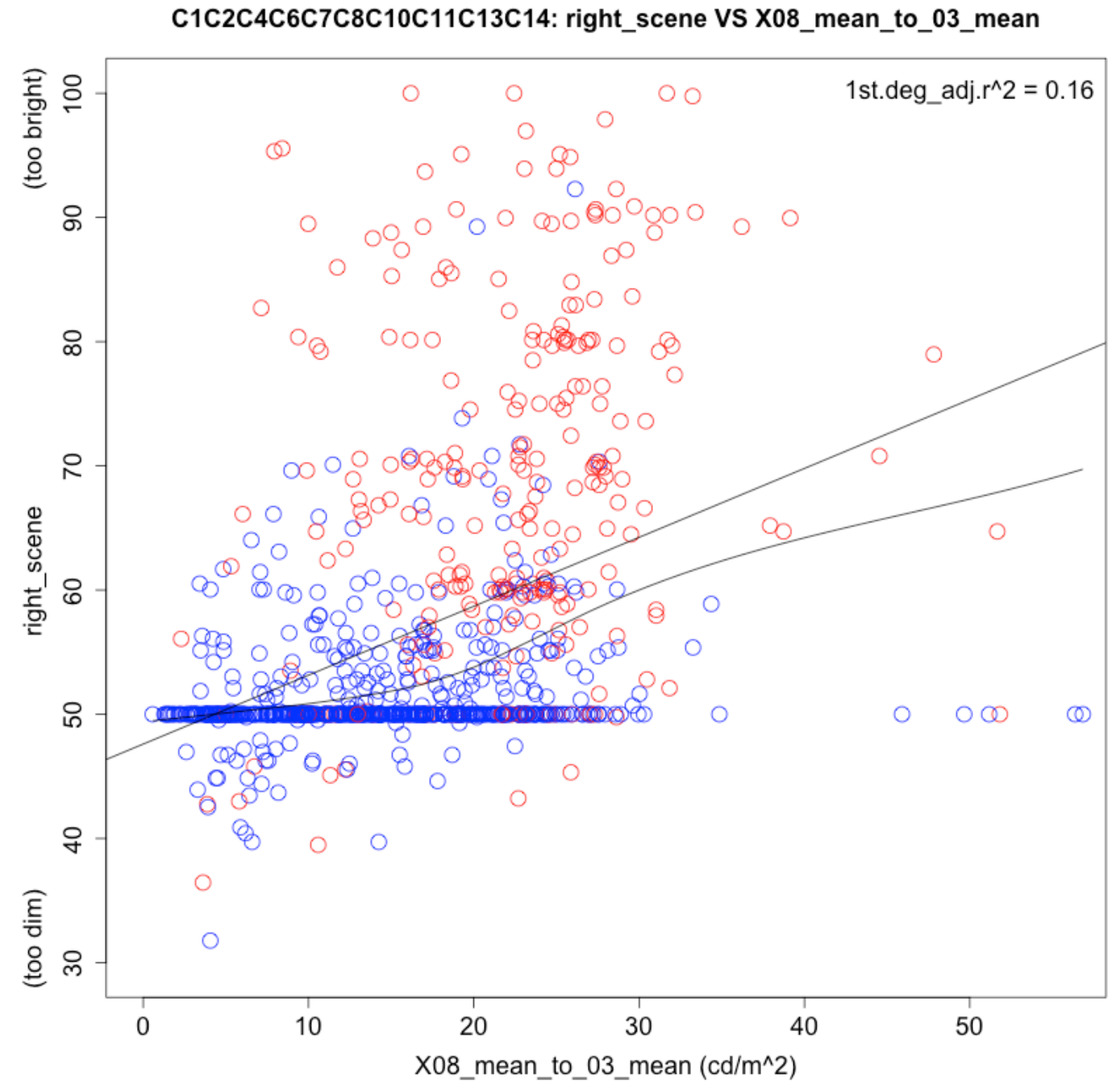
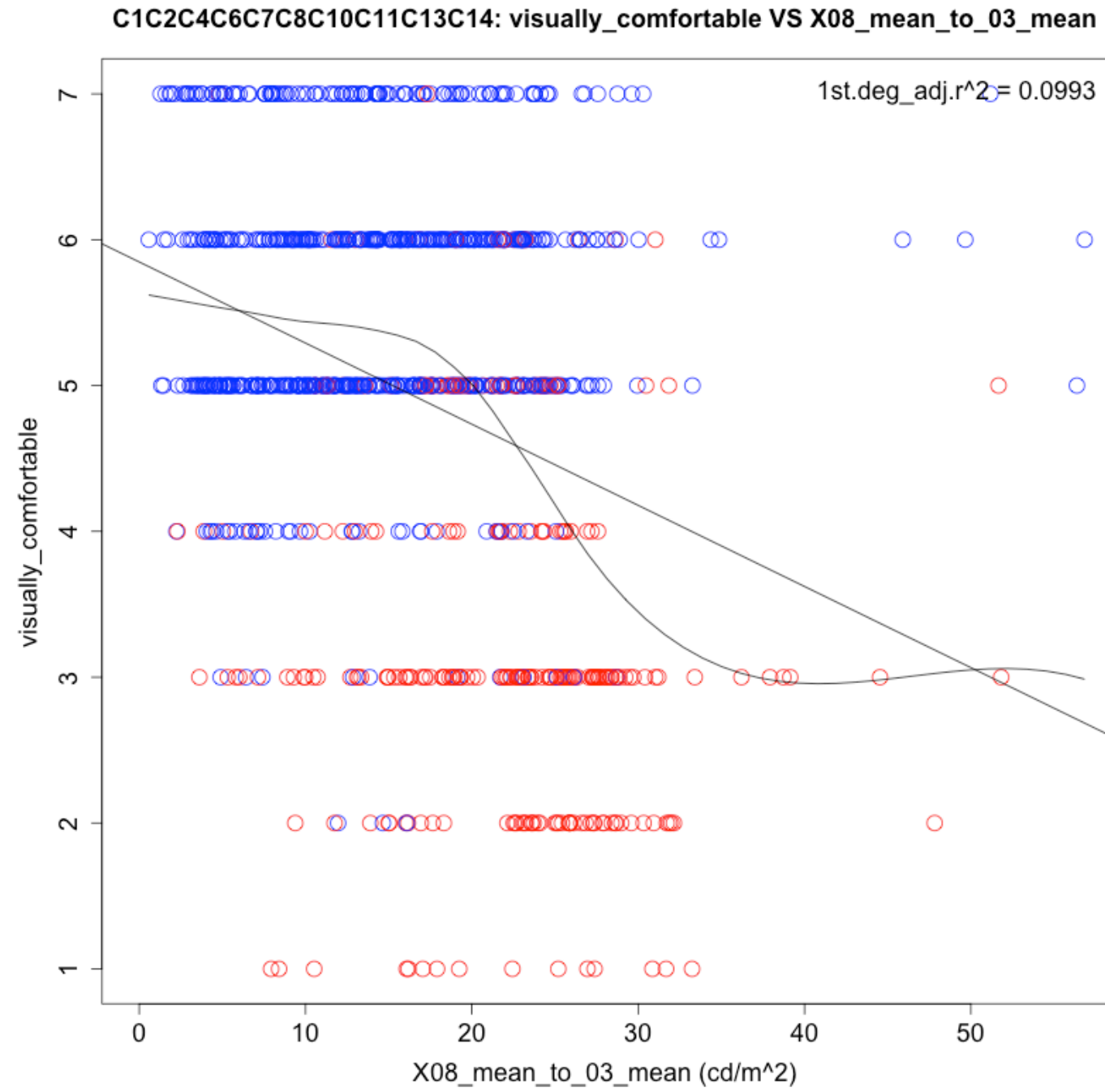


Figure 81 – Ratio of mean luminance between task (X03) and window (X08) versus subjective ratings of QUI (left) and right_scene (right) for the composite data set

C8 & C10: X08_mean_to_03_mean & visually_comfortable

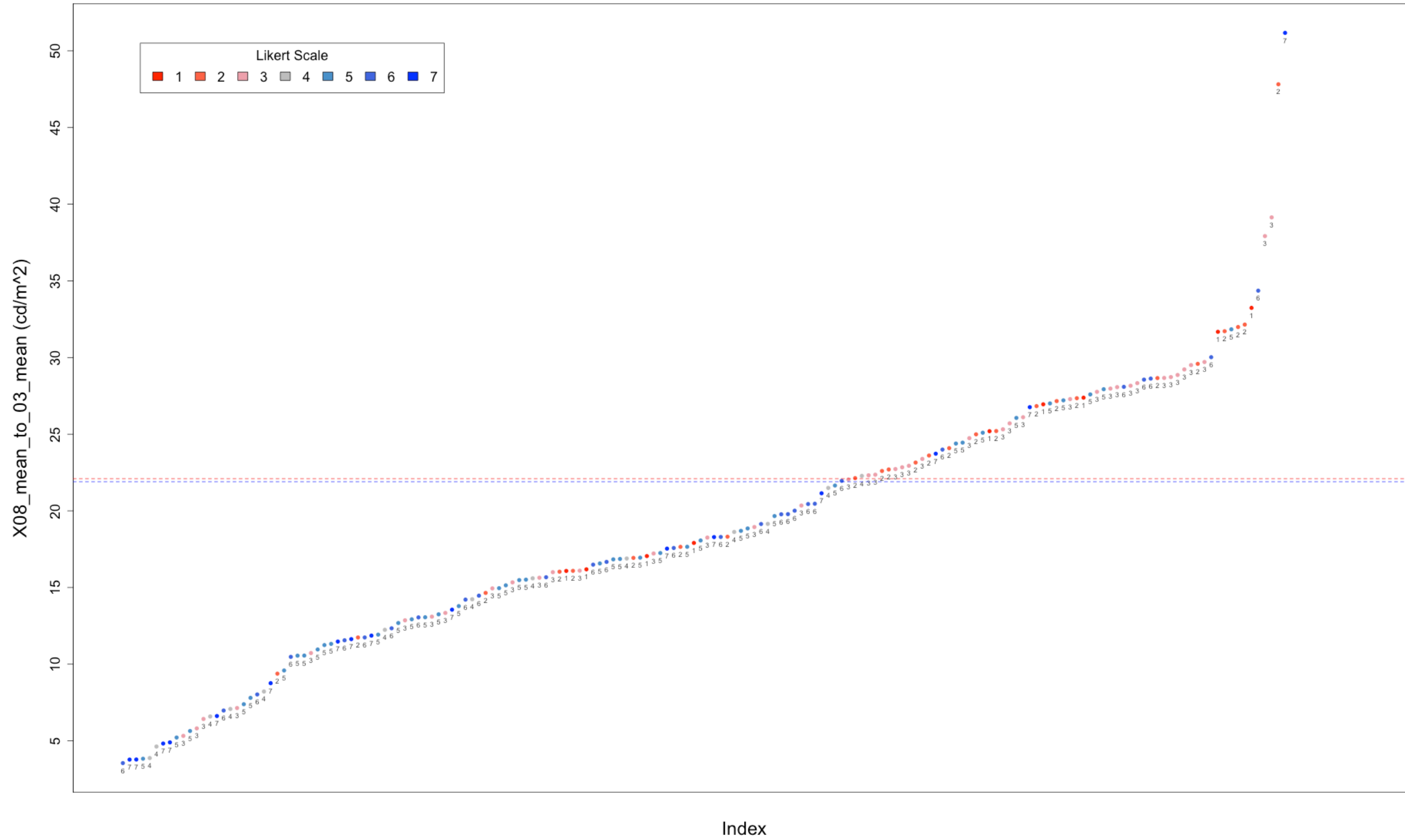


Figure 82 – Ratio of mean luminance between task (X03) and window (X08) for C8 & C10, results ordered by metric and color-coded by response to Q11

Table 42 – X08_mean_to_03_mean range and preliminary criteria

C8C10: X08_mean_to_03_mean Range						
Min.	1 st Qu.	Median	Mean	3 rd Qu.	Max.	σ
0.6	9.5	15.6	16.0	22.2	56.8	8.4
Preliminary criteria:						
x < 22			Likely to be comfortable			
-			Bounded-BCD			
x > 22			Likely to be uncomfortable			

4.4 Multiple regressions and subjective responses

While this research focused primarily on single regression analysis aimed at describing the strengths and limitations of individual metrics, the pursuit of logical multiple-metric models was pursued through multiple linear regression methods. Metrics with the highest squared correlation coefficients were organized in a correlation matrix along with other metrics of interest in order to determine which metrics were not highly correlated with one another. Table 43 reveals just the first column of this matrix highlighting the top ranked overall metric. Because of Inkarojrit's (2005) work in this area, it was also hypothesized that participants' measure of sensitivity to brightness may be an important factor and was therefore included selectively in multiple regression models. These models were intentionally limited to a maximum of four variables. Table 44 through Table 49 show results for individual single regressions and corresponding multiple regression models for some of the strongest metrics that were not highly correlated themselves. Values in red indicate the variable did not contribute to the model in a statistically significant manner and these were subsequently removed from the model (Table 44, Table 45).

The best significant model identified for its ability to fit the results of QU1 produced an $adjR^2=0.36$, $F_{4,687} = 98.38$, $p\text{-value} < 0.01$ and is detailed in Table 47 and was built using:

1. Participants' measured sensitivity to brightness (SB_just_uncomfortable)

2. Standard deviation of window luminance (X08_standard_deviation)
3. 50th percentile luminance value from the lower window (X10_50th_percentile)
4. Percent of 40° horizontal band > 2000 cd/m² (X20_percent_above_2000_cd)

The best significant model identified for its ability to fit the results of right_scene produced an $_{adj}R^2=0.49$, $F_{3,688} = 221.5$, p-value < 0.01 is detailed in Table 46 and was built using:

1. Standard deviation of window luminance (X08_standard_deviation)
2. 50th percentile luminance value from the lower window (X10_50th_percentile)
3. Mean luminance of the 40° horizontal band (X20_mean)

One additional model is reported due to its overall strength and logic. Figure 81 shows the relationship between the key variables in this model. It produced an $_{adj}R^2=0.32$, $F_{3,688} = 107.9$, p-value < 0.01 for QU1, as detailed in Table 48, and an $_{adj}R^2=0.45$, $F_{3,688} = 190.7$, p-value < 0.01 for right_scene, as detailed in Table 49. It was built using:

1. X08_standard_deviation
2. X20_percent_above_2000_cd
3. X20_percent_below_1000_cd

Table 43 – Correlation matrix between top 20 metrics (and selected metrics) to X08_standard_deviation

Top 20, Plus Selected Metrics	X08_standard_deviation
X08_standard_deviation	1.0000
X10_25 th _percentile	0.5582
X10_50 th _percentile	0.4667
X08_25 th _percentile	0.5629
X08_mean	0.7338
X20_mean	0.6629
X13_75 th _percentile	0.5906
X14_10 th _percentile	0.5806
X10_10 th _percentile	0.4436
X20_percent_below_1000_cd	0.4744
X23_50 th _percentile	0.6203
X20_75 th _percentile	0.5616
X14_25 th _percentile	0.5627
X20_25 th _percentile	0.5871
X14_2 nd _percentile	0.5756
X20_90 th _percentile	0.4264
X18_50 th _percentile	0.6400
X20_50 th _percentile	0.5722
X19_25 th _percentile	0.6211
X08_50 th _percentile	0.4140
X03_evalglare_mL0003_dgp	0.6360
X20_standard_deviation	0.7186
X01_evalglare_mL0005_dgp	0.5971
X01_mean	0.6293
X01_standard_deviation	0.7067
via_01	0.6352
MD_daq01_illuminance_topcanon	0.5692
X01_evalglare_mL0005_lum_sources	0.7520
X20_percent_above_2000_cd	0.4063
X01_brightest_10percent	0.5953
X01_98 th _percentile	0.4758
X01_percent_above_2000_cd	0.4436
X13_mean	0.5090

Table 44 – Multiple regression: QU1 versus SB_just_uncomfortable + X08_standard_deviation + X10_50th_percentile + X20_mean

Single Regression						
DV	Metric					
		adjR ²	F-statistic:	# variables	DF	p-value
QU1	SB_just_uncomfortable	0.005796	5.046	1	693	2.50E-02
QU1	X08_standard_deviation	0.2973	293.4	1	690	2.20E-16
QU1	X10_50 th _percentile	0.2436	223.5	1	690	2.20E-16
QU1	X20_mean	0.2425	222.2	1	690	2.20E-16
Multiple Regression Summary						
			Estimate	Std. Error	t value	Pr(> t)
	(Intercept)		7.202	0.1913	37.643	2.00E-16
	SB_just_uncomfortable		-0.2119	0.0365	-5.803	9.94E-09
	X08_standard_deviation		-0.0003986	0.0000	-8.363	3.41E-16
	X10_50 th _percentile		-0.001233	0.0002	-4.952	9.27E-07
	X20_mean		0.0005523	0.0005	1.204	2.29E-01
		adjR ²	F-statistic:	# variables	DF	p-value
QU1	multiple-model	0.3569	96.85	4	687	2.20E-16
Multiple Regression ANOVA Table						
		DF	Sum Sq	Mean Sq	F value	Pr(>F)
	SB_just_uncomfortable	1	11.13	11.13	7.3005	7.06E-03
	X08_standard_deviation	1	522.56	522.56	342.862	2.20E-16
	X10_50 th _percentile	1	54.56	54.56	35.8006	3.52E-09
	X20_mean	1	2.21	2.21	1.4488	2.29E-01
	Residuals	687	1047.07	1.52		
Using: Composite_data_set_Computer_split53						

Table 45 – Multiple regression: right_scene versus SB_just_uncomfortable + X08_standard_deviation + X10_50th_percentile + X20_mean

Single Regression						
DV	Metric					
		adjR ²	F-statistic:	# variables	DF	p-value
right_scene	SB_just_uncomfortable	-0.0005569	0.6138	1	693	4.34E-01
right_scene	X08_standard_deviation	0.4244	510.4	1	690	2.20E-16
right_scene	X10_50 th _percentile	0.3688	404.8	1	690	2.20E-16
right_scene	X20_mean	0.3302	341.7	1	690	2.20E-16
Multiple Regression Summary						
		Estimate	Std. Error	t value	Pr(> t)	
	(Intercept)	40.190102	1.2873553	31.219	2.00E-16	
	SB_just_uncomfortable	1.2508044	0.2457054	5.091	4.61E-07	
	X08_standard_deviation	0.0039734	0.0003207	12.39	2.00E-16	
	X10_50 th _percentile	0.0152188	0.0017	9.087	2.00E-16	
	X20_mean	-0.0130207	0.0031	-4.217	2.80E-05	
		adjR ²	F-statistic:	# variables	DF	p-value
right_scene	multiple-model	0.5069	178.6	4	687	2.20E-16
Multiple Regression ANOVA Table						
		DF	Sum Sq	Mean Sq	F value	Pr(>F)
	SB_just_uncomfortable	1	82	82	1.1871	2.76E-01
	X08_standard_deviation	1	42617	42617	617.6808	2.20E-16
	X10_50 th _percentile	1	5362	5362	77.7148	2.20E-16
	X20_mean	1	1227	1227	17.7847	2.81E-05
	Residuals	687	47400	69		
Using: Composite_data_set_Computer_split53						

Table 46 – Multiple regression: right_scene versus X08_standard_deviation + X10_50th_percentile + X20_mean

Single Regression						
DV	Metric					
		adjR ²	F-statistic:	# variables	DF	p-value
right_scene	X08_standard_deviation	0.4244	510.4	1	690	2.20E-16
right_scene	X10_50 th _percentile	0.3688	404.8	1	690	2.20E-16
right_scene	X20_mean	0.3302	341.7	1	690	2.20E-16
Multiple Regression Summary						
		Estimate	Std. Error	t value	Pr(> t)	
	(Intercept)	46.0289947	0.5951	77.352	2.00E-16	
	X08_standard_deviation	0.0040222	0.0003	12.326	2.00E-16	
	X10_50 th _percentile	0.0153788	0.0017	9.022	2.00E-16	
	X20_mean	-0.0147608	0.0031	-4.726	2.78E-06	
		adjR ²	F-statistic:	# variables	DF	p-value
right_scene	multiple-model	0.4891	221.5	3	688	2.20E-16
Multiple Regression ANOVA Table						
		DF	Sum Sq	Mean Sq	F value	Pr(>F)
	X08_standard_deviation	1	41110	41110	5.75E+02	2.20E-16
	X10_50 th _percentile	1	4793	4793	6.70E+01	1.29E-15
	X20_mean	1	1597	1597	2.23E+01	2.78E-06
	Residuals	688	49188	71		
Using: Composite_data_set_Computer_split53						

Table 47 – Multiple regression: QU1 versus X08_standard_deviation + X10_50th_percentile + X20_percent_above_2000_cd

Single Regression						
DV	Metric					
		adjR ²	F-statistic:	# variables	DF	p-value
QU1	SB_just_uncomfortable	0.005796	5.046	1	693	2.50E-02
QU1	X08_standard_deviation	0.2973	293.4	1	690	2.20E-16
QU1	X10_50 th _percentile	0.2436	223.5	1	690	2.20E-16
QU1	X20_percent_above_2000_cd	0.1626	135.2	1	690	2.20E-16
Multiple Regression Summary						
			Estimate	Std. Error	t value	Pr(> t)
	(Intercept)		7.2	0.1864	38.623	2.00E-16
	SB_just_uncomfortable		-0.2023	0.0367	-5.507	5.15E-08
	X08_standard_deviation		-0.0003712	0.0000	-9.814	2.00E-16
	X10_50 th _percentile		-0.001537	0.0003	-5.443	7.28E-08
	X20_percent_above_2000_cd		7.605	3.2830	2.316	2.08E-02
		adjR ²	F-statistic:	# variables	DF	p-value
QU1	<i>multiple-model</i>	0.3605	98.38	4	687	2.20E-16
Multiple Regression ANOVA Table						
		DF	Sum Sq	Mean Sq	F value	Pr(>F)
	SB_just_uncomfortable	1	11.13	11.13	7.342	6.90E-03
	X08_standard_deviation	1	522.56	522.56	344.8126	2.20E-16
	X10_50 th _percentile	1	54.56	54.56	36.0043	3.19E-09
	X20_percent_above_2000_cd	1	8.13	8.13	5.3655	2.08E-02
	Residuals	687	1041.15	1.52		
Using: Composite_data_set_Computer_split53						

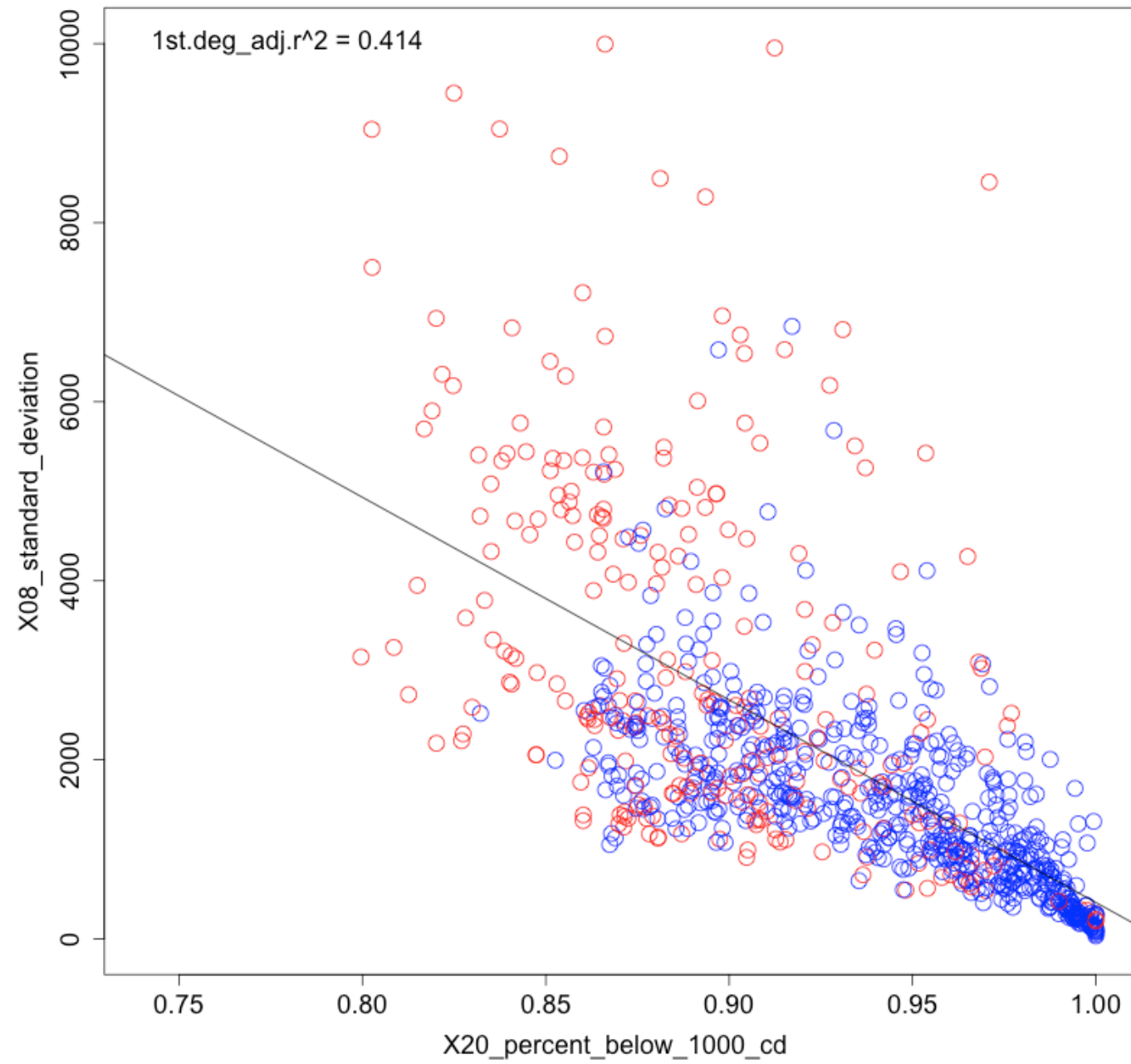
Table 48 – Multiple regression: QU1 versus X08_standard_deviation + X20_percent_above_2000_cd + X20_percent_below_1000_cd

Single Regression						
DV	Metric					
		adjR ²	F-statistic:	# variables	DF	p-value
QU1	X08_standard_deviation	0.2973	293.4	1	690	2.20E-16
QU1	X20_percent_above_2000_cd	0.1626	135.2	1	690	2.20E-16
QU1	X20_percent_below_1000_cd	0.2137	188.8	1	690	2.20E-16
Multiple Regression Summary						
		Estimate	Std. Error	t value	Pr(> t)	
	(Intercept)	-6.982	3.238	-2.156	3.14E-02	
	m01	-0.0003841	0.00003925	-9.787	2.00E-16	
	m164	12.65	4.717	2.682	7.50E-03	
	m10	13.25	3.271	4.052	5.66E-05	
		adjR ²	F-statistic:	# variables	DF	p-value
QU1	<i>multiple-model</i>	0.317	107.9	3	688	2.20E-16
Multiple Regression ANOVA Table						
		DF	Sum Sq	Mean Sq	F value	Pr(>F)
	X08_standard_deviation	1	488.52	488.52	301.8147	2.20E-16
	X20_percent_above_2000_cd	1	8.84	8.84	5.4608	1.97E-02
	X20_percent_below_1000_cd	1	26.57	26.57	16.4167	5.66E-05
	Residuals	688	1113.6	1.62		
Using: Composite_data_set_Computer_split53						

Table 49 – Multiple regression: right_scene versus X08_standard_deviation + X20_percent_above_2000_cd + X20_percent_below_1000_cd

Single Regression						
DV	Metric					
		adjR ²	F-statistic:	# variables	DF	p-value
right_scene	X08_standard_deviation	0.4244	510.4	1	690	2.20E-16
right_scene	X20_percent_above_2000_cd	0.2563	239.1	1	690	2.20E-16
right_scene	X20_percent_below_1000_cd	0.3176	322.5	1	690	2.20E-16
Multiple Regression Summary						
			Estimate	Std. Error	t value	Pr(> t)
	(Intercept)		142.1	22.29	6.376	3.34E-10
	m01		0.003446	0.0002702	12.752	2.00E-16
	m164		-68.47	32.48	-2.108	3.54E-02
	m10		-96.83	22.52	-4.3	1.96E-05
		adjR ²	F-statistic:	# variables	DF	p-value
right_scene	multiple-model	0.4516	190.7	3	688	2.20E-16
Multiple Regression ANOVA Table						
		DF	Sum Sq	Mean Sq	F value	Pr(>F)
	X08_standard_deviation	1	41110	41110	535.768	2.20E-16
	X20_percent_above_2000_cd	1	1368	1368	17.825	2.75E-05
	X20_percent_below_1000_cd	1	1419	1419	18.487	1.96E-05
	Residuals	688	52792	77		
Using: Composite_data_set_Computer_split53						

C1C2C4C6C7C8C10C11C13C14: X08_standard_deviation VS X20_percent_below_1000_c



C1C2C4C6C7C8C10C11C13C14: X20_percent_above_2000_cd VS X20_percent_below_1000_c

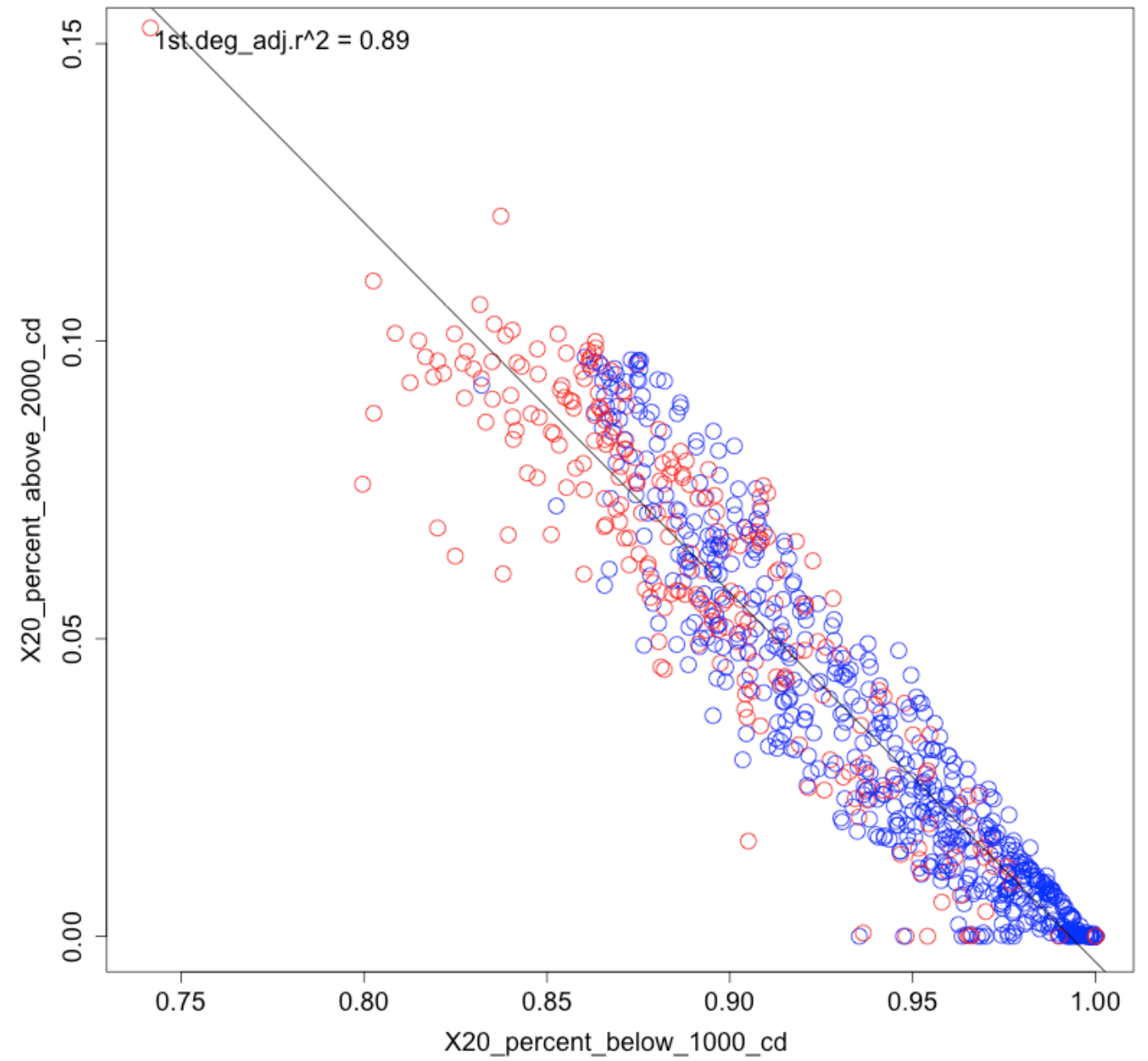


Figure 83 – Scatter plot and first-degree line of fit between X08_standard_deviation versus X20_percent_below_1000_cd (left) and X20_percent_above_2000_cd versus X20_percent_below_1000_cd (right)

4.5 *Sensitivity to brightness*

4.5.1 Self-reported general sensitivity versus measured sensitivity to brightness

Inkarojrit (2005) suggested that self-reported sensitivity to brightness was an influential factor in blind operation behavior. Thus, this dissertation examined self-reported sensitivity to brightness as well as measured sensitivity to brightness as described in Section 3.4.3. Figure 84 reveals a rather low squared correlation coefficient between the self-reported and measured sensitivity to brightness ($_{adj}r^2=0.04$). That said, a quick inspection suggests that the relationship appears to hold at the extremes of the data range. That is, participants who self-reported as not very sensitive to brightness did not select the brightest light source for the JU threshold in the measured sensitivity to brightness test. Similarly, participants who self-reported as very sensitive to brightness did not select the dimmest light source for the JU threshold in the measured sensitivity to brightness test.

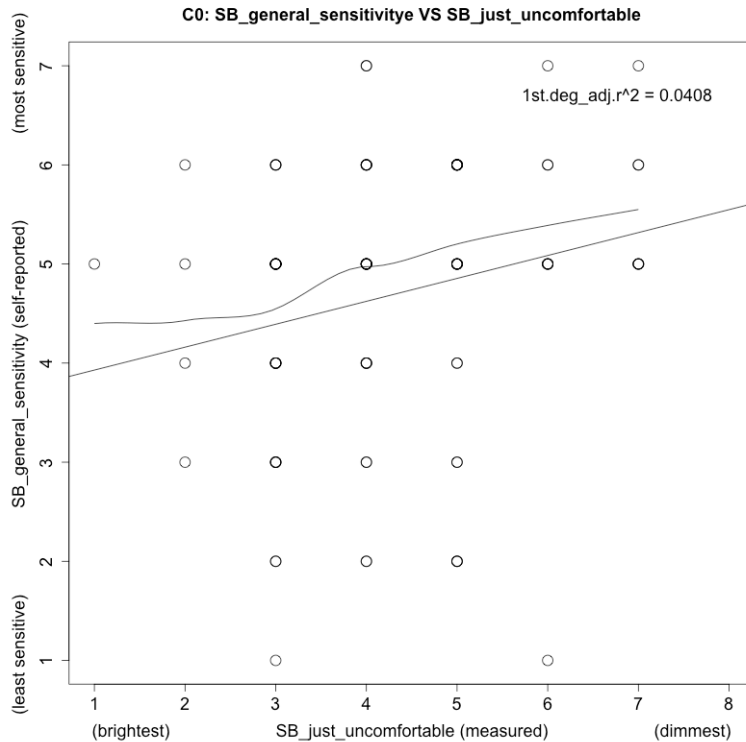


Figure 84 - Relationship between self-reported and measured sensitivity to brightness

4.5.2 Measured sensitivity to brightness and seasonal effects

A Welch paired two-way t-test was conducted to determine if there was a significant difference between the measured sensitivity to brightness results from the summer and fall repeated measure design. The mean measured sensitivity to brightness for the rating “Just Uncomfortable Glare” (Table 10) for summer was 3.94 on the eight-point scale shown in Table 50 as compared to 4.64 for fall (Figure 85). The difference in means is 0.71 and is statistically significant at the 99% confidence interval ($t = -2.6329$, $df = 90.991$, $p\text{-value} = 0.009947$). This effect represents approximately a 9% linear shift in sensitivity within the given scale, such that people were more sensitive to brightness during fall than during summer. The sensitivity difference between fall and summer shown in this study represents approximately 130 lux measured vertically at the eye (1000 lux measured normal to the glare source) or 100 cd/m^2 in

the mean luminance of the glare source. The light source was tested before, midway through and at the completion of the study and was found to be consistent given the bounds of measurement accuracy.

Table 50 – Measured sensitivity to brightness conditions description with red arrows illustrating the approximate “seasonal” effect

Measured Sensitivity to Brightness Test		
Dimming setting	E_v measured at 0.37m (14.5"), normal to light intensity boxes (lux)	E_v measured at 0.44m (17.5"), at the seated user's eye (lux)
E, 1= brightest	8791	1385
F, 2	7423	1175
G, 3	5473	893
H, 4	4273	707
I, 5	3310	565
J, 6	2550	452
K, 7	1881	357
L, 8= dimmest	1234	262

4.5.3 Measured sensitivity to brightness and age effects

Tests of significant differences between the three age groups were conducted using Welch two-way t-tests. While the participant sample design was organized into three age groups (18-29 years, 30-49 years, 50-70 years), age range data were recorded in five bins (18-29 years, 30-39 years, 40-49 years, 50-59 years, 60-70 years). Basic scatter plots were created using all five age-range bins.

The t-tests revealed that participants in the 50-70 years age range self-reported as statistically more sensitive to brightness than either of the two younger age groups. Therefore, the two younger age groups were combined and compared to the oldest age group and this t-test

also revealed significant differences ($t = 3.838$, $df = 65.276$, $p\text{-value} < 0.01$) with a difference between group means of approximately one on a seven point scale. The measured sensitivity to brightness did not reveal significant differences between age groups.

The scatter plot and first-degree line of fit between age range and both sensitivity to brightness tests are revealed in Figure 86 (self-reported at left, measured at right). The loess lines in Figure 86 and the results in Table 51 and Table 52 reveal curious variations in sensitivity to brightness by age range suggesting the middle age ranges (30-59 years) were generally less sensitive.

Unfortunately, tests for sensitivity to brightness between age groups using data from JU conditions in the room with daylight were not possible since there were significant differences in outdoor conditions (e.g. southwest-facing irradiance, outdoor global horizontal illuminance, etc.) for days with participants from the three age groups. This was a surprising occurrence since the participants from different age groups were rather evenly distributed across months.

Table 51 – Self-reported sensitivity to brightness by age group

Self-reported Sensitivity to Brightness (7 point Likert scale)		
Age Range	Mean	Mean
60-70 years	5.6	5.4***
50-59 years	5.1	
40-49 years	3.8	4.4
30-39 years	4.6	
18-29 years	4.3	4.3
***significant differences from other 2 groups ($p < 0.01$)		

Table 52 – Measured sensitivity to brightness by age group

Measured Sensitivity to Brightness (8 point intensity scale)		
Age Range	Mean	Mean
60-70 years	5.1	4.6
50-59 years	3.8	
40-49 years	4.7	4.0
30-39 years	3.7	
18-29 years	4.3	4.3
no significant differences ($p>0.1$ for all 3 groups)		

C0 SB_just_uncomfortable_summer_fall

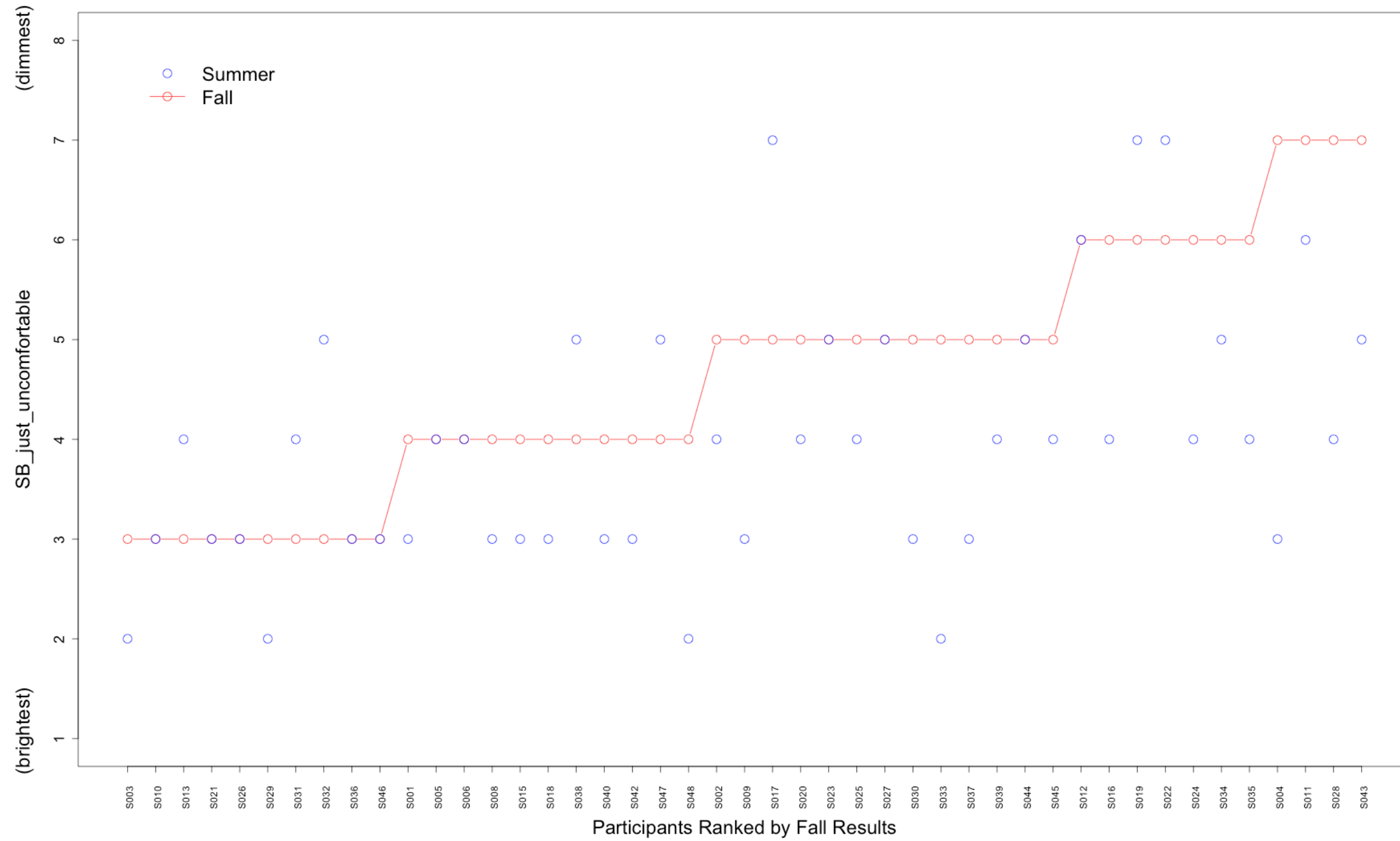


Figure 85 – Measured sensitivity to brightness test results for summer and fall

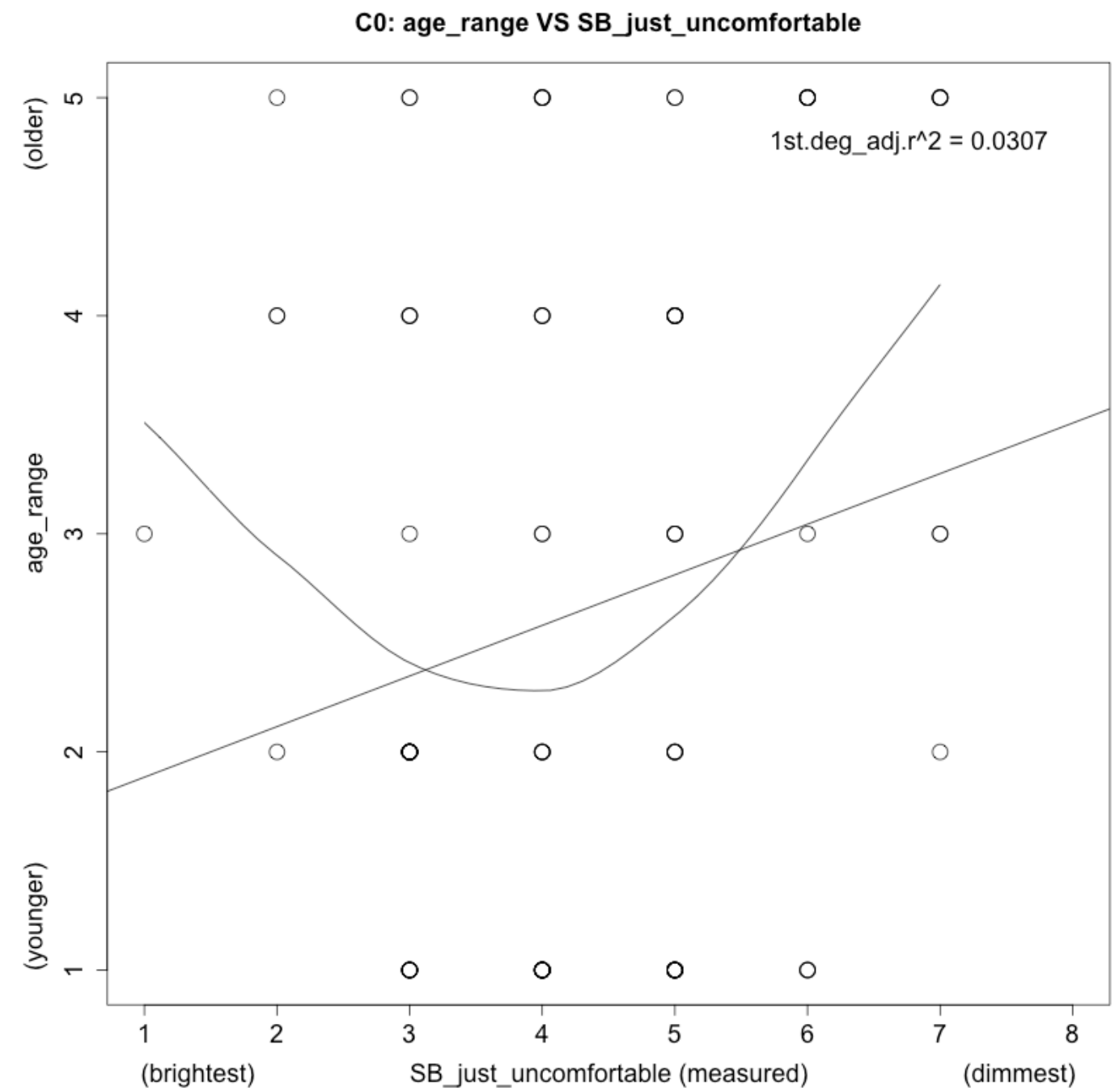
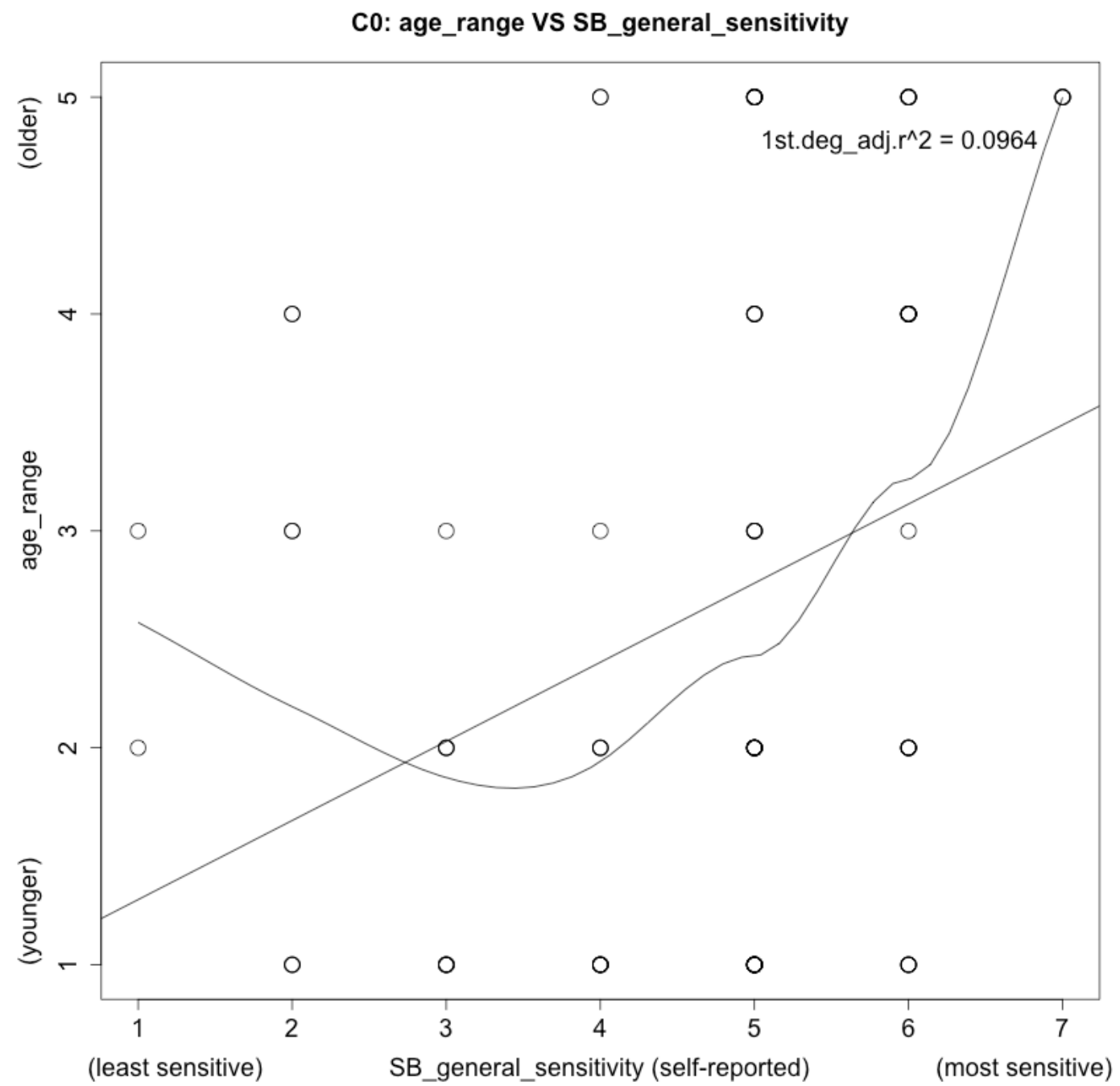


Figure 86 – Self-reported sensitivity to brightness (left), measured sensitivity to brightness (right)

4.6 Productivity and performance

4.6.1 Perceived productivity

Participants perceived themselves having approximately 10% (precisely 12.3%) higher productivity during MP conditions (C1C8C11) as compared to paired JU conditions (C4C10C13), ($t=-9.81$, $DF=162$, $p\text{-value}=<0.001$). Participants did not perceive any personal productivity differences for MP scenes with daylight (C1C8) as compared to MP scenes with integrated lighting (C7C11), ($t=-0.45$, $DF=120$, $p\text{-value}=0.67$).

4.6.2 Creativity

There were no significant differences between creativity, word count or average time per word for C1, C4, C9 and C10. There were several instances where the sensitivity to brightness tests conducted first thing in the morning in the windowless chamber (C0), had lower word count and time per word in the creativity test than for C1, C4, C9 and C10. For example, participants spent approximately one minute longer per word on C1 than for C0 ($t= -2.98$, $DF=40$, $p\text{-value}=0.0024$) and recorded approximately three more words on average in C1 than for C0 ($t=-2.08$, $DF=40$, $p\text{-value}=0.0217$).

Table 53 - Creativity test descriptive statistics

Creativity Results						
Word Count	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
C0	1	5	8	9	12	30
C1	3	7	10	12	14	50
C4	2	8	11	14	19	43
C9	5	7	10	13	16	37
C10	4	8	12	13	17	32
Time per Word (seconds)	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
C0	36	66	107	152	186	920
C1	49	103	165	217	297	682
C4	65	114	216	268	331	912
C9	43	88	188	244	296	718
C10	40	96	203	251	340	825

4.6.3 Objective performance tests

Objective performance results analyses were focused on examining the differences between MP and JU scenes with the hypothesis of diminished performance in JU scenes. Therefore C10 and C13 were considered important conditions because they occurred in the afternoon such that participants were likely to be able to create JU scenes. Caution was taken to only create pairs that either shared close immediate time periods or were balanced with morning and afternoon conditions to avoid bias due to learning effects and test-retest fatigue. Table 54 shows the tested groups and the performance tests available for each group, along with a summary of the paired one-way t-test results. It can be seen that Stroop (Type 1) results revealed significant differences between MP and JU conditions with the mean of group differences (for percent correct) ranging from 0.51%-1.15%. Thus, Stroop results for MP scenes were roughly 1% better than for JU scenes. There were no significant differences in Landolt rings or typing test results. Note that only Stroop Type 1 data were prepared for analysis.

Table 54 – Objective performance test results for selected condition groups and available objective tests

Objective Visual Performance Results				
MP Cond.	JU Cond.	Common Perf. Tests	Significant Results	Mean of Diff.
C8	C10	Proofreading, Stroop1	Stroop: t = 2.1265, df = 51, p-value = 0.01916	1.15%
C1C8	C4C10	Proofreading, Stroop1	Stroop: t = 3.2421, df = 155, p-value = 0.0007264	0.99%
C7C8	C4C10	Proofreading, Stroop1	Stroop: t = 1.7365, df = 187, p-value = 0.04206	0.51%
C11	C13	Landolt rings, typing	None	
C1C11	C4C13	Landolt rings, typing	None	
C7C11	C4C13	Landolt rings, typing	None	

The results in Table 54 were constructed using filtered data such that C1, C7, C8, C11 data were included if $QU5 \geq 5$, and C4, C10, C13 data were included if $QU5 \leq 3$ (this is essentially the same as Computer_split53, but is referred to as Paperwork_split53 because QU5 was used). The Stroop results from C8 versus C10 data were tested again using the X08_standard_deviation preliminary recommended criteria (see Table 24) to filter which data to include rather than Paperwork_split53. Thus, C8 data had $X08 \sigma \leq 2500 \text{ cd/m}^2$ while C10 data had $X08 \sigma \geq 4000 \text{ cd/m}^2$, and only cases with paired data were included in a paired one-way t-test. This filtering method resulted in shifting the mean of the Stroop result differences from 1.15% as shown in Table 54 for C8 versus C10 to 1.65% and improved the confidence level to <0.01 ($t = 3.2166$, $df = 108$, $p\text{-value} = 0.000856$). Next, all data for C1, C4, C8, C10 were combined and split into groups based upon X08_standard_deviation as described above rather than on MP and JU scenes as shown in Table 54. This grouping method resulted in shifting the mean of the Stroop result differences from 0.99% as shown in Table 54 for C1C8 versus C4C10 to 1.49% using Welch two-sample, one-way t-test ($t = 2.0039$, $df = 44.358$, $p\text{-value} = 0.0256$). While still well below 0.05 confidence level, the p-value increased, and this can be attributed to too few degrees of freedom and the inability to use paired t-test methods due to the grouping

technique. Finally, this grouping method was applied to all Stroop conditions (C1C4C7C8C9C10C11C14) and the difference in the means between groups was 1.02% ($t = 1.7035$, $df = 51.7$, $p\text{-value} = 0.04724$). This grouping technique was applied to proofreading using the same set of conditions and no significant differences between groups were identified. The same approach was applied to all typing conditions (C1C4C7C8C11C12C13C14) and applied to proofreading as well, with no significant differences between groups identified.

4.7 Controlling blinds and electric lights

4.7.1 Controlling blinds

Traditional automated blind controls rely on exterior illuminance or irradiance data. For MP conditions (C1C2C6C7C8C11C14), blind height is reported relative to southwest-facing exterior irradiance (Figure 87). As can be seen, vertical irradiance on the southwest façade is not a strong indicator of blind height ($_{adj}r^2=0.05$). Figure 88 shows the median blind closure for MP conditions generally occurred between 100-175 W/m^2 . While a few participants left the blind completely up with exterior vertical irradiance as high as 600-700 W/m^2 , in over 75% of the cases when participants left blinds up, the exterior vertical irradiance was below 150 W/m^2 . Approximately 75% of the participants lowered blinds at least 25% of the way down when exterior vertical irradiance exceeded 430 W/m^2 .

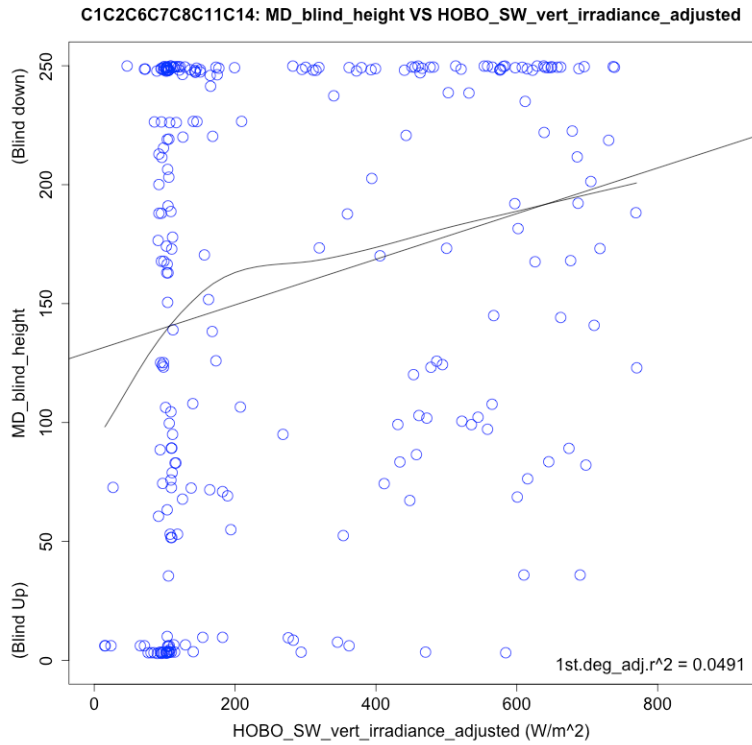


Figure 87 - Southwest irradiance versus blind height; MP conditions

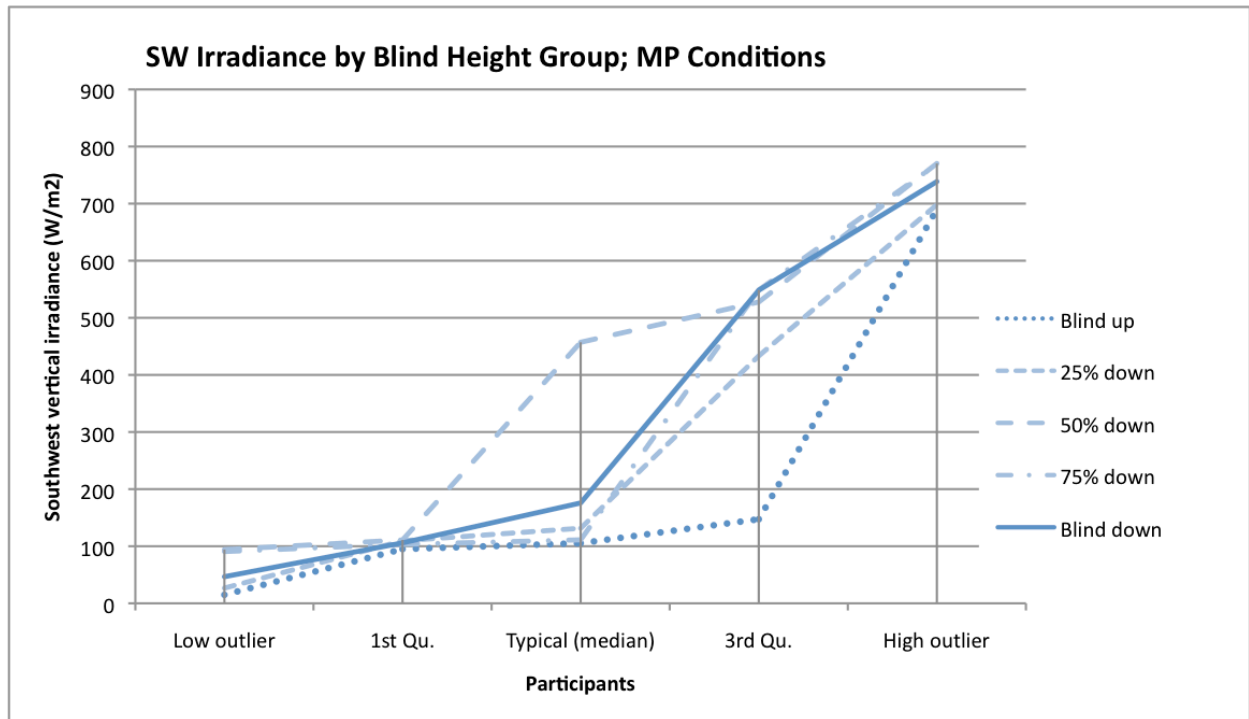


Figure 88 – Summary data for southwest irradiance by blind height group; MP conditions

One of the strongest indicators ($adjr^2=0.45$) of blind height from MP conditions was the “sum of the solid angles of all glare sources” identified by the multiplier “five times the mean scene luminance” (X01_evalglare_mL0005_omega_sources). All of the MP condition (C1C2C6C7C8C11C14) blind height values are reported relative to this metric in Figure 89. Figure 90 shows the median blind closure for MP conditions generally occurred between values of 0.15-0.25 for the sum of solid angles of glare sources (summed steradian). While a few participants left the blind completely up with summed steradian values as high as 0.35, in over 75% of the cases when participants left blinds up, the sum of solid angles of glare sources was below 0.27. Approximately 75% of the participants lowered blinds at least 25% of the way down to maintain a similar value (< 0.27 for the sum of solid angles of glare sources).

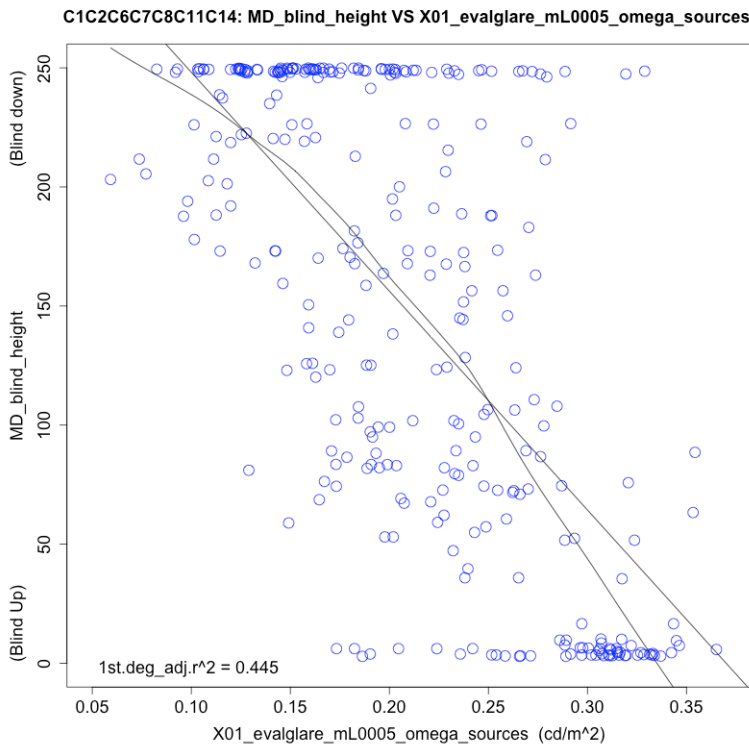


Figure 89 – Sum of solid angles of glare sources versus blind height; MP conditions

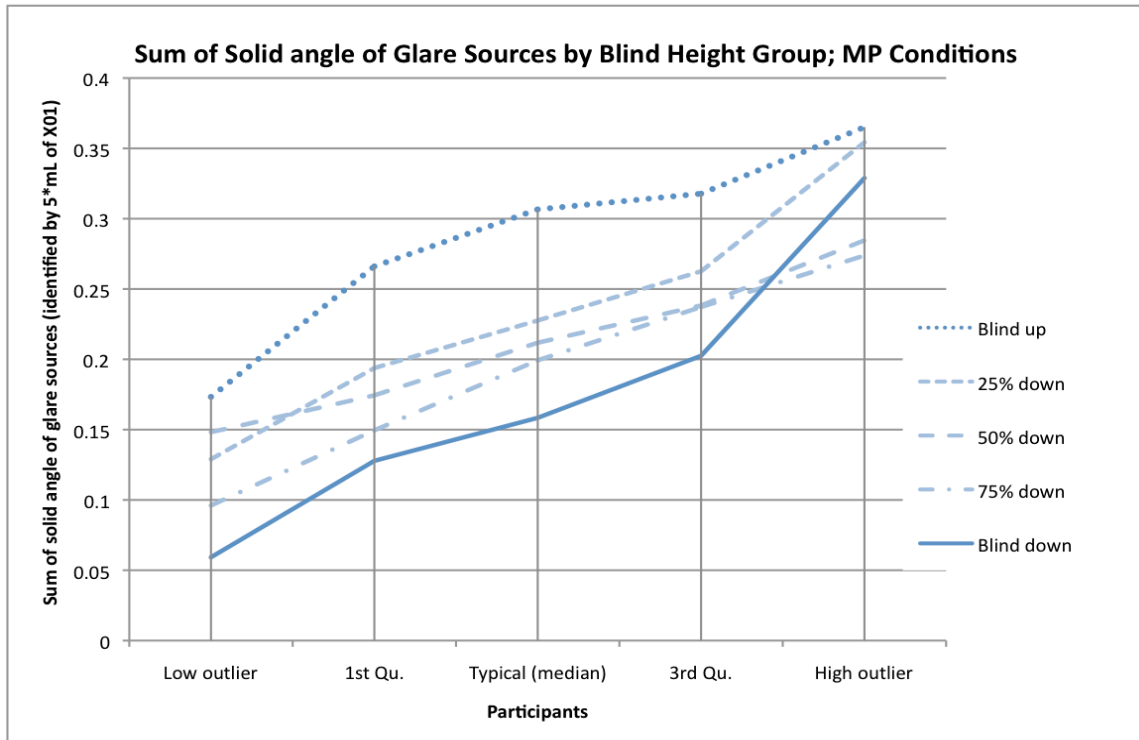


Figure 90 – Summary data for the sum of solid angles of glare sources by blind height group; MP conditions

Mean window luminance is a logical luminance-based blind control measure. Blind height is reported for MP conditions relative to mean window luminance (X08_mean) in Figure 91. As can be seen, mean window luminance has a strong relationship with blind height ($_{adj}r^2=0.34$). Figure 92 shows the median blind closure for MP conditions generally occurred to maintain mean window luminance values between 1100-1500 cd/m^2 . While a few participants left the blind completely up with mean window luminance as high as 3500 cd/m^2 , in over 75% of the cases when participants left blinds up, the mean window luminance was below 1500 cd/m^2 . Approximately 75% of the participants lowered blinds at least 25% of the way down when mean window luminance exceeded 2000 cd/m^2 .

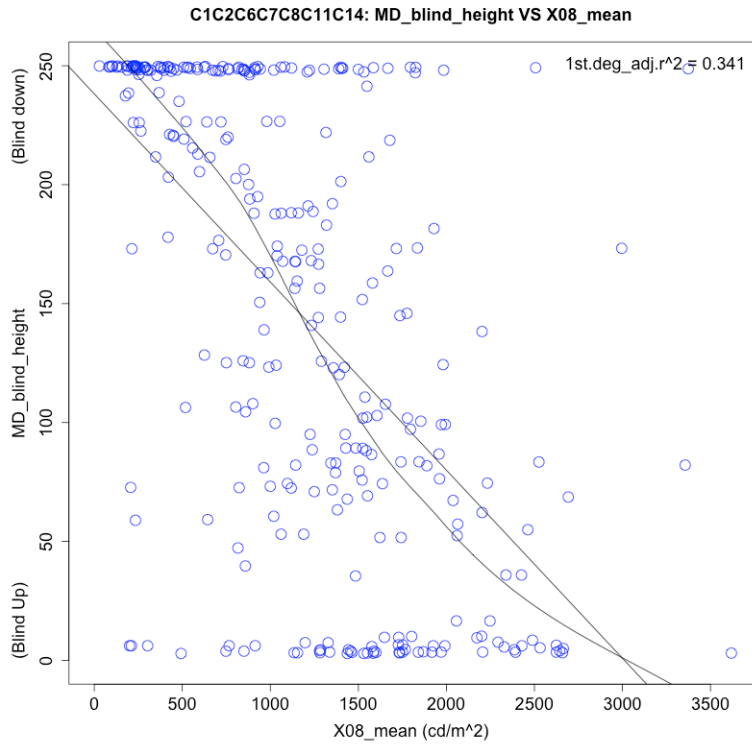


Figure 91 – Mean window luminance versus blind height; MP conditions

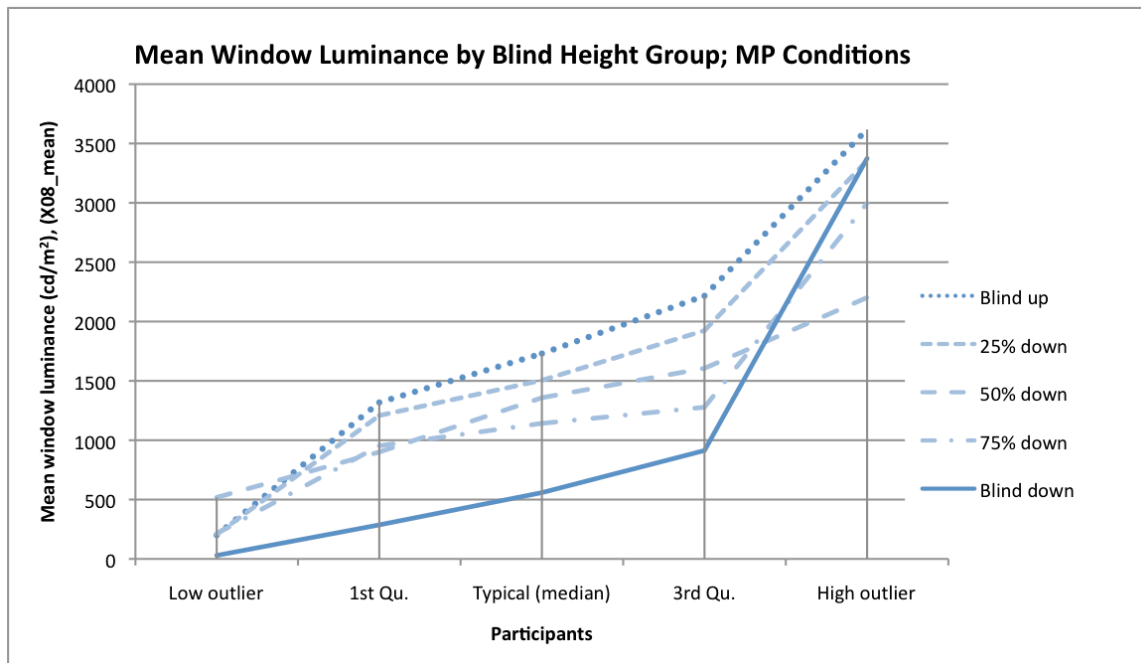


Figure 92 - Summary data for the mean window luminance by blind height group; MP conditions

Given the strength of X08_standard_deviation to predict visual comfort, blind height is reported for MP conditions relative to this metric (X08_standard_deviation) in Figure 93. As can be seen, standard deviation of window luminance does not have as strong of a relationship with blind height as X08_mean ($adjr^2=0.14$). Figure 94 shows the median blind closure for MP conditions generally occurred to maintain standard deviation of window luminance values between 1850-2150 cd/m^2 . As can be seen in Figure 94, there is a substantial difference between X08_standard_deviation for blinds all the way down versus any of the other height settings, but not good separation between different heights. This makes sense given that the metric is measuring variability and blinds closed provides the greatest uniformity while any of the other settings would preserve a high degree of variability. For this reason, this metric may be more useful for controlling the tilt of the louvers rather than the blind height.

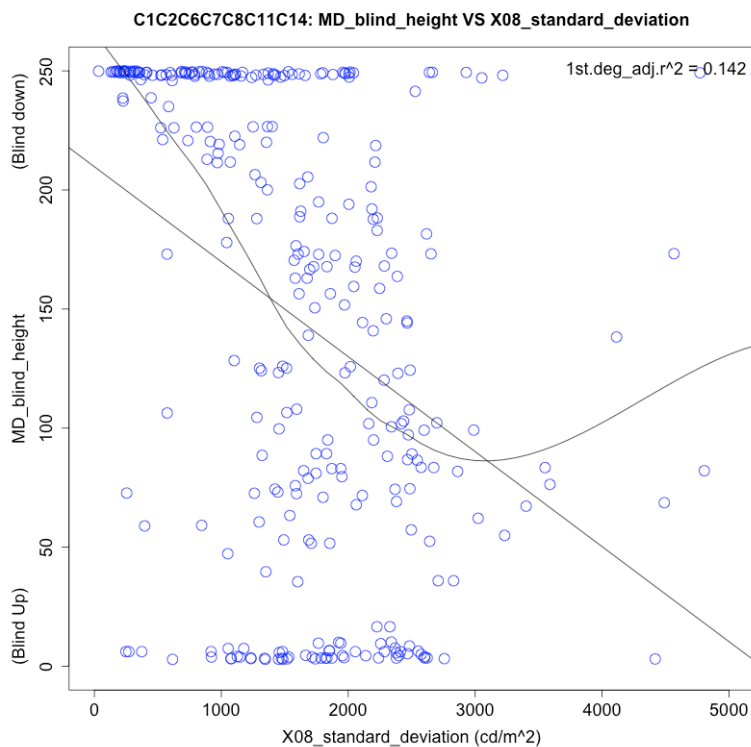


Figure 93 – Standard deviation of window luminance versus blind height; MP conditions

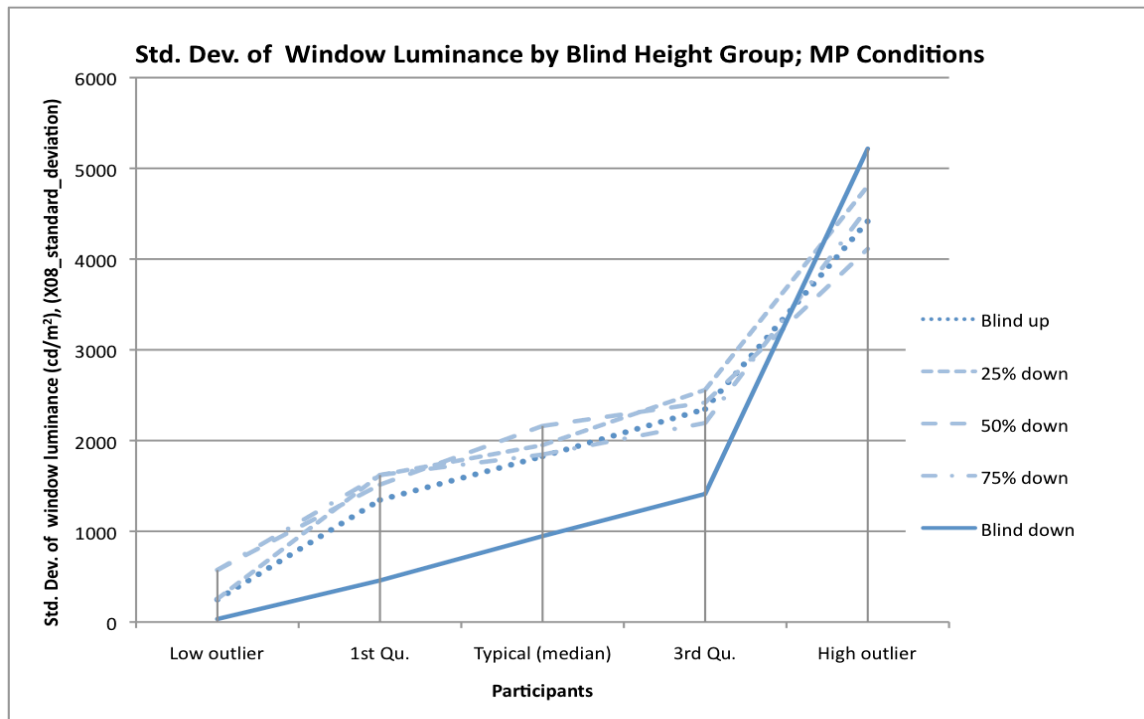


Figure 94 - Summary data for the std. dev. of window luminance by blind height group; MP conditions

4.7.2 Controlling electric lights

Traditional daylight harvesting systems rely on E_{ceiling} as a control signal to determine how much to dim the electric lights in response to daylight available. It is generally understood that E_{ceiling} serves as a proxy for E_{desktop} due the challenges of locating sensors on the desktop (i.e. desk clutter, shadowing). In this study, the $\text{adj}r^2$ between E_{desktop} and E_{ceiling} was 0.63 and was 0.74 between horizontal illuminance at the top of the monitor and ceiling illuminance. All of the MP integrated lighting conditions' (C2C7C11C14) electric light dimming signals are reported relative to E_{ceiling} in Figure 95. As can be seen, E_{ceiling} is not a strong indicator of dimmer choice ($\text{adj}r^2=0.05$). Figure 96 shows the median dimmer choice for MP conditions generally occurred between 750-1000 lux of ceiling illuminance. While a few participants dimmed the light to completely off and maintained E_{ceiling} as low as 50 lux, in over 75% of the cases when

participants dimmed lights to off, there was at least 400 lux of daylight available at the ceiling. Approximately 75% of the participants who dimmed lights between 20-40% maintained at least 650 lux on the ceiling.

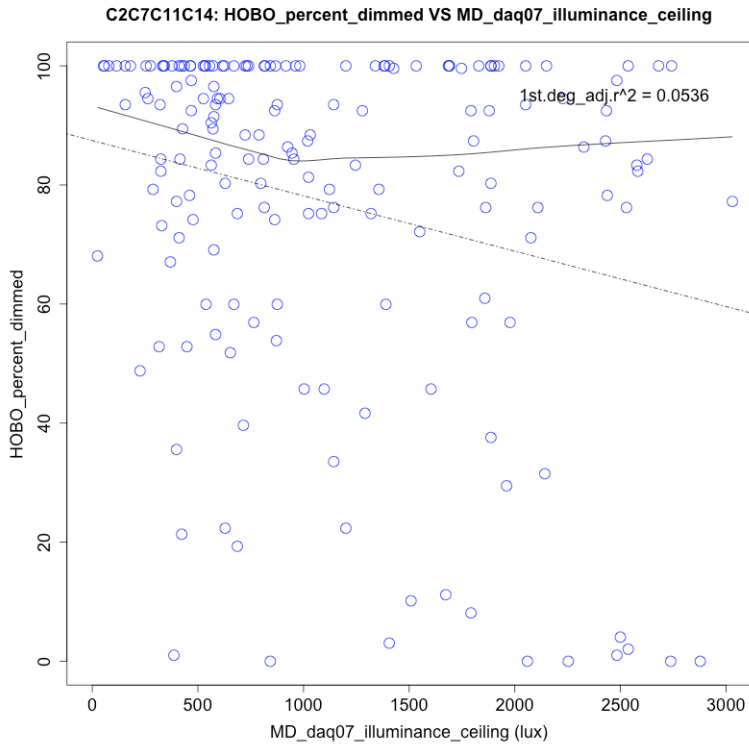


Figure 95 – E_{ceiling} versus dimmer choice; MP integrated lighting conditions

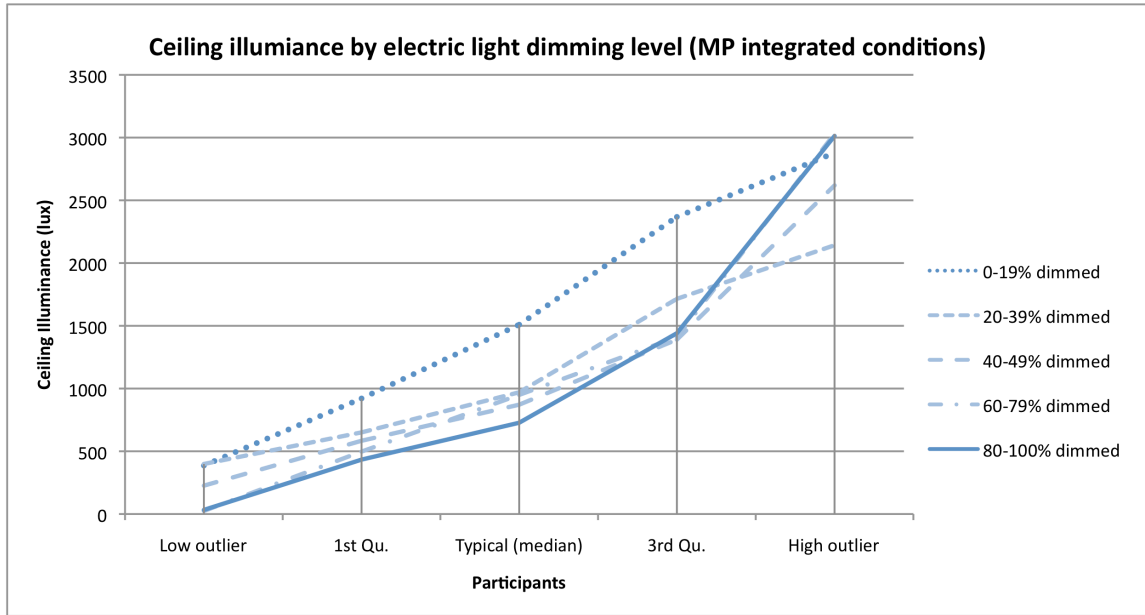


Figure 96 – Summary data for E_{ceiling} by dimming group; MP integrated lighting conditions

Illuminance measured horizontally at the top of the computer monitor performed much better than ceiling illuminance. All of the MP integrated lighting conditions' (C2C7C11C14) electric light dimming signal are reported relative to illuminance at the top of the monitor in Figure 97. As can be seen, illuminance at the top of the monitor is a relatively strong indicator of dimmer choice ($_{\text{adj}}r^2=0.28$) as compared to ceiling illuminance. Figure 98 shows the median dimmer choice for MP conditions generally occurred between 650-1700 lux of illuminance at the top of the monitor. While a few participants dimmed the light to completely off and maintained illuminance at the top of monitor as low as 50 lux, in over 75% of the cases when participants dimmed lights to off, there was at least 450 lux of daylight available at the top of the monitor. Approximately 75% of the participants who dimmed lights between 20-40% maintained at least 1300 lux at the top of the monitor.

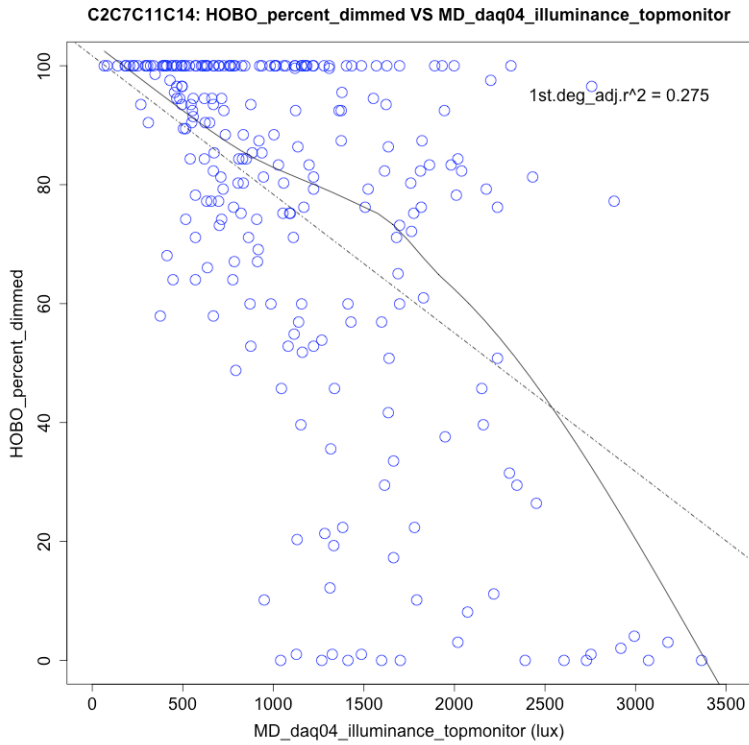


Figure 97 – Horiz. illum. at top of monitor versus dimmer choice; MP integrated lighting conditions

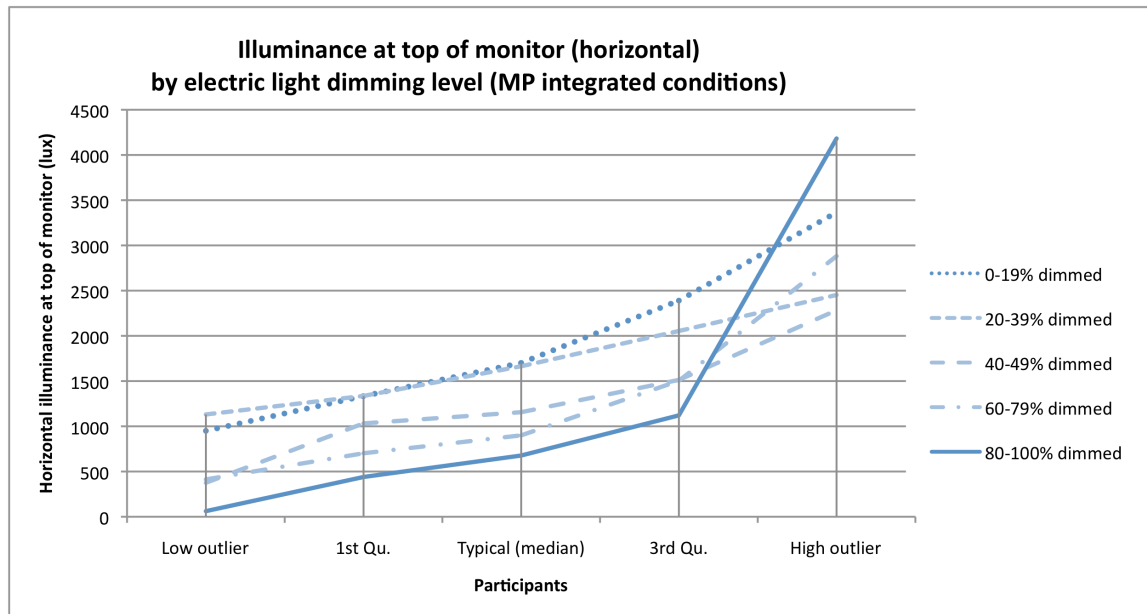


Figure 98 - Summary data for horiz. illum. on monitor by dimming group; MP integrated lighting conditions

One of the strongest predictors of dimmer choice was the luminance ratio between the 25th and 75th percentile pixel values for the desk task mask ((X05_25th_to_75th_percentile). All of the MP integrated lighting conditions' (C2C7C11C14) electric light dimming signals are reported relative to this desktop luminance ratio in Figure 99. As can be seen, this luminance ratio represents a strong indicator of dimmer choice ($_{adj}r^2=0.41$) as compared to illuminance measures. Figure 112 shows that the median dimmer choice for MP conditions generally occurred between the values of 0.17-0.23 for the 25th/75th percentile luminance ratio in X05. While a few participants dimmed the light completely off maintaining a ratio as low as 0.06, in over 75% of the cases when participants dimmed lights to off, there was a ratio of at least 0.15. Approximately 75% of the participants who dimmed lights between 20-40% maintained at least 0.2 between the 25th/75th percentile luminance values in X05.

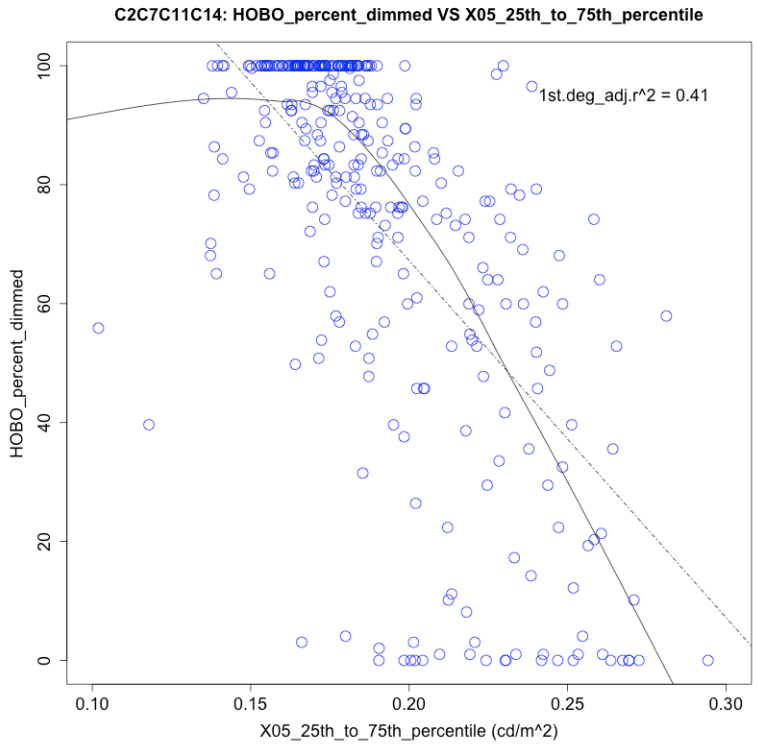


Figure 99 – 25th:75th pixel luminance of desktop (X05) versus dimmer choice; MP integrated lighting conditions

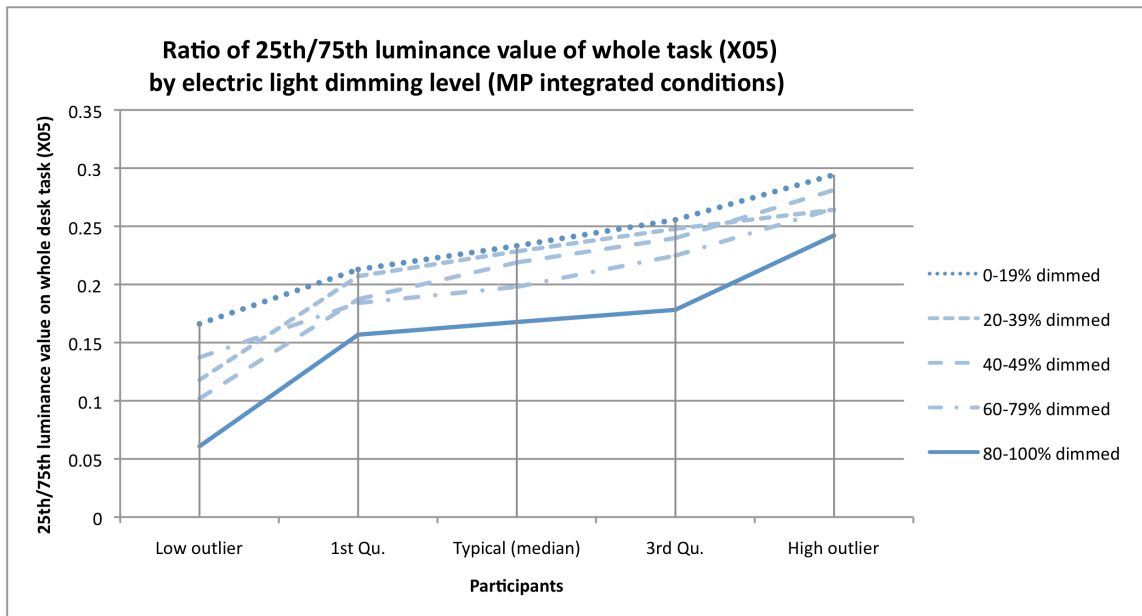


Figure 100 - Summary data 25th:75th pixel lum. of desktop by dimming group; MP int. lighting conditions

4.8 End of day participant feedback

At the end of the day on both participant-days, three questions were asked with regard to the participants' strategy for controlling the electric lights, the blinds, and if they were trying to light a particular part of the room. Results for these questions are documented in Table 55 through Table 57. At the end of the second participant-day only, participants were asked to describe any changes they would make to the office space layout, about their satisfaction with their ability to control the electric lights and blinds, and whether they would be in favor of using these particular technologies in their own office space. These results are documented in Table 59 and Table 58.

Table 55 – Open-ended responses at end of each day regarding participants’ electric lighting control strategy

Question: What was your strategy with the electric lighting?							
	Minimize electric light	Balance interior surface brightness	Fine tune for personal preference	Reduce glare / avoid eye strain	Provide sufficient lighting for tasks	Brighten room	Total count
Participant-day 1	21	16	12	12	9	4	53
Participant-day 2	19	9	12	12	12	6	51
Combined	40	25	24	24	21	10	104

Table 56 - Open-ended responses at end of each day regarding participants' motorized blind control strategy

Question: What was your strategy with the motorized blind control?									
	Reduce glare	Fine tune for personal preference	Provide indirect/diffuse lighting	Maximize daylight	Reduce interior brightness	Block glare & brightness with top blind, maintain view below	Block view of cars, or pedestrian distractions	Reduce heat gain	Total count
P-Day 1	25	15	9	6	7	8	3	1	74
P-Day 2	28	13	16	10	3	1	3	0	74
Comb.	53	28	25	16	10	9	6	1	148

Table 57 - Open-ended responses at end of each day regarding participants' integrated lighting objectives

Question: Were you trying to light a particular part of the room?									
	Entire space	Desk	No focus	Ceiling	Left_scene	Back Wall (behind participant)	Front_scene	Floor area	Total count
P-Day 1	16	15	9	8	3	2	1	1	55
P-Day 2	13	13	12	8	1	1	2	0	50
Comb.	29	28	21	16	4	3	3	1	105

Table 58 - Likert responses at end of second participant-day regarding satisfaction with lights and blinds

End of day Likert responses (Very Strongly Disagree = 1 - Very Strongly Agree = 7)	
Likert Item	Mean
I am satisfied with the control of the electric lights	5.35
I am satisfied with the control of the motorized blinds	4.87
I would like these electric lights in my office	4.69
I would like these motorized blinds in my office	5.45

Table 59 – Open-ended responses at end of the second participant-day regarding changes desired in the office

Please describe any changes you would make to the office set up to make it more comfortable. For example, would you move the desk location or direction? Would you change anything about the electric lights, blinds, walls or windows? Please explain.				
<i>Main Themes</i>	<i>Categories</i>	<i>Declarative Statement</i>	<i>Count (max. 45 possible)</i>	<i>Percent of participants</i>
Comfort	Furniture	The chair was uncomfortable	2	4%
	Thermal	The air blowing on me was annoying	1	2%
	Acoustics	The blinds were too loud or disruptive	1	2%
Aesthetics	Finishes	I would add artwork or color to the walls and/or plants to the space	13	29%
		The desk was too reflective	1	2%
Light	Electric Light	I would like more variability in the electric lighting design	6	13%
		The electric light fixtures were too bright or glaring	2	4%
		I do not like fluorescent lights	2	4%
	Task Lighting	I would add task lighting or a desk lamp	4	9%
	Natural Light	I want even more natural light in the office	3	7%
Blinds	Control of blinds	The blinds were sometimes difficult to control and/or I could not adjust them as desired	12	27%
	Materiality of blinds	I did not like the perforations in the lower part of the blinds	2	4%
Window	Window Size	The window was too big	1	2%
	View	The cars and people outside were sometimes distracting	1	2%
Spatial	Desk Location	I would rather the desk face the window at a 45 degree angle	5	11%
		I would rather sit with the window at my back	7	16%
		I would rather face west, instead of east	2	4%
		I would rather the desk face the window at a 90 degree angle	5	11%
	Document Holder	I would move the document holder closer or to the left of the computer monitor	6	13%
	Electric Light Location	I would prefer a different location for the overhead electric light	4	9%
General	Overall	I liked the space and would not change anything about it	9	20%

4.9 Subjective questionnaire items relative to one another

The relationship between subjective questionnaire items relative to one another was examined to determine construct validity of questionnaire items. These data can also help determine if specific items can be omitted in future laboratory or field studies.

As shown in Figure 101, QU1 and QU2 are generally the Likert items best correlated with other Likert items. QU1 and QU2 are highly correlated ($r^2=0.92$) themselves suggesting construct validity. QU1 and QU4 are also highly correlated ($r^2=0.90$), and QU5 is the Likert item with the lowest correlation to other Likert items. The semantic differential items are not as highly correlated with each other as the Likert items are with each other, nor are they as highly correlated with Likert items as the Likert items are internally. Of the semantic differential items, *right_scene* (too dim – too bright) was the item most highly correlated with the Likert items ($r^2=0.53$ with QU1). This is meaningful since *right_scene* is the questionnaire item with the highest overall correlation with lighting metrics. This shows that a simple linear model does not adequately address the relationship between QU1 and *right_scene* given that the most highly rated scenes on QU1 tended to be slightly too bright on the *right_scene* item.

C1C2C4C6C7C8C10C11C13C14Computer_split53 All Subjective vs All Subjective

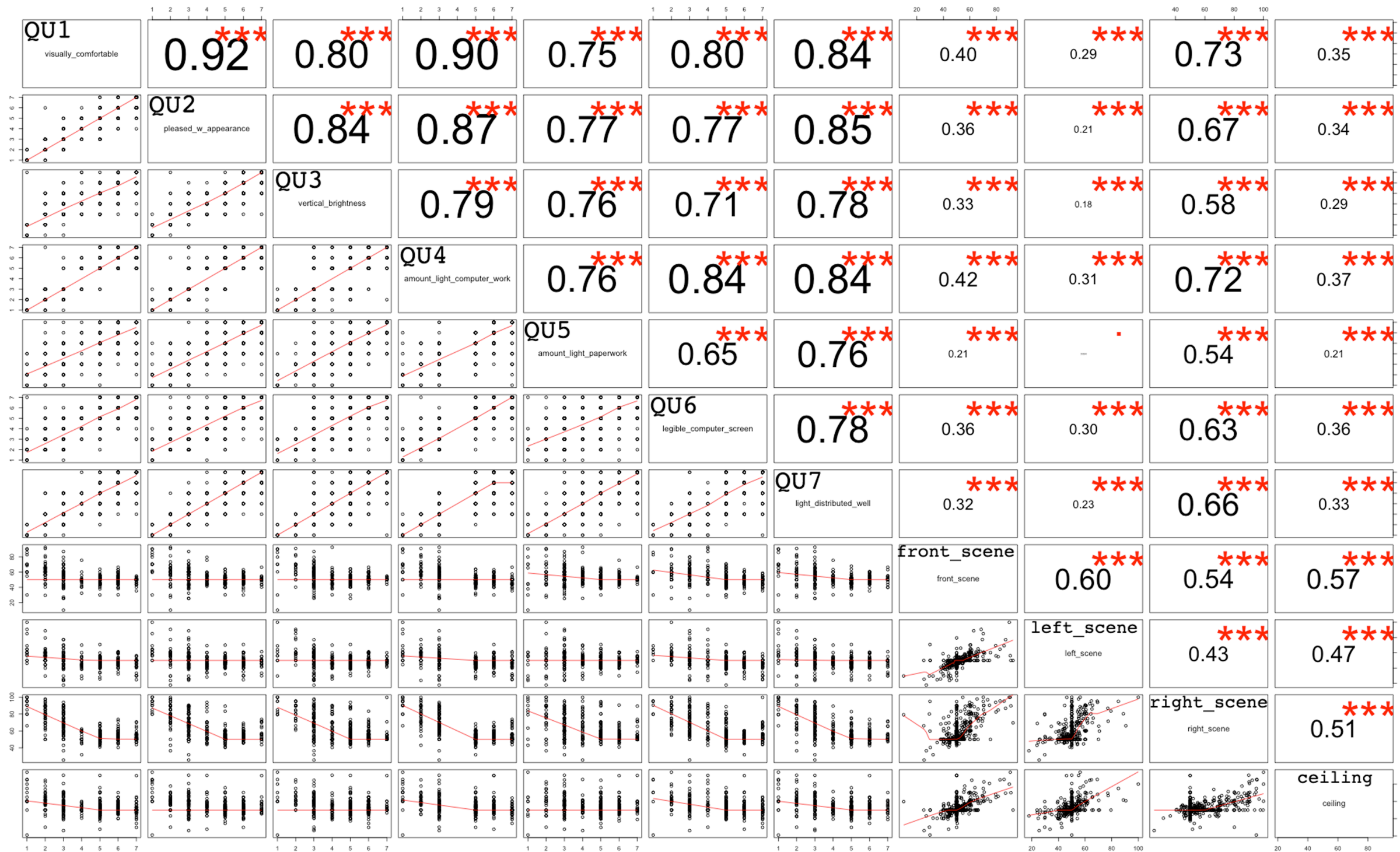


Figure 101 – Correlation scatter plot matrix between subjective questionnaire items (r^2 using Composite_data_set_Computer_split53)

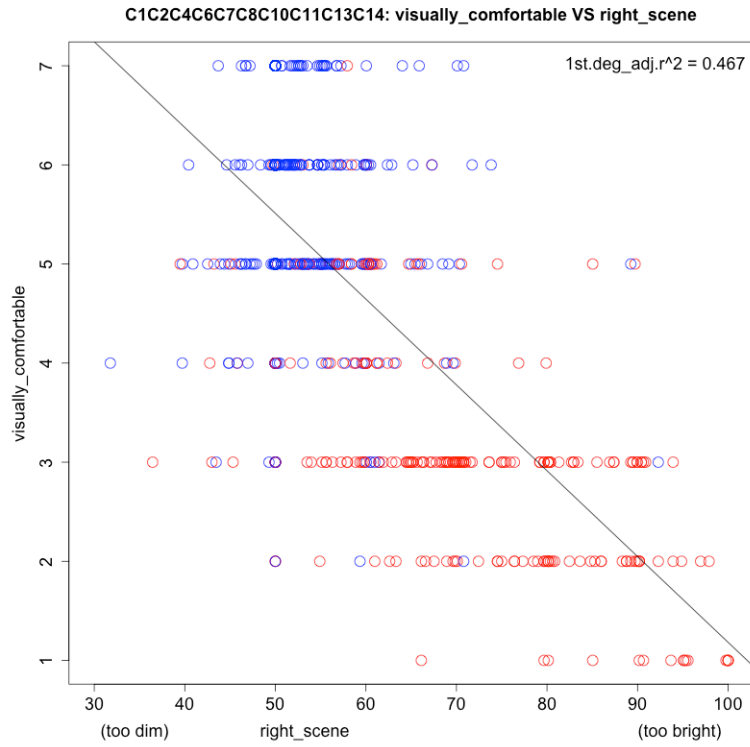


Figure 102 - Scatter plot with linear fit and $\text{adj}r^2$ for the questionnaire items “right_scene” and QU1 (using Composite_data_set)

5 Discussion

5.1 Comparing MP versus JU scenes

Section 4.1.1 presented basic descriptive statistics on several illuminance- and luminance-based lighting metrics for MP (most preferred) and JU (just uncomfortable) scenes. As expected, there was a wide range in variance of both MP and JU scenes. As noted in Section 4.1.3, the results for most metrics showed statistically significant differences for MP and JU scenes in the direction expected. That said, some metrics more consistently differentiated between MP and JU scenes. There is always some overlap in metrics comparing MP and JU scenes between-subjects due to the variability of human preference and acceptance, and in most cases within-subjects due to daylight variability across time. However, some metrics did not reliably differentiate within-subjects even over short time periods, such as the IESNA recommended daylight source to task luminance ratio (X08_mean_to_03_mean) as shown in Figure 79. This should be considered a fundamental requirement of any design metric. However, most metrics were challenged to differentiate MP and JU scenes below a specific threshold (e.g. daylight glare probability below 0.25, while the max occurrence = 0.4), and those that differentiated across a wider range of the metric results can be considered stronger candidates for design guidance or environmental control (e.g. standard deviation of window luminance below 3000 cd/m², while the max occurrence = 10,000 cd/m²). One explanation for the consistent result that metrics could not adequately differentiate between MP and JU scenes at some low light level is that the daylight conditions present during some JU conditions were not bright

enough to create JU scenes, rather these scenes were simply less comfortable than (or maybe equally comfortable as) MP scenes.

5.1.1 Preference for MP integrated lighting scenes over MP daylight-only scenes

Section 4.1.3 reported that the availability of personally controlled electric lighting to supplement available daylight is preferable to daylight alone, and resulted in approximately a 5% preference increase in this study. Note that this study only examined supplementing daylight with a recessed ceiling light source and differing results may be found with wall washers, pendant fixtures, or task lights. Section 4.2 reported that participants agreed that they were able to improve MP daylight-only conditions by adding electric light, and participants “agreed” or “strongly agreed” that they were able to worsen MP daylight-only conditions by adding electric light in a manner they felt was inappropriate. In MP integrated lighting scenes, participants typically added 125-200 lux of supplemental electric light at the desktop to the available daylight (dimming lights by a mean of 73%) including 30% of participants who elected to turn the electric lights off completely (effectively creating daylight-only scenes). Furthermore, participants’ acceptance threshold for maximum dimming in these cases (e.g. to support aggressive energy savings) was a mean of 96% dimmed with a minimum of 40% dimmed, and their acceptance for minimum dimming was a mean of 35% dimmed with minimum of 0% dimmed. Forty percent of participants accepted electric lights at full output in MP integrated scenes. Essentially, these data suggest that participants agreed or strongly agreed that dimming the electric light in accordance with the daylight available was important, and that it was possible for participants to perceive the space as too bright if electric lights were not dimmed in response to daylight available. This is counter to the notion in the literature review (Section 2.2.1.1) that posited that daylight-sensing

electric lighting controls could at best go unnoticed, and indicates that people prefer lights to be appropriately dimmed in response to daylight available.

5.2 *Illuminance-based metrics*

5.2.1 E_{desktop}

E_{desktop} is the most commonly referenced metric in daylighting design and research.

Using the composite data set, the squared correlation coefficient for this metric with QU1 was $_{\text{adj}}r^2=0.09$, for right_scene was also $_{\text{adj}}r^2=0.09$, and for QU5 (paper-based reading) was $_{\text{adj}}r^2=0.11$; not as high as E_v metrics detailed in Section 5.2.2.

In this study, the range of E_{desktop} in all MP conditions was 50-5000 lux with a mean of 1100 lux and a standard deviation of 850 lux. For MP conditions under daylight only, the E_{desktop} spanned the same range (50-5000 lux) with a mean of 1250 lux with a standard deviation of 1000 lux. For JU conditions only, E_{desktop} spanned a much wider range (400-41000 lux) with a higher mean and standard deviation ($\bar{x}=4300$, $\sigma=7000$ lux). Few previous studies (outlined in Section 2.3.1) reported preferred E_{desktop} levels under daylight alone (300 lux) or in integrated lighting environments (typically 400-800 lux) and the findings from this study were generally higher than levels previously published. This is likely due to the abundant daylight resource available in this study.

This study provides some guidance for determining an upper illumination comfort threshold. One could reference the mean E_{desktop} of JU scenes (4300 lux) or the bounded-BCD approach (2000 lux) as shown in Figure 103. These data could be referenced by metrics that require an upper horizontal illuminance threshold such as Daylight Saturation Percentage (Collaborative for High Performance Schools 2009) which, interestingly, suggests 400 foot-

candles (10 times the ambient criteria of 40 foot-candles; roughly 4300 lux) as the upper limit, or Useful Daylight Illuminance (Nabil & Mardaljevic 2005; Mardaljevic et al. 2009) which references the lower level closer to the upper bounded-BCD (2000-2500 lux). However, as Figure 103 also demonstrates, any upper horizontal illuminance threshold must be applied with knowledge that some individuals may accept, or even prefer, horizontal illuminance values as high as 5000 lux (pilot data in December showed mean of MP daylight only as 3600 lux), and only the most extreme cases can be confidently identified as JU.

C1, C4, C8, C10, C11 & C13: MD_daq08_illuminance_desktop & visually_comfortable

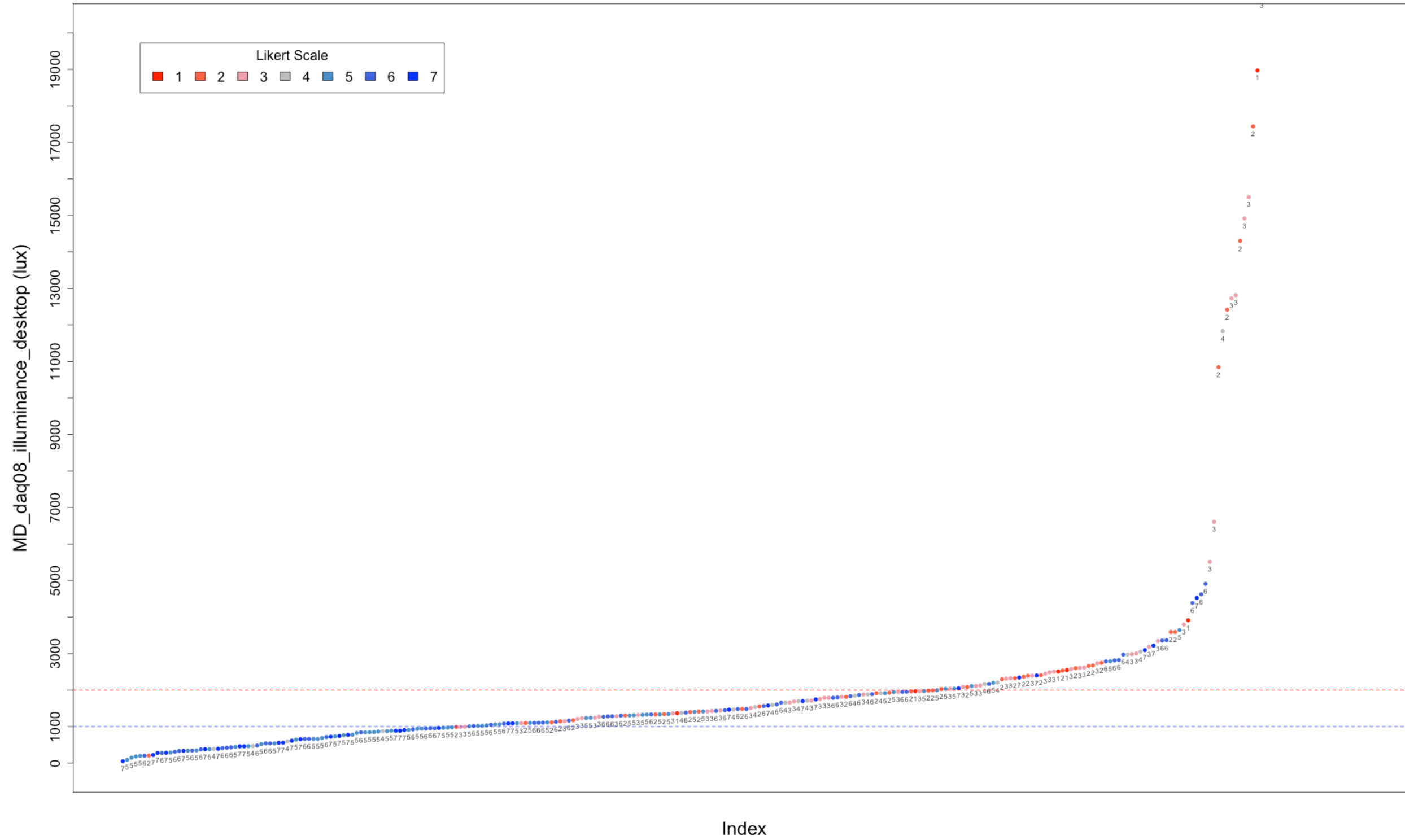


Figure 103 – E_{desktop} results for C1, C4, C8, C10, C11 & C14 (6/29-9/20) ordered by metric and color-coded by response to QU1

5.2.2 E_v

The highest overall squared correlation coefficient for an illuminance-based metric (using the composite data set) was for `right_scene` and E_v at the top of the monitor¹⁶ measured in the participants' viewing direction, producing $r^2=0.2982$, whereas the highest luminance-based metric was with standard deviation of the window luminance producing a much higher squared correlation coefficient ($r^2=0.4252$). The next highest squared correlation coefficient for an illuminance-based metric was for QU6 and E_v on the NE wall ($r^2=0.2852$) and E_v at the top of monitor in the participants' viewing direction ($r^2=0.2833$), while the best luminance-based metric for QU6 produced $r^2=0.2877$ (25th percentile of the window).

The bounded-BCD for E_v measured at the top of the monitor was 875-1250 lux as shown in Figure 74 ($\bar{x} = 798$ lux, $\sigma = 500$ lux). As expected, similar criteria were identified for E_v measured from seated participants' eye position (1000-1500 lux; Figure 104). The values from the top of the monitor could be useful criteria for luminous environmental control systems as well as in simulation-based design analysis, whereas the values from the seated users' perspective are limited to simulation-based design analysis because it is not a feasible physical control point. This issue is elaborated upon in Section 5.5.1.

While no illuminance-based metrics ranked highest for any subjective items, it was not uncommon for them to rank in the top 20. However, it is interesting to note that E_v , rather than

¹⁶ The vertical illuminance at the top of the monitor produced a slightly better r^2 (0.2982) for `right_scene` than did the vertical illuminance at the seated eye position (0.2662). In fact, it outperformed the seated eye position on most subjective items. As expected, these two values were highly correlated ($r^2=0.94$), with a mean difference of 134 lux (17.3%).

horizontal illuminance measures, dominated these. The only horizontally measured illuminance metrics that ranked in the top 20 metrics for any subjective item were E_{desktop} for QU5 ($r^2=0.1282$), and E_{ceiling} for QU5 ($r^2=0.1181$) and left_scene ($r^2=0.1428$). It should be restated that QU5 was the only subjective item that had difficulty separating between JU and MP scenes as was shown in Table 18. Even in these cases, there was an E_v measure that performed essentially equally well or better than the horizontal measures. The squared correlation coefficient for E_v at the participants' eye position with QU1 was $\text{adj}r^2=0.18$, and at the top of the monitor it was $\text{adj}r^2=0.16$. It is not surprising that the horizontal illuminance measures ranked highly for the questions addressing paper-based (QU5) as paper-based tasks are more often completed on a horizontal surface.

The finding that luminance-based measures outperformed illuminance-based measures is somewhat contrary to Newsham et al. (Newsham, Aries, et al. 2008) who noted that E_{desktop} outperformed the best luminance-based measure (luminance ratio 75%:25% pixel value, 0.36 versus 0.31). However, their study did not use subjective ratings of human visual preference and acceptance directly as the variable of comparison; rather they used the subjects' electric lighting dimmer choice while performing typical office activities, including paper-based tasks. It could be that the differing result is partly due to the variable used for comparison (dimmer choice rather than subjective responses to comfort questions), and it could also be explained by differences in the amount of paper-based tasks in the two studies. Desktop illuminance ranked higher using QU5 (paper-based tasks) than it did for all other subjective items in this dissertation.

C8 & C10: MD_daq01_illuminance_topcanon & visually_comfortable

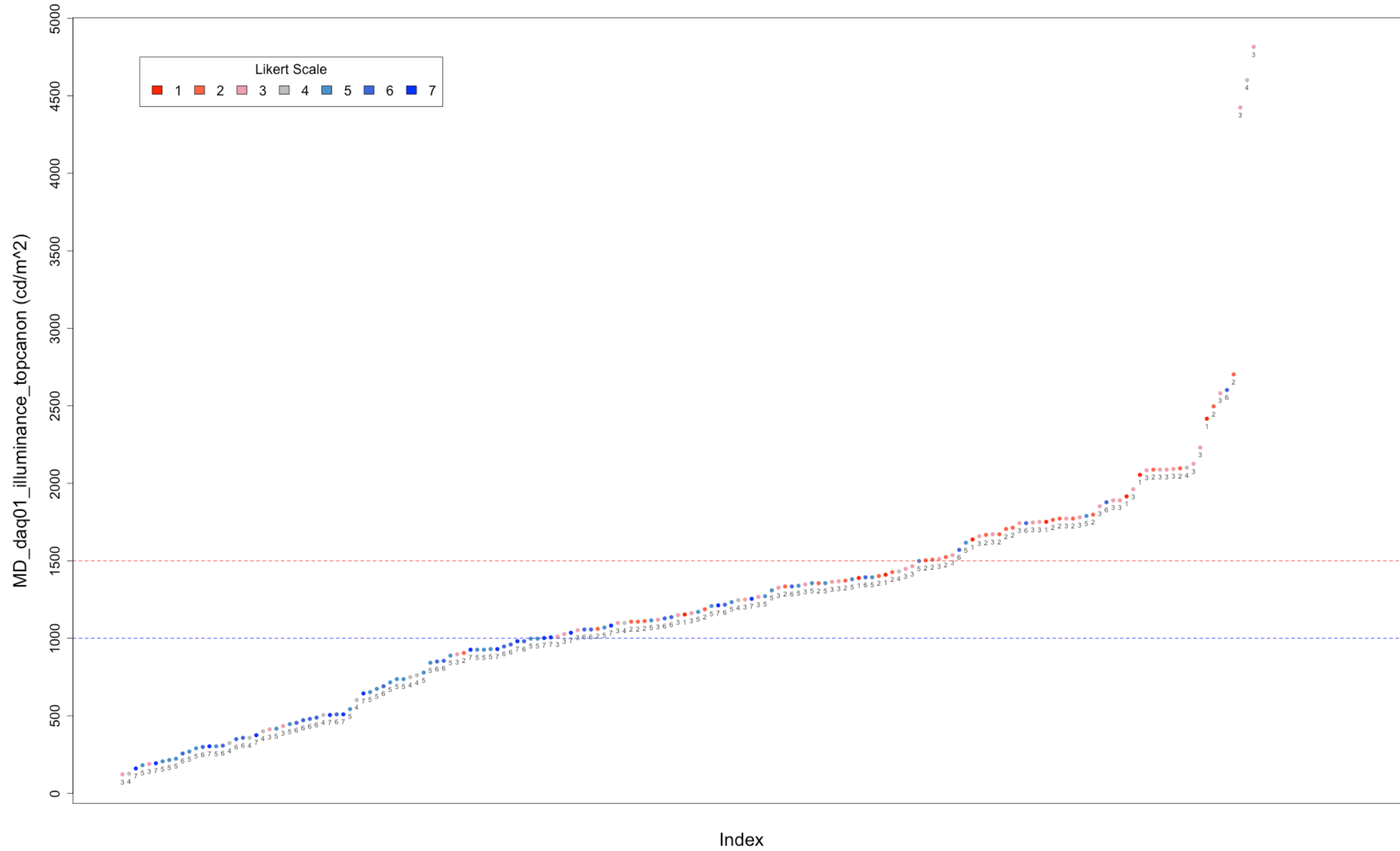


Figure 104 - E_v (at top of Canon in seated participants' viewing direction) for C8 & C10, results ordered by metric and color-coded by response to Q11

5.3 *Luminance-based metrics*

Luminance-based metrics had higher squared correlation coefficients than illuminance-based metrics for all subjective items (see Section 8.1 for top 20 metrics ranked by squared correlation coefficients for each subjective item). A few previous studies have suggested that luminance-based metrics are associated with comfort or control parameters as was described in Sections 2.2.2.4, 2.2.2.5, and 2.3.2. Findings from this study are compared to existing literature in the following sections.

Luminance metrics based upon the horizontal 40° band within the FOV (X20) and window masks (X08 and X10) are the most common among the top 20 metrics for right_scene. No metrics based upon the entire scene (X01) rank in the top 20, nor did any based upon illuminance or irradiance data, nor for DGI/DGP or any other glare indices, nor for luminance ratios or contrast ratios.

5.3.1 Luminance ratios

The most common luminance-based metric referenced by design guides and reported by daylighting research are basic luminance ratios, typically between task:background and bright light source:task. The results from X08_mean_to_03_mean are the luminance ratios for the *daylight source:task* as outlined by the current IESNA Lighting Handbook. The squared correlation coefficient for this metric with QU1 was $\text{adj}r^2=0.10$ and for right_scene was $\text{adj}r^2=0.16$ across the composite data set. According to the handbook, the result of this metric should not exceed 10:1 (20:1 is for daylight source to adjacent background). For this metric the MP scenes

range from 0.5:1 to 57:1 with a mean of 14:1, and the JU scenes ranged from 3.6:1 to 52:1 with a mean of 22:1. The mean values for the MP luminance ratios (14:1) are within the range suggested by Egan (1983) and the 10th Lighting Handbook; however, approximately half of the participants had one or more MP scenes with a luminance ratio in excess of 1:20 (Figure 35).

Existing literature does not explicitly state how these luminance ratios should be calculated in spaces with daylight and the method dramatically impacts the result (see Table 60 and Figure 105). The regression analysis used only the X08_mean_to_03_mean luminance ratio; however, other luminance ratios are defensible within the current loose definition. Figure 105 illustrates several logical interpretations of the luminance ratio metric as currently defined for a single comfortable daylight-only scene. This figure interprets the task definition consistently as X03 (X04, X05, X06, or X07 could also be argued) and changes only the bright light source definition and produces a range of luminance ratios from 5:1 to 102:1. Further definition is required for this metric to be useful. While this metric, as interpreted in this dissertation, does not consistently differentiate between MP and JU scenes (Figure 79) or establish a clear bounded-BCD (Figure 82), it is possible that other variations on this metric could prove stronger. The simplicity of this metric is its greatest strength, but available literature is not available to defend the current recommendations (Boyce 1987; Veitch 2001). Future research is warranted to establish a consistently applicable calculation method and defensible recommended criteria.

A few other promising luminance-ratio metrics from previous research are not reviewed in detail since their r^2 results did not rank among the highest metrics investigated in this dissertation. These include the COV of the entire scene (X01_cov) and the ratio of the 75th:25th luminance value in the entire scene (X01_25th_to_75th_percentile). The new Lighting Handbook (DiLaura et al. 2011) describes the coefficient of variation, or standard deviation divided by

mean, (herein COV) as a useful metric for describing the “average difference from the average” or the “dispersion of the data” and Howlett et al. (2007) suggested it as a promising metric in a scoping study. While it is not a simple luminance ratio of different regions within a scene, it does address both adaptation and variance extremes, similar to simple luminance ratios. Nonetheless, this metric did not produce squared correlation coefficients in the top 20 for any subjective item (Table 22), in fact COV was calculated for all masks and none of them produced high correlation coefficients. The same can be said for the ratio between the 25th and 75th percentile luminance values in X01, one of the strongest metrics found previously (Newsham, Aries, et al. 2008). This underscores potential challenges to generalizability.

Table 60 – Example range of luminance ratios for single scene

S001 2011.06.29 14:11 (Likert scores of 5)	
Scene values (cd/m²)	
03_mean	79
01_90th_percentile	373
08_mean	1403
5*01_mean	(5*285)=1425
01_brightest_10percent	1880
03_evalglare_mL0005_lum_sources	1894
01_98th_percentile	3824
01_evalglare_mL0005_lum_sources	4417
01_maximum	8096
Luminance Ratio (values shown:X03_mean)	
01_90th_percentile	5:1
08_mean	17.7:1
5*01_mean	17.9:1
01_brightest_10percent	23.7:1
03_evalglare_mL0005_lum_sources	23.8:1
01_98th_percentile	48:1
01_evalglare_mL0005_lum_sources	56:1
01_maximum	102:1

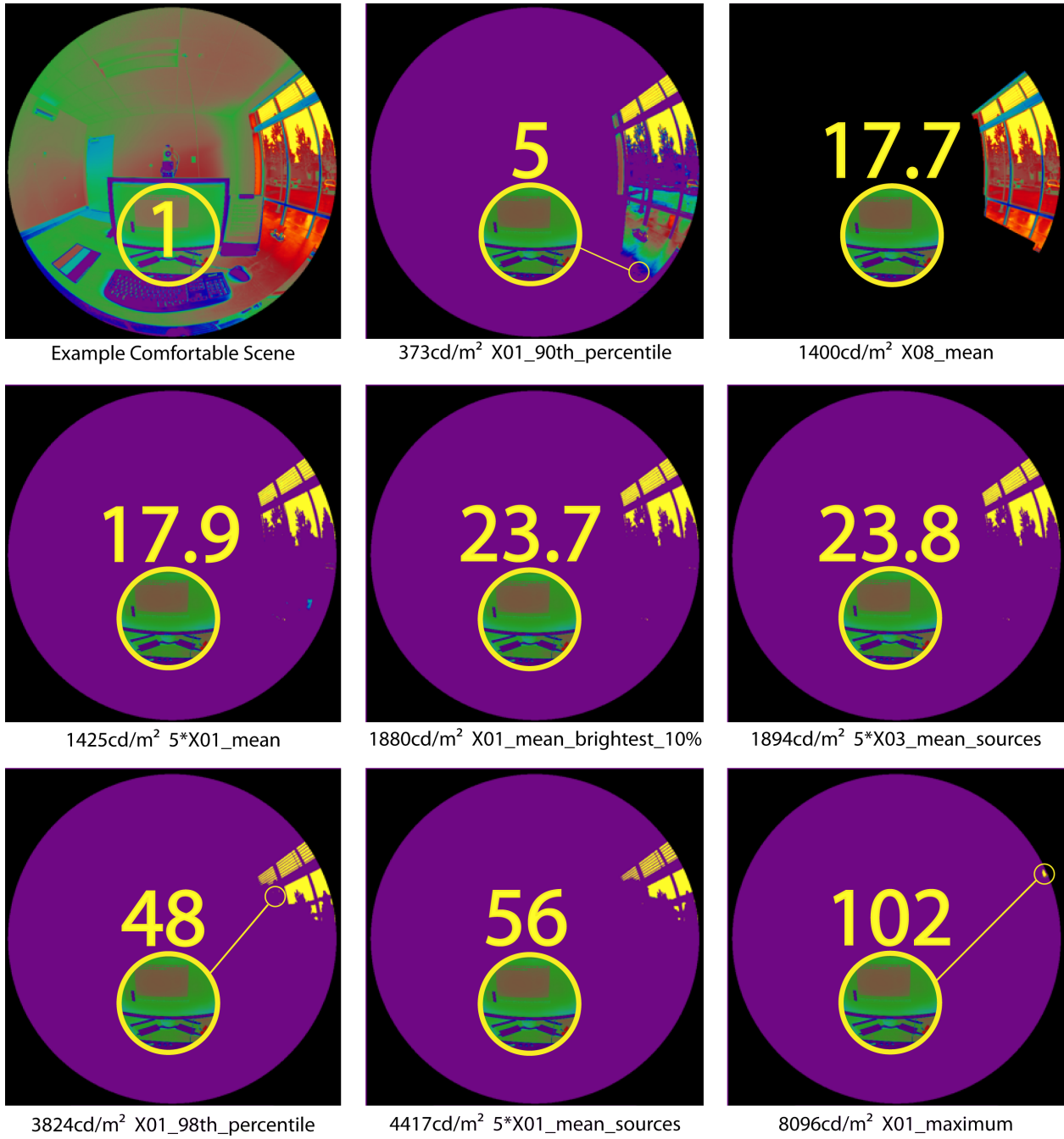


Figure 105 – Example comfortable scene with multiple source:task luminance ratios represented

5.3.2 Standard Deviation of Window Luminance

As described in Section 4.3, standard deviation of the window luminance (X08_standard_deviation) was the highest overall lighting metric for nearly all subjective items. This is an encouraging finding for several reasons. Given this dataset, it outperforms all current best practice lighting design metrics with regard to its ability to describe the variance in a range of subjective ratings of visual preference and acceptance in an office with daylight. Again, given this dataset, the results of this metric appear to separate into three categories of subjective response (Figure 42): scenes likely to be comfortable, scenes likely to be uncomfortable and scenes that fall within a bounded-BCD. Standard deviation is a logical and commonly understood description of variability. Since the window region is often perceived as the brightest light source in spaces with daylight, focusing on the variability of this region is an intuitive approach to support luminance-based design analysis as well as for automated blinds control. In most office applications, defining the window area is straightforward as it is typically defined by clear architectural boundaries, thus supporting both field research and simulation-based design analysis using this metric. It is relatively easy to calculate and is computationally inexpensive. Several readily available software applications can compute the metric given a defined set of luminance values, thus it does not require an additional specific software application to calculate. The metric is simple and firmly defined, thus will inherently resist subtle manipulation aimed at improving the fit of the metric to a given sample as can be found in human factors lighting research (Chauvel et al. 1982; Nazzari 2005; Wienold & Christoffersen 2006). Often, this practice leads to overfitting the algorithm to the specific sample rather than improving the metric's ability to describe the variability of the population.

While standard deviation of window luminance has many positive attributes, there are also some drawbacks. This metric requires masking a specific region of a HDR for analysis. This can be done crudely in Photosphere using an approximate rectangular definition but it is more accurately accomplished following the steps described in Section 3.6. That said, once the luminance values are available, calculating standard deviation is easily accomplished. Because of the demands of the required mask, the metric is highly specific to space and position. That is, every space and every workstation position within a space requires that a unique mask be defined for analysis due to changes in window patterns from space to space or due to the changes in proximity to the window within a given space. This means that either field research or simulation analysis will likely require building a unique mask for each position and view direction of interest. Future research can examine what resolution of analysis points is required to adequately characterize a given space using this metric. Because of these limitations, it is also useful to examine metrics that are based upon position-independent masks (e.g., X01, X19, X20). Using these masks will reduce analysis time because they can be consistently applied across a wide range of spaces and positions.

In practice, this metric is likely to be more useful for blind control purposes than for simulation-based daylighting design analysis purposes. This is because the metric is insensitive to a host of architectural factors that impact daylighting performance inside the envelope. For example, it cannot address basic architectural aspects such as room depth, interior finishes or furnishings. Therefore, it is advisable to calculate this metric as one of several useful inputs for design analysis purposes.

Figure 107 summarizes the range of results for standard deviation of window luminance as found in C8C10 and reports the minimum, 1st quartile, median, mean, 3rd quartile and

maximum results in numerical and graphical manner. It also summarizes the results of each of the subjective responses that correspond to the presented luminance results (see Figure 106 for a reference scale). This graphic is provided to give the reader a more intuitive understanding of how the metric reacts across a wide range of visual conditions for a single space across time. It is interesting to note that extremely low standard deviation was rated as uncomfortable and the semantic differential results note that the space was too dim overall. This is likely the result of a participant who felt they had to close the blinds to avoid glare (note small sun spots peeking through blind cord holes), but in so doing, felt the space was too dim and rated it as uncomfortable. The cluster of “too dim” ratings in Figure 41-right provides further evidence of this finding. This seems to indicate that people may feel a need for a certain amount of variability, and it is possible that future research will identify a lower “sufficiency” threshold for this or other metrics.

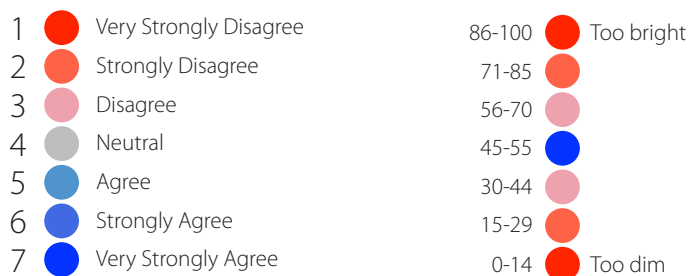


Figure 106 - Scale for use with summary range of the metrics figures

C8C10: X08_standard_deviation

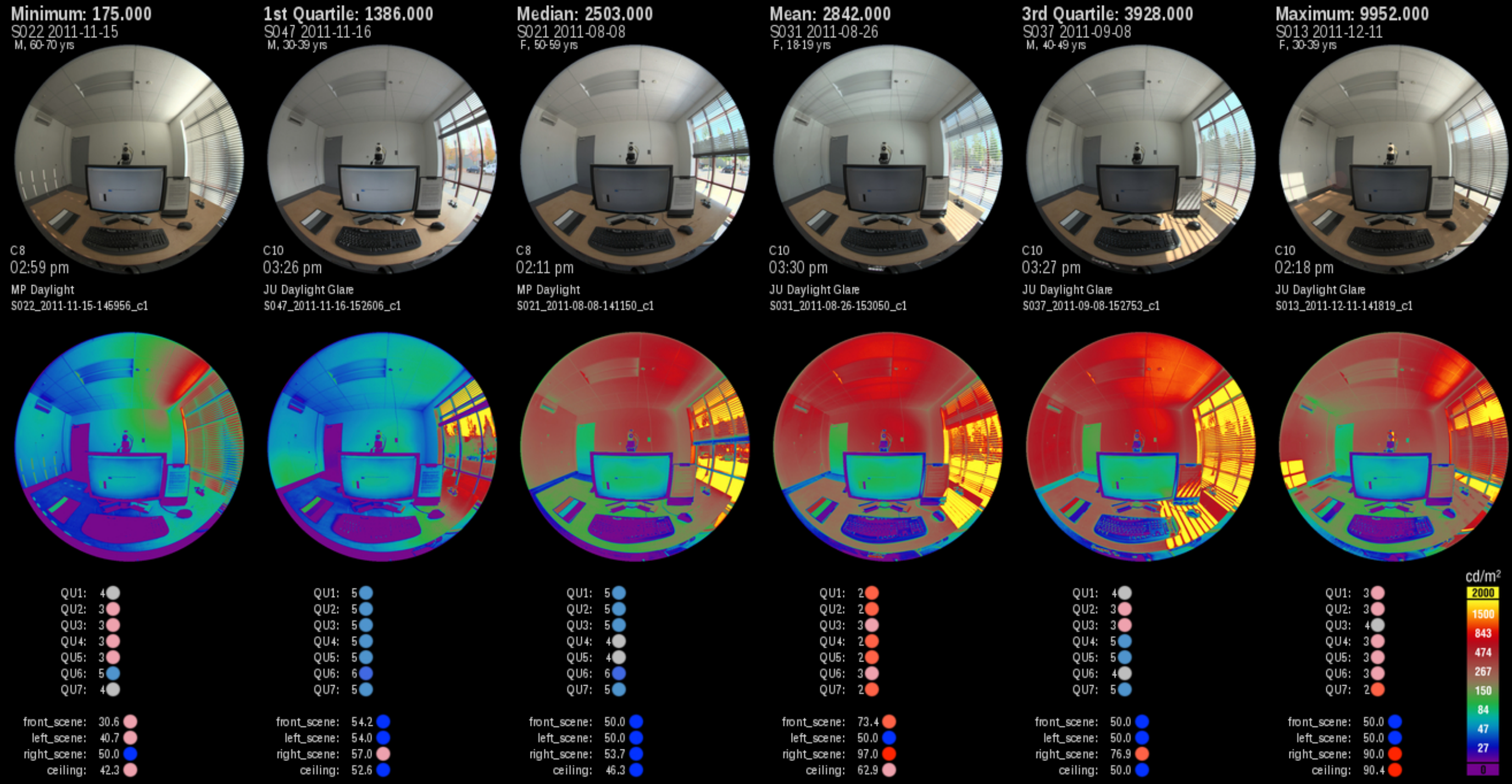


Figure 107 – Summary range of the results for standard deviation of window luminance (X08_standard_deviation) including tone-mapped image, false color luminance plot, and subjective response data (minimum result at left, maximum result at right)

5.3.3 Mean luminance of 40° horizontal band (X20)

The mean luminance of the 40° horizontal band produced one of the highest squared correlation coefficients with `right_scene` ($adjr^2=0.30$ for the composite data set). It is another example of a very simple metric and therefore shares many of the attributes with the standard deviation of window luminance (see 0). However, it also has the benefit of being a space-independent metric. That is, it can be applied directly to any space or position within a space without modification. This metric appears to be robust across time within the space studied herein; however, it may prove too simplistic as it is applied to a broad range of designs. It is advisable to use this metric in combination with other metrics that describe variability, such as the standard deviation of the window luminance or standard deviation of the same 40° horizontal band.

Figure 108 summarizes the range of results for mean luminance of 40° horizontal band as found in C8C10 as well as corresponding subjective responses. This graphic provides a visual representation of a wide range of visual conditions for a single space across time. Similar to the scenario described in the previous section for standard deviation of window luminance, it is interesting to note that extremely low mean luminance of 40° horizontal band was rated as uncomfortable because it was too dim. In this case, it seems to be due to very dark outdoor conditions rather than extreme sunlight forcing blinds closed as noted in the previous section for standard deviation of window luminance. The clusters of “too dim” ratings in Figure 46-right and Figure 109 provide further evidence of this finding.

C8C10: X20_mean

Minimum: 51,140
 S035 2011-10-05
 M, 18-19 yrs



C10
 01:36 pm
 JU Daylight Glare
 S035_2011-10-05-133610_c1

1st Quartile: 277,600
 S027 2011-08-20
 F, 18-19 yrs



C8
 02:10 pm
 MP Daylight
 S027_2011-08-20-141016_c1

Median: 509,200
 S018 2011-10-03
 F, 30-39 yrs



C8
 01:27 pm
 MP Daylight
 S018_2011-10-03-132714_c1

Mean: 533,400
 S021 2011-08-08
 F, 50-59 yrs



C8
 02:11 pm
 MP Daylight
 S021_2011-08-08-141150_c1

3rd Quartile: 749,800
 S010 2011-12-10
 F, 30-39 yrs

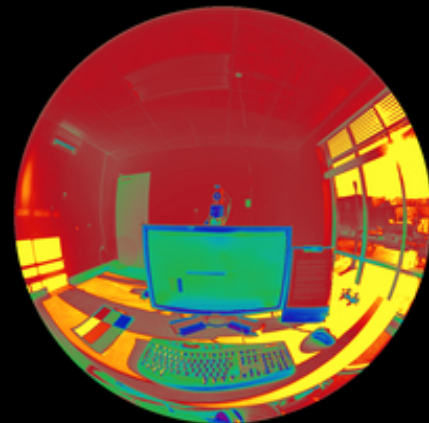
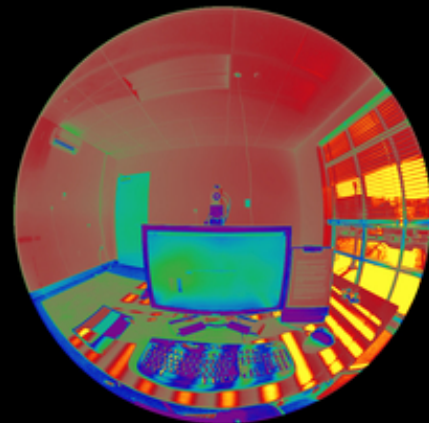
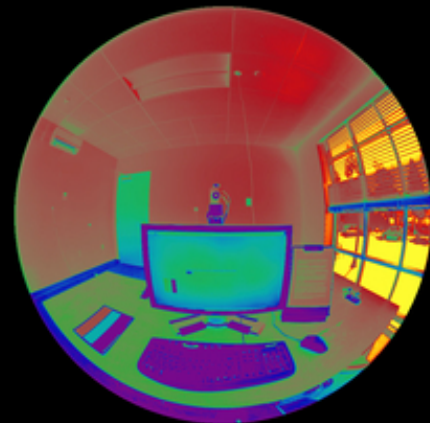
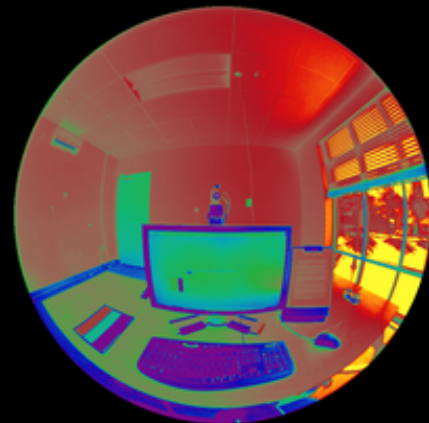
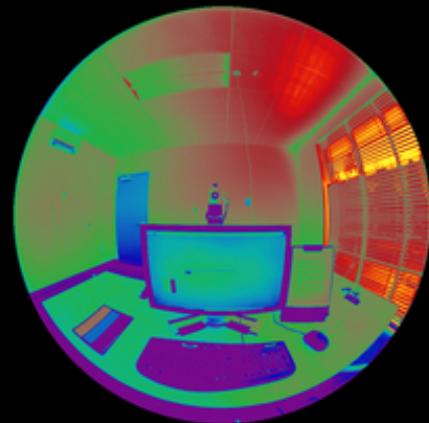
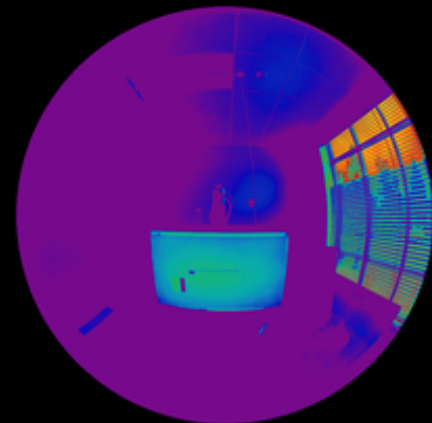


C8
 01:53 pm
 MP Daylight
 S010_2011-12-10-135322_c1

Maximum: 1674,000
 S010 2011-12-10
 F, 30-39 yrs



C10
 02:19 pm
 JU Daylight Glare
 S010_2011-12-10-141951_c1



- QU1: 3 ●
- QU2: 2 ●
- QU3: 3 ●
- QU4: 2 ●
- QU5: 1 ●
- QU6: 4 ●
- QU7: 3 ●

- QU1: 7 ●
- QU2: 6 ●
- QU3: 5 ●
- QU4: 7 ●
- QU5: 4 ●
- QU6: 7 ●
- QU7: 5 ●

- QU1: 5 ●
- QU2: 5 ●
- QU3: 5 ●
- QU4: 5 ●
- QU5: 3 ●
- QU6: 5 ●
- QU7: 5 ●

- QU1: 5 ●
- QU2: 5 ●
- QU3: 5 ●
- QU4: 4 ●
- QU5: 4 ●
- QU6: 6 ●
- QU7: 5 ●

- QU1: 5 ●
- QU2: 5 ●
- QU3: 3 ●
- QU4: 3 ●
- QU5: 5 ●
- QU6: 3 ●
- QU7: 3 ●

- QU1: 2 ●
- QU2: 3 ●
- QU3: 5 ●
- QU4: 3 ●
- QU5: 5 ●
- QU6: 2 ●
- QU7: 3 ●

- front_scene: 44.6 ●
- left_scene: 23.8 ●
- right_scene: 43.0 ●
- ceiling: 50.0 ●

- front_scene: 45.3 ●
- left_scene: 30.1 ●
- right_scene: 52.3 ●
- ceiling: 47.9 ●

- front_scene: 50.0 ●
- left_scene: 50.0 ●
- right_scene: 50.0 ●
- ceiling: 50.0 ●

- front_scene: 50.0 ●
- left_scene: 50.0 ●
- right_scene: 53.7 ●
- ceiling: 46.3 ●

- front_scene: 28.7 ●
- left_scene: 43.7 ●
- right_scene: 46.7 ●
- ceiling: 43.2 ●

- front_scene: 64.3 ●
- left_scene: 56.1 ●
- right_scene: 54.9 ●
- ceiling: 50.0 ●

Figure 108 - Summary range of the results for mean luminance of the 40° horizontal band (X20_mean) including tone-mapped image, false color luminance plot, and subjective response data (minimum result at left, maximum result at right)

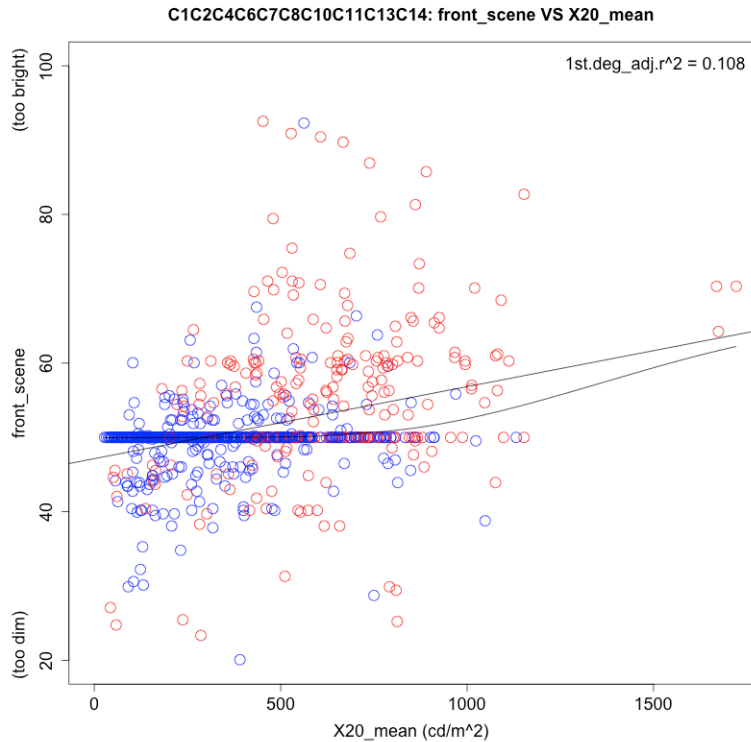


Figure 109 - Mean Luminance of 40° horizontal band (X20) versus subjective ratings of front_scene for the composite data set

5.3.4 The 10th percentile luminance value of the ceiling (X14)

The 10th percentile luminance value of the ceiling (one of the darker spots on the ceiling) produced one of the highest squared correlation coefficients with right_scene ($_{adj}r^2=0.29$ for the composite data set). Given that daylighting experts typically cite bright ceilings as a beneficial attribute, it was somewhat surprising to find an upper luminance threshold associated with uncomfortable scenes (250 cd/m² as shown in Figure 52). However, in this space, very bright ceilings are likely to correspond with bright sunlit scenes due to the highly reflective inverted curved upper blind. More intuitively, there were cases where very dim ceilings were rated as uncomfortable as illustrated in Figure 110 and Figure 111.

C8C10: X14_10th_percentile

Minimum: 12.030
 S035 2011-10-05
 M, 18-19 yrs

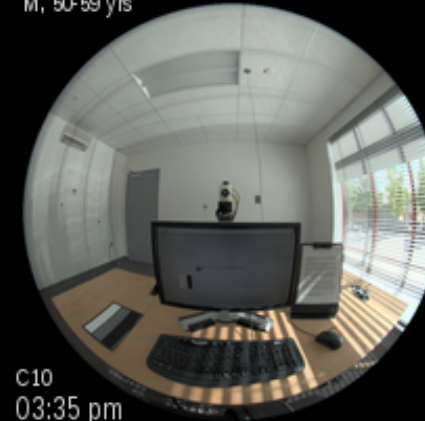
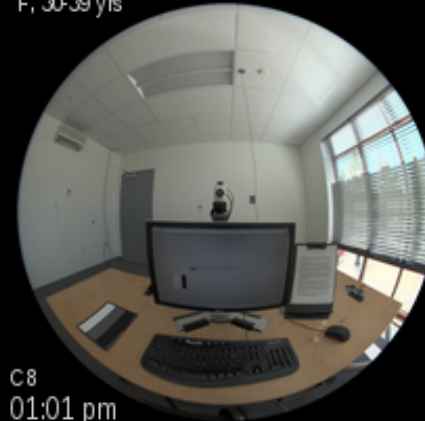
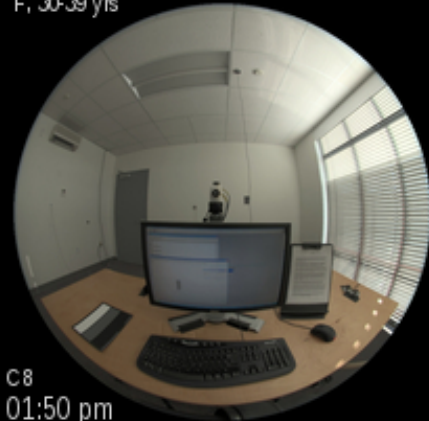
1st Quartile: 96.500
 S011 2011-12-19
 F, 30-39 yrs

Median: 200.500
 S034 2011-08-31
 M, 18-19 yrs

Mean: 196.800
 S032 2011-10-12
 F, 30-39 yrs

3rd Quartile: 273.000
 S018 2011-08-01
 F, 30-39 yrs

Maximum: 467.000
 S045 2011-09-16
 M, 50-59 yrs



C10
 01:36 pm
 JU Daylight Glare
 S035_2011-10-05-133610_c1

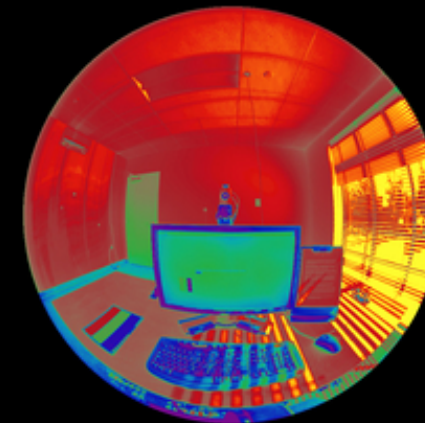
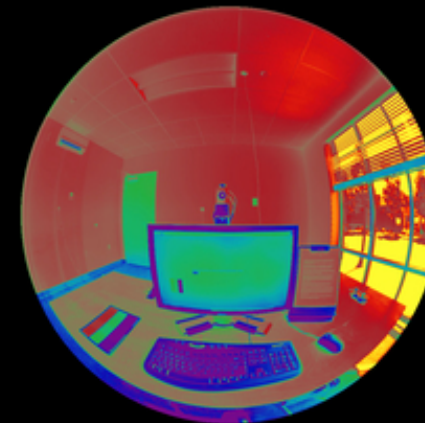
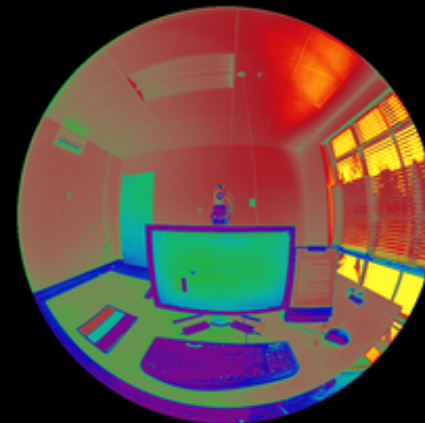
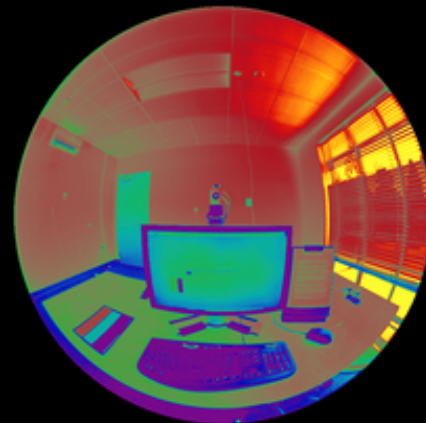
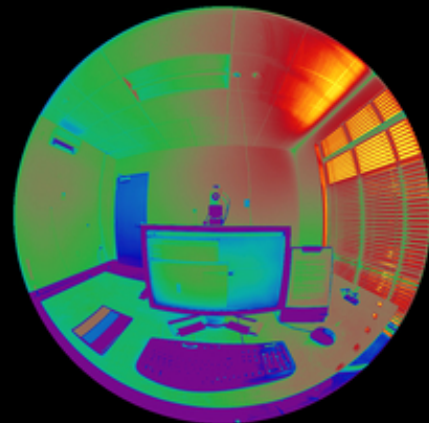
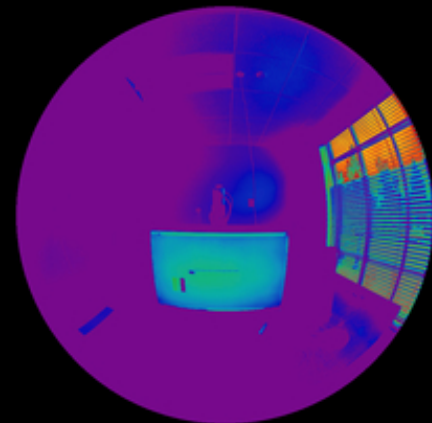
C8
 01:50 pm
 MP Daylight
 S011_2011-12-19-135004_c1

C8
 03:02 pm
 MP Daylight
 S034_2011-08-31-150224_c1

C8
 01:01 pm
 MP Daylight
 S032_2011-10-12-130147_c1

C10
 02:40 pm
 JU Daylight Glare
 S018_2011-08-01-144004_c1

C10
 03:35 pm
 JU Daylight Glare
 S045_2011-09-16-153543_c1



QU1:	3	●
QU2:	2	●
QU3:	3	●
QU4:	2	●
QU5:	1	●
QU6:	4	●
QU7:	3	●
front_scene:	44.6	●
left_scene:	23.8	●
right_scene:	43.0	●
ceiling:	50.0	●

QU1:	4	●
QU2:	4	●
QU3:	3	●
QU4:	4	●
QU5:	3	●
QU6:	4	●
QU7:	4	●
front_scene:	54.7	●
left_scene:	50.0	●
right_scene:	63.1	●
ceiling:	58.4	●

QU1:	6	●
QU2:	6	●
QU3:	6	●
QU4:	6	●
QU5:	6	●
QU6:	6	●
QU7:	6	●
front_scene:	50.0	●
left_scene:	50.0	●
right_scene:	55.4	●
ceiling:	50.0	●

QU1:	6	●
QU2:	6	●
QU3:	6	●
QU4:	6	●
QU5:	6	●
QU6:	6	●
QU7:	6	●
front_scene:	50.0	●
left_scene:	50.0	●
right_scene:	52.8	●
ceiling:	50.0	●

QU1:	3	●
QU2:	3	●
QU3:	5	●
QU4:	5	●
QU5:	3	●
QU6:	5	●
QU7:	5	●
front_scene:	58.2	●
left_scene:	50.0	●
right_scene:	69.2	●
ceiling:	50.0	●

QU1:	1	●
QU2:	2	●
QU3:	2	●
QU4:	1	●
QU5:	3	●
QU6:	4	●
QU7:	1	●
front_scene:	68.5	●
left_scene:	90.7	●
right_scene:	66.1	●
ceiling:	60.7	●

Figure 110 - Summary range of the results for the 10th percentile pixel value of the ceiling (X14_10th_percentile) including tone-mapped image, false color luminance plot, and subjective response data (minimum result at left, maximum result at right)

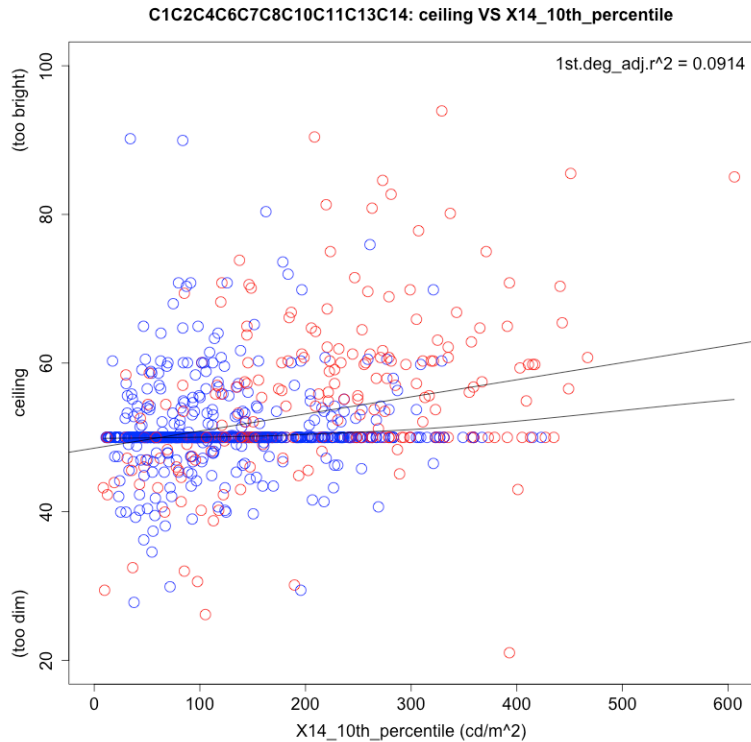


Figure 111 - Mean Luminance for the 10th percentile pixel value of the ceiling (X14_25th_percentile) versus subjective ratings of “ceiling” brightness using the composite data set

5.3.5 Mean window luminance

Sutter et al. (2006) reported that only 25% of people accepted mean window luminance greater than 3200 cd/m², and Lee et al. (2007) used 2000 cd/m² of mean window luminance as a “sky brightness” control signal for roller blinds at the NYT headquarters. This study found that only 25% of participants who elected to leave blinds open during MP conditions accepted mean window luminance above approximately 2250 cd/m², and that the typical participant who left blinds open for MP conditions accepted approximately 1750 cd/m². Participants who lowered blinds between 25-75% of the way down typically accepted mean window luminance between 1100-1500 cd/m², while 25% accepted a range between 1250-2000 cd/m² (Figure 92). The bounded-BCD for this metric is between 2000-2500 cd/m² as seen in Figure 112 and its ability to

predict visual comfort was $\text{adj}r^2=0.23$ (Figure 113) and to predict whether the `right_scene` was too dim or too bright was $\text{adj}r^2= 0.33$.

These are generally lower mean window luminance values than reported by Sutter et al. and Lee et al. This is somewhat surprising since user overrides of the NYT headquarters' blinds system tend to be for opening rather than closing (Ashmore 2011). One possible explanation for the differences is that the NYT headquarters uses blinds to occlude a greater amount of view than the blind used in this study, thus occupants may accept brighter window luminance in favor of views. Other research supports this notion (Tuaycharoen & Tregenza 2007; Boubekri & Boyer 1992; Chauvel et al. 1982).

C8 & C10: X08_mean & visually_comfortable

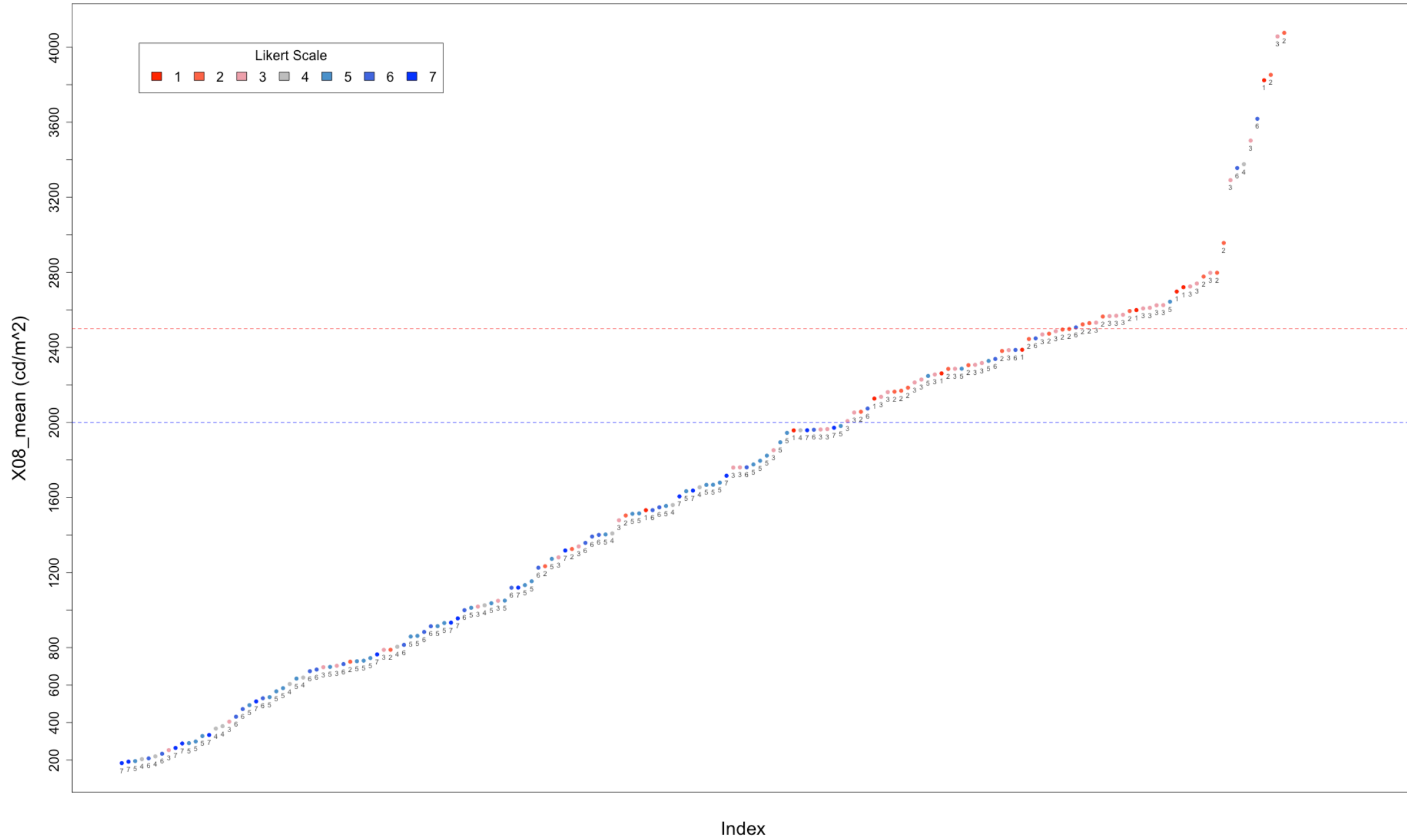


Figure 112 - Mean of window luminance (X08_mean) for C8 & C10, results ordered by metric and color-coded by response to Q1

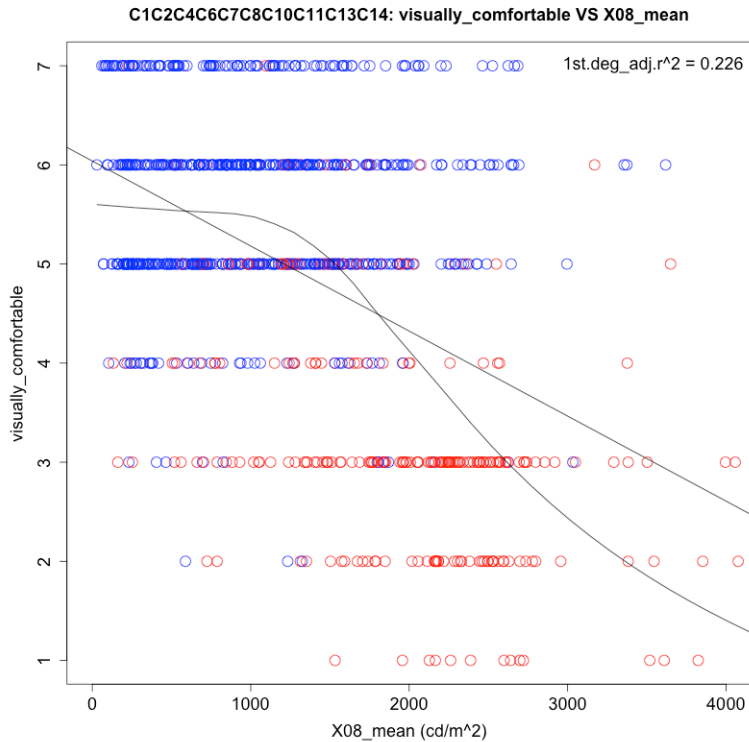


Figure 113 - Mean Luminance of the window (X08) versus QU1 for the composite data set

5.3.6 Daylight Glare Probability

DGP values were relatively low for the entire study with a maximum value of approximately 45%. The range of DGP values for the entire data set are shown in Table 61. It is surprising that some of the seemingly excessively glaring scenes did not have higher DGP values. As shown in Figure 58, DGP consistently differentiates between MP and JU conditions above a value of 25%; however, below this threshold it did not do so reliably. This is to be expected given that the DGP algorithm was founded upon a data set that included very few data producing DGP of 25% or lower (Wienold & Christoffersen 2006). Wienold (2009; Reinhart & Wienold 2011) states that DGP values below 35% are “imperceptible glare,” 36-40% are “perceptible glare,” 41-45% are “disturbing glare” and above 45% are “intolerable glare.” In this dissertation over 75% of the scenes produced DGP results less than 25% across all conditions.

Considering only JU scenes that were rated with a Likert score of three or lower on QU1 (i.e. participants disagreed that the space was visually comfortable), 75% of the scene produced DGP values below 27%. Only three of 201(1.5%) JU scenes rated as uncomfortable on QU1 were above DGP 35% and none were above 40%. Finally, there was very little difference between the means for DGP in MP conditions (21.6%) versus JU conditions (24.2%). Together, these findings suggest that the metric, as it is currently defined, is not sensitive enough for use as a daylighting design guide or as part of an automated blind control algorithm as a singular metric.

Table 61 – Summary DGP results for all conditions (top) JU conditions rated below 3 on QU1 only (bottom)

All Conditions DGP Results						
DGP Metric	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
X03_evalglare_mL0005_dgp	16.49%	19.36%	21.64%	22.06%	23.97%	44.03%
X01_evalglare_mL0005_dgp	16.49%	19.20%	21.53%	22.00%	24.08%	44.56%
X01_evalglare_th2000_dgp	16.49%	19.08%	21.54%	21.93%	24.07%	44.41%
X01_evalglare_th5000_dgp	16.49%	18.75%	21.00%	21.65%	24.11%	44.55%
JU Scenes(C4C5C10C13_QU1_Likert_below_3) DGP Results						
X03_evalglare_mL0005_dgp	0.1678	0.2342	0.2539	0.2551	0.2716	0.3868
X01_evalglare_mL0005_dgp	0.1679	0.2305	0.2531	0.2534	0.2732	0.3662
X01_evalglare_th2000_dgp	0.1649	0.2307	0.2536	0.254	0.2744	0.3802
X01_evalglare_th5000_dgp	0.1649	0.2256	0.2542	0.2516	0.2725	0.3682

Together, Table 62 and Figure 114 document another limitation of glare indices, and in this case DGP. Glare indices attempt to account for adaptation by incorporating a glare source identification step that is typically based upon a multiplier of the mean luminance of the task or the entire scene (see Sections 2.3.2.2 and 2.3.2.3). When direct sunlight enters the space and is perceived as glare, it can also be incorrectly included in the calculation of the adaptation component, essentially reducing the intensity or solid angle of the glare sources identified. This limitation can be exacerbated when calculating DPG by defining a task region as recommend by Evalglare (Wienold 2008). In scenes where sunlight enters the task region (Figure 114-left_a), it

can make the glare source identification threshold artificially high and cause glare sources to be missed. Ultimately, the resultant DGP can be lower than might otherwise be expected.

Table 62 illustrates the difference between two scenes captured on a sunny afternoon. The JU scene has a lower DGP value (32%) than the MP scene (45%). Figure 114 illustrates the same scenes graphically (JU at left, MP at right) where the first row shows the tone-mapped scenes (a), the second row shows the luminance false color (b), and the third (c) and fourth (d) rows illustrate the glare source identification results. It is interesting to note that in this example the glare source identification method (either five times the mean luminance of the circle task or the entire scene) does not produce meaningful differences in the DGP value. The comparison between the two scenes (MP and JU) clearly reveals the challenge presented to glare metrics (DGP in this case) as sunlight slips through blinds and increases the adaptation level.

Table 62 includes standard deviation of window luminance, which correctly differentiates the two scenes, along with other recommended metrics for comparison. Figure 115 demonstrate the range of DGP based upon five times the mean luminance of the circle task for C8C10.

Table 62 – DGP results from a MP and a JU scene for a single participant, with other selected metrics

Participant 36, round 2, 2011-10-17		
	C13 (JU)	C14 (MP)
X01 mean (cd/m ²)	1092	1682
X03 mean (cd/m ²)	455	130
5* X01 mean (cd/m ²)	5460	8410
5* X03 mean (cd/m ²)	2275	650
DGP X01 5*mL	32%	45%
DGP X03 5*mL	32%	44%
X08 standard deviation (cd/m ²)	9043	3073
X20 mean (cd/m ²)	890	848
X14 10 th percentile (cd/m ²)	451	367
X20 percent above 2000 cd	11%	8%
X20 percent below 1000 cd	80%	88%
X10 50th percentile	1876	790
X01 standard deviation (cd/m ²)	3615	7300

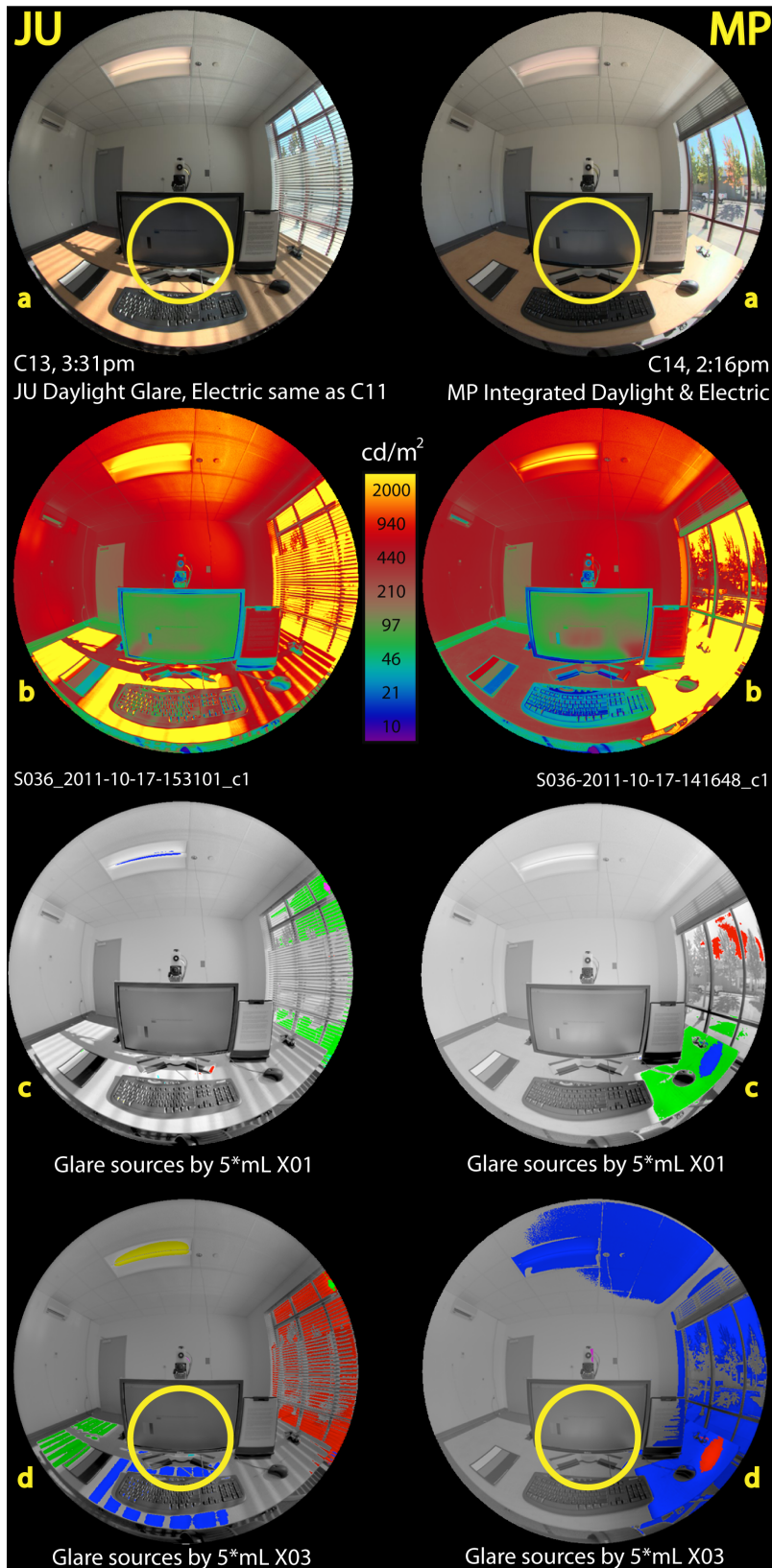


Figure 114 – Limitation of the circle task (X03) multiplier for glare source identification when using DGP

C8C10: X03_evalglare_mL0005_dgp

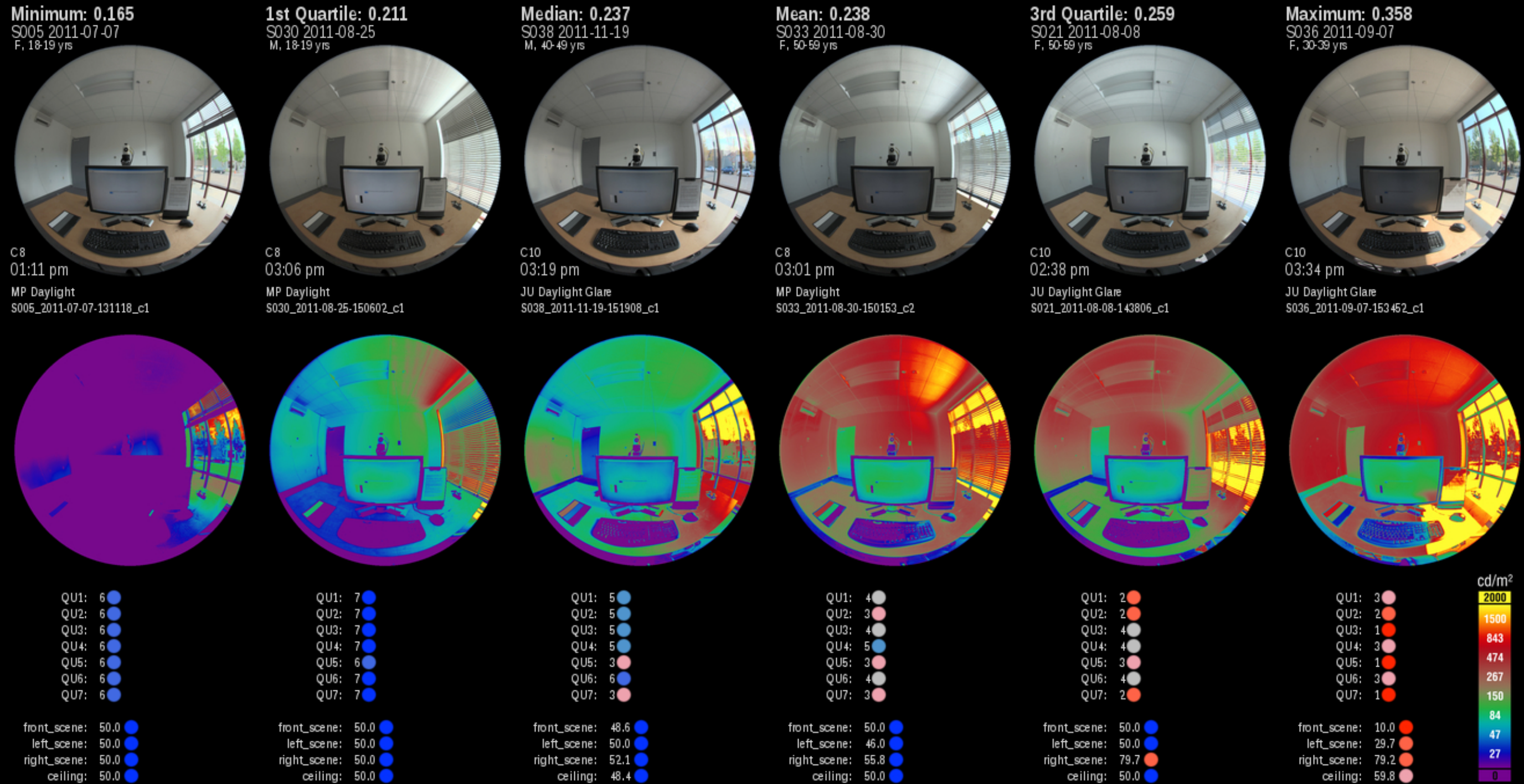


Figure 115 - Summary range of the results for DPG using 5*mL X03 mean luminance (X03_evalglare_mL0005_dgp) including tone-mapped image, false color luminance plot, and subjective response data (min. result at left, max. result at right)

5.3.7 Multiple regressions

This dissertation focused primarily on single regressions to determine which of a wide range of individual metrics proved most valuable when discerning between MP and JU scenes as well as fitting participants' subjective preference and acceptance responses to measured data. Multiple regressions models were studied to determine if a select group of no more than four variables could be combined to improve the predictive capabilities. Multiple regression models are inherently more complex than single regressions, are difficult to visualize (Figure 116), and therefore, they are more difficult to put into useful terms for practitioners with regard to recommended design criteria. However, because multiple regression models are also inherently stronger at predicting the variation in a subjective response than single regressions, and because this improved strength could be useful for both computational design analysis techniques and environmental control purposes, a few of the stronger models are discussed.

The strongest multiple regression model was for the semantic differential rating (too dim – too bright) of the window wall ($_{adj}R^2=0.49$) and was built upon three variables:

1. Standard deviation of window luminance (X08_standard_deviation)
2. 50th percentile luminance value from the lower window
(X10_50th_percentile)
3. Mean luminance of the 40° horizontal band (X20_mean)

The strongest multiple regression model for the basic visual comfort question (QU1) produced an $_{adj}R^2=0.36$ and was built upon four variables:

1. Participants' measured sensitivity to brightness (SB_just_uncomfortable)
2. Standard deviation of window luminance (X08_standard_deviation)

3. 50th percentile luminance value from the lower window
(X10_50th_percentile)
4. Percent of 40° horizontal band > 2000 cd/m2 (X20_percent_above_2000_cd)

One additional model is discussed due to its overall strength and sound logic. It produced an $\text{adj}R^2=0.32$ for QU1 and $\text{adj}R^2=0.45$ for right_scene, not as high for either of the models listed above, but nearly as strong for both. It was built using:

1. X08_standard_deviation
2. X20_percent_above_2000_cd
3. X20_percent_below_1000_cd

When considering multiple regression models it is important to include only statistically significant variables. This helps to ensure that each variable represents a unique construct of the luminous environment. Certain multiple regression models may be more useful to guide iterative design analysis purposes, while others may be more useful in control applications, such as dimming electric light fixtures or adjusting motorized blinds. While the measured sensitivity to brightness variable improves the predictive capability of the second model shown above, it is unlikely that this information would be available in most design analysis cases. However, in control applications, similar data could be learned by the control system over time as participants manipulated the controls (if the system recorded conditions before and after occupant overrides).

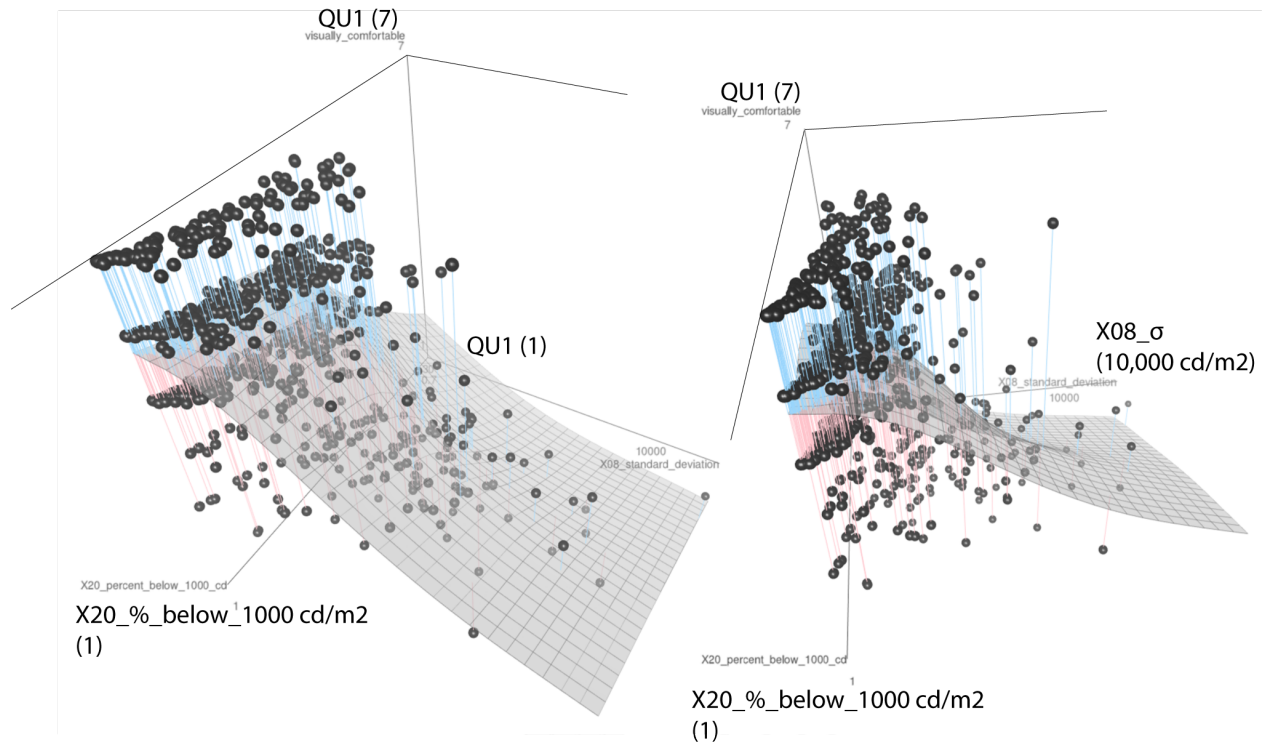


Figure 116 - Two different views of an example two-variable three-dimensional fit plot using QU1, X20_percent_below_1000_cd, and X08_standard_deviation

5.3.8 Usefulness and limitations of absolute thresholds

Absolute luminance thresholds have several strengths and limitations. One of their greatest strengths is their simplicity, but this is also their downfall. It is well established that wide variability in human preference and acceptance of luminous conditions exists between individuals. Wide variability in luminous conditions also exists between different spaces and for a space with daylight, over time. There is also evidence that human sensitivity and expectations for light change with time of day (Newsham, Aries, et al. 2008) and season (Section 4.5). Therefore, it is not likely that any absolute threshold, whether it is illuminance- or luminance-based, will decisively differentiate between comfortable and uncomfortable luminous conditions in all cases. However, absolute thresholds appear to be useful at establishing extreme upper as

well as extreme lower thresholds that are highly likely to be considered uncomfortable. This research design was better suited at addressing the very bright extremes, but some evidence of very dim extremes were identified and discussed above throughout Section 5.3.

The use of absolute thresholds is likely to be more generalizable between individuals, between spaces and across time if it is translated from a singular value into a bounded-BCD criteria as is discussed extensively in Section 4.3. Together, Sections 4.4 and 5.3.7 also suggest that absolute thresholds can be more successful in fitting participants' subjective response to luminous conditions with measured data if metrics based upon fixed thresholds (e.g. X20_percent_below_2000_cd, X20_percent_above_2000_cd, X20_mean, X08_mean) are considered together with metrics describing variability (e.g. X08_standard_deviation).

5.3.9 Preliminary nature of recommended design criteria

The recommended criteria described in Section 4.3 must be interpreted as preliminary. These data are likely to be strongly influenced by the space configuration, the view direction relative to daylight sources and, possibly, by subtle differences in position relative to daylight sources while maintaining similar view direction. Some of these effects (view-direction, space configuration) can be illustrated by comparing findings from the two-day pilot study with the six-month study. The two study spaces are relatively similar. Both are private offices with large southwest-facing windows that were relative unobstructed and were fitted with louver blinds. However, in the pilot study the participants faced northwest and in the six-month study the participants faced southeast. Furthermore, the blind type and configuration were different. In the pilot study, two-inch white louver blinds were used and participants had the ability to tilt and lower blinds in two side-by-side windows differently. Whereas in the six-month study there was a single louver blind and participants could tilt the blind differently for the upper and lower parts

of the window. It appears that these architectural differences produce substantially different output with regard to some of the metrics tested while others perform similarly.

There are several confounding differences between the pilot and the six-month study, including widely varying sun angles, sky conditions and blind types; the differences between the results of some metrics appear to persist even when isolating many of these factors. For example, the percent above 2000 cd/m² was calculated for both the pilot study and the six-month study. Figure 117 shows two comparisons between the pilot study and the six-month study. In one example (Figure 117-top), data from the pilot study captured on December 16th at 13:56 (Figure 117-top-left) is compared to data from the six-month study captured on December 19th at 14:16 (Figure 117-top-right), both on relatively clear sunny days with partially deployed blinds. In the pilot study the percent of the scene above 2000 cd/m² is 16% while the six-month study shows only 4.5%. In a second example (Figure 117-bottom), data from the pilot study captured on December 16th at 14:55 (Figure 117-bottom-left) is compared to data from the six-month study captured on December 10th at 14:19 (Figure 117-bottom-right), both on relatively clear sunny days with blinds mostly open. In the pilot study the percent of the scene above 2000 cd/m² is 19% while the six-month study shows only 9%. According to the preliminary criteria suggested by the six-month study, all of these scenes are either “likely to be uncomfortable” or in the bounded-BCD region. This indicates some robustness of the metric, but these criteria are likely to incorrectly predict more scenes within the pilot study space as “likely to be uncomfortable.” This is likely due to the different viewing direction and the subsequent relationship of the sun patch within the FOV (i.e., in the pilot study space the sun hits the wall in the FOV), along with the variability in occupants’ responses.

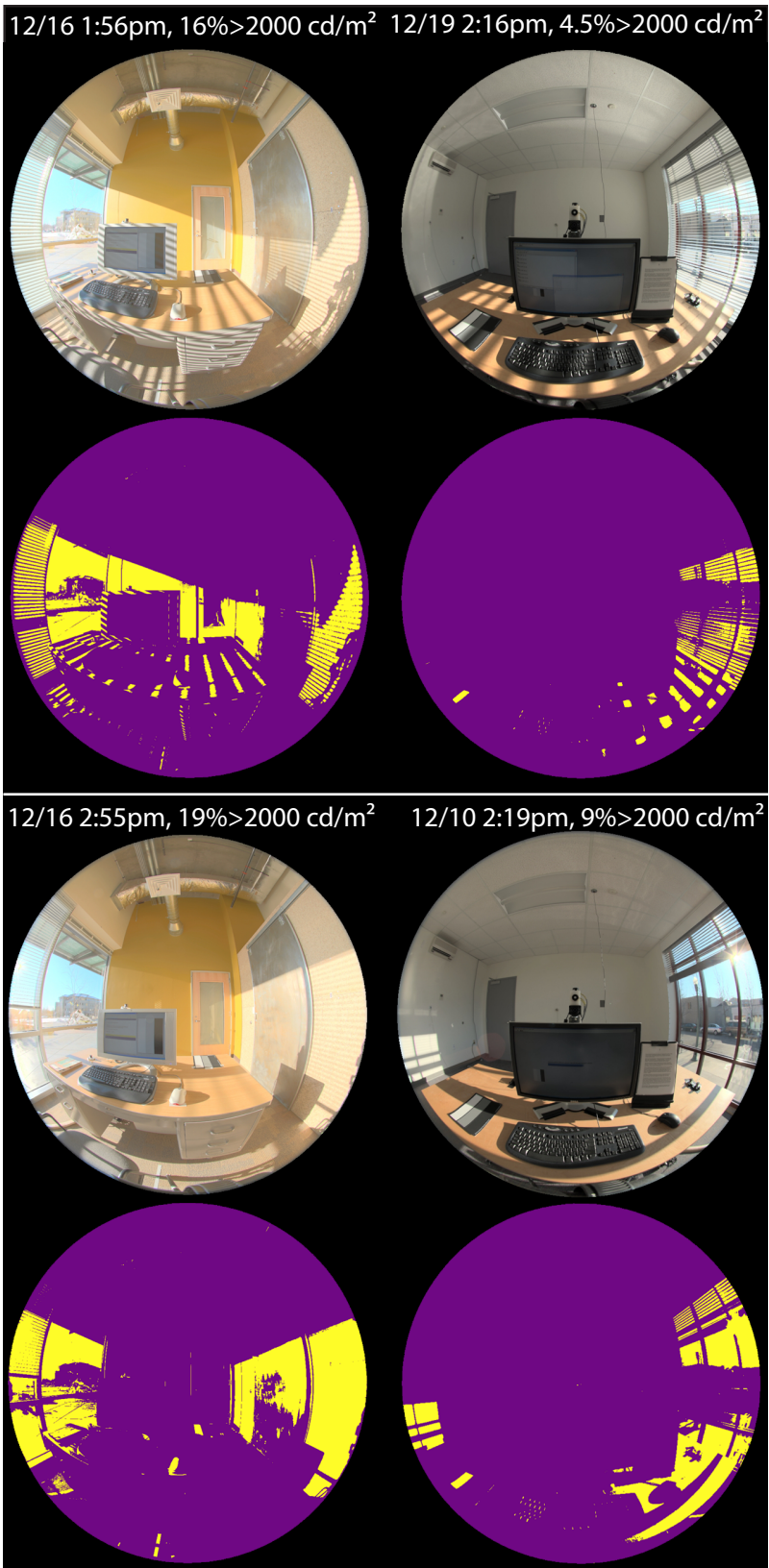


Figure 117 – Similar date- & time-stamped JU scenes; pilot (left), 6-month study (right); yellow > 2000 cd/m²

Fortunately, some metrics appear to be robust against this phenomenon. For example, standard deviation of window luminance performs very similarly between the pilot study and the six-month study. This metric was not originally tested during the pilot phase and was calculated after it emerged as a strong metric from the six-month study. This provides some initial corroboration.

Figure 118 shows the results for the pilot study with participants' results ordered by the results for the scene rated as just disturbing (JD). The metric correctly differentiates preferred (P) and JD scenes in all cases. Like the six-month study, there are some cases where JU scenes have lower standard deviation of scene luminance than other participants' P scenes. Figure 120 represents the ability of the metric to explain the variance in QU1 (visually_comfortable) and shows an $\text{adj}r^2=0.28$ in this sample. Finally, Figure 119 takes these data, organizes them by the metric result, and color-codes them by the response to QU1. The preliminary thresholds established from the six-month study are plotted for the bounded-BCD. The results from this metric are very similar to the findings from the six-month study, with the exception of a few cases that have higher standard deviation than the six-month study. This suggests that the potential for glare in the pilot study space is indeed higher than the six-month study space. Most importantly, the preference (P) data follow the criteria established in the six-month study. These findings are a first, but important, step toward establishing the reliability of this metric and the corresponding design criteria.

Pilot: X08_standard_deviation

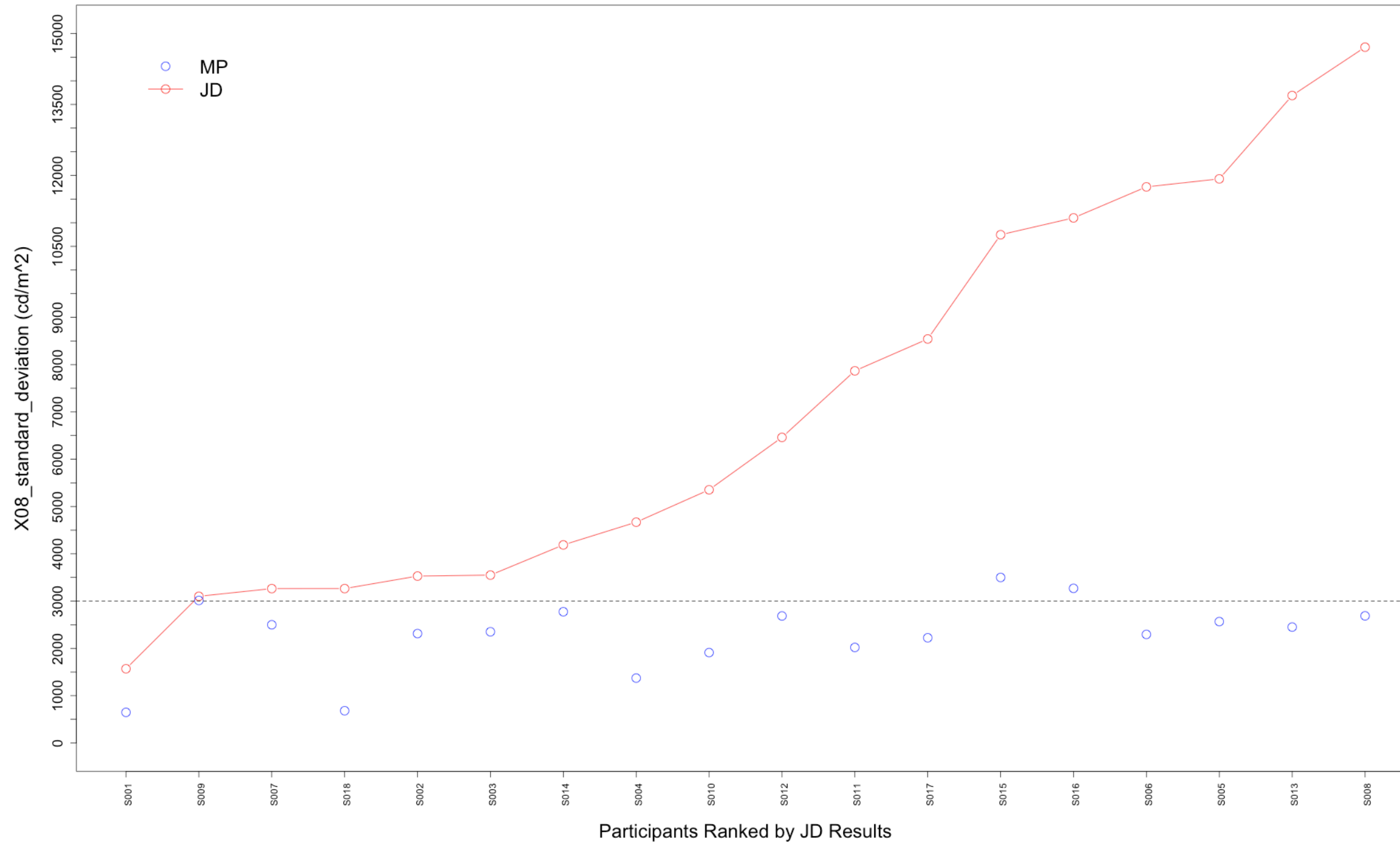


Figure 118 – Standard deviation of window luminance (X08-pilot) for pilot-preferred (MP) & pilot-just disturbing (JU) ranked by JU results, showing separation threshold from six-month study (3000 cd/m^2)

Pilot: X08_standard_deviation & visually_comfortable

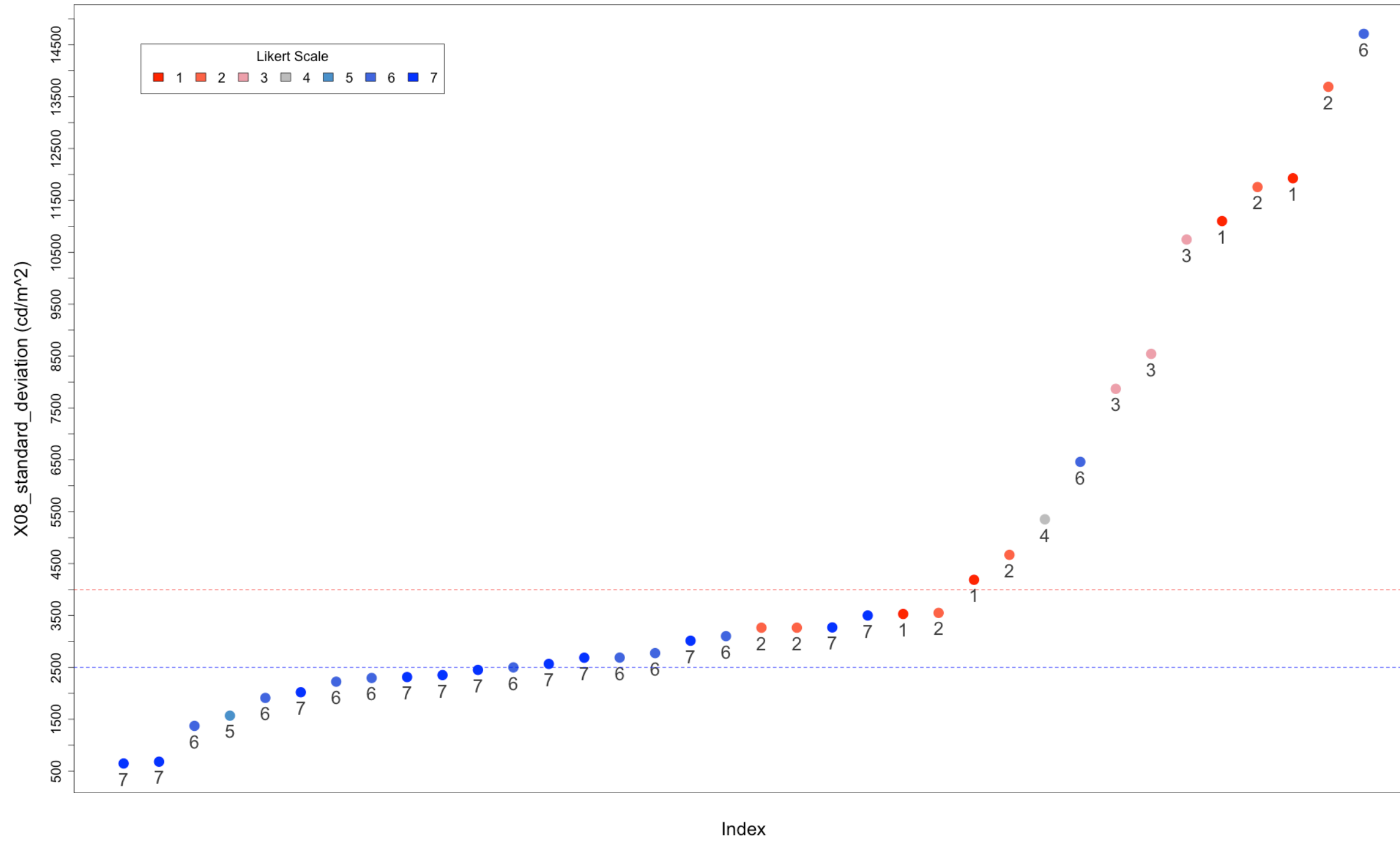


Figure 119 - Standard deviation of window luminance (X08-pilot) for pilot-preferred (MP) & pilot-just disturbing (JU), results ordered by metric and color-coded by response to QU1, showing the bounded-BCD of six-month study

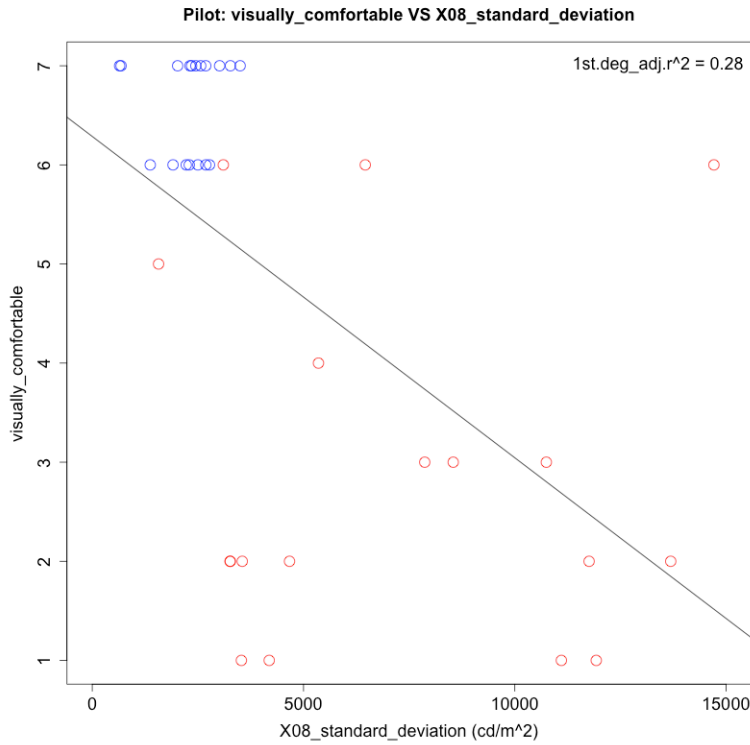


Figure 120 - Standard deviation of window luminance (X08-pilot) by QU1

Despite this initial corroboration for standard deviation of window luminance, these findings suggest that the performance criteria must be interpreted as preliminary in nature. The results for the pilot from the metric percent of the scene above 2000 cd/m² show that it can adequately and reliably differentiate MP and JU scenes within-subjects, but it, like other metrics, will likely need to be fine-tuned to space- and position-specific considerations across buildings or different facade orientations within a building. This may limit some of the metrics' usefulness in the near-term as generic design performance criteria, and suggests that further research from a wide range of space types, orientations, positions and viewing directions within spaces is necessary to confirm, refine or reshape the criteria. However, some metrics, such as standard deviation of window luminance, appear to be robust across at least two similar spaces. Future

research will reveal which metrics are highly dependent upon various factors (space, view direction, latitude, etc.), and which are more generalizable. Finally, the potential differences that may emerge for some metrics from future research do not necessarily present the same limitation for applications of environmental control as they do for recommended design criteria. This is because environmental control applications will require some level of site calibration and commissioning, and this can allow for fine-tuning of the metrics' recommended criteria to specific spaces.

5.4 Visual performance at moderately high daylight levels

Only a few types of visual performance test results were available for comparison during afternoon conditions (when JU scenes were more common) in close temporal proximity to one another. Of these (proof-reading, Stroop color-word matching, Landolt rings and typing), only Stroop color-word matching showed any decrement in visual performance under JU conditions as compared to MP conditions. These statistically significant decrements ranged from 0.51-1.65% for the conditions examined. While these findings do not outright refute the assertion of Hopkinson and Collins (1970) that "...acute subjective discomfort arises from situations which give rise to little or no decrement in visual performance..." they do begin to support an alternative hypothesis. This is especially true when viewed in the context of the relatively minimal decrement in visual performance under generally sufficiently lighted spaces as shown in Rea's RVP models. Section 2.1.1.1 provides an example using the RPV model to illustrate as little as a 0.3% decrement in RVP of paper tasks from a reduction to 400 lux from 650 lux of horizontal illumination (other factors being held constant). This dissertation examined the BCD, not extreme discomfort glare or disability glare scenarios. It is possible that research under a

range of more extreme discomfort glare scenes could lead to a similar plateau and escarpment model for uncomfortably bright light levels as defined by Rea's RVP models for low light levels.

Objective measures of creativity were also examined. While no significant differences were found between MP and JU conditions, a statistically significant increase was found for scenes with daylight (either MP or JU) as compared with to the single JU condition conducted in the sensitivity to brightness room without daylight. This non-daylit JU condition was always completed first thing in the morning and therefore practice effects could be confounding this finding result.

This study only examined short-term effects of discomfort glare. This study did not attempt to account for lost productivity from the lost time or distraction of correcting glare occurrences through blind manipulation that may occur over longer periods in office settings. Interestingly, participants perceived themselves having approximately 10% higher productivity during MP conditions as compared to paired JU conditions, which is higher than any of the measured performance differences. In order to help justify the expense of automated and motorized blinds, a connection to benefits beyond energy savings is necessary in many cases. These objective visual performance findings, regardless of their small effect, can begin to support life-cycle analysis that accounts for occupant satisfaction and performance improvements associated with advanced facades, such as the inclusion of motorized automated louver blinds. The perceived performance findings may also be an important aspect of justifying these occupant comfort technologies.

5.5 *Controlling motorized blinds and electric lights*

Existing best practices for the automatic control of electric lights and motorized blinds relative to daylight available produced relatively weak fits with participants' respective electric lighting dimmer choice and blind position choice. These relationships are discussed in this section.

Participants in this study typically closed blinds for MP conditions when exterior vertical irradiance exceeded 100-175 W/m² (Figure 88). This is notably lower than the mean closure range of 300-450 W/m² as noted by others (Reinhart & Voss 2003; Mahdavi 2009; Sutter et al. 2006) but falls within the range reported by Mahdavi who reported 35-40% of closure occurred between 100-200 W/m². Nonetheless, exterior vertical irradiance produced a weak squared correlation coefficient ($_{adj}r^2=0.05$) with the brightness rating of the window wall (`right_scene`) for the composite data set as well as blind height ($_{adj}r^2=0.05$) for MP conditions. Several luminance-based measures produced much higher fits (`X01_evalglare_mL0005_omega_sources`, $_{adj}r^2=0.45$; `X08_mean`, $_{adj}r^2=0.34$) with blind height for MP conditions. Some guidance for controlling blind height is offered in Section 4.7.1 by splitting participants' chosen blind height for MP conditions into groups and reporting the median and range of values that occurred for each metric for each blind height group. However, it is important to distinguish between a metric (such as `X01_evalglare_mL0005_omega_sources` or `X08_mean`) that fits a variable such as blind height well and a metric (such as `X08_standard_deviation`) that fits participants' response to QU1 (this space is visually comfortable) well. In MP conditions, blind height was the result of a participant's choice when creating the most preferable lighting condition possible. However, metrics that fit blind height data well do not necessarily correspond directly to subjective ratings of visual comfort. Thus, metrics that correlate well with subjective ratings of comfort should be

prioritized over, and perhaps coupled with, metrics that fit chosen blind height or blind tilt data for MP conditions in future applications of luminance-based metrics to automatically control blind position.

With regard to electric lighting control, one of the strongest predictors of dimmer choice was the luminance ratio between the 25th and 75th percentile pixel values for the desk task mask (X05_25th_to_75th_percentile), and this proved far more capable of fitting participants' dimmer choice ($adjr^2=0.41$) than illuminance-based measures (ceiling, $adjr^2=0.05$; top of monitor = choice $adjr^2=0.28$) in MP integrated lighting conditions. The strong result is encouraging, but must be tempered by the challenges of acquiring these data in office applications. Obviously, an HDR sensor (camera) cannot be located very near to the occupant's eye position in an actual office space. Thus, an alternate location must be found, such as the top of the monitor, ceiling or back wall. The merits and limitations of these locations are discussed in the next Section. Furthermore, it is not currently known if these alternate measurement locations would produce measurement results for this metric having a similarly strong fit with participants' dimmer choice.

5.5.1 Challenges facing luminance-based environmental control

Limitations and challenges of luminance-based environmental control systems have largely been established elsewhere (Sarkar & R. G. Mistrick 2006; R. Mistrick & Sarkar 2005; Newsham & Arsenault 2009) and include concerns with regard to privacy, sensor location, cost of sensors and their capabilities to perform multiple secondary functions (occupancy/vacancy sensing, security, fire detection, lighting control and blind control). The most critical limitation is establishing reliable luminance-based metrics and associated comfort criteria that can be used as

control parameters of lights and blinds. This dissertation has provided substantial progress in this area.

Beyond establishing these control criteria, perhaps the largest challenge is the actual or perceived intrusion of privacy with regard to using cameras as luminance sensors. This can be combated several ways. One is by stressing the coupled security benefit of a distributed camera network. Another approach is to make the sensors look less like cameras, only retain the information as a table of luminance values rather than in a graphical manner, capture the data at sufficiently low resolution, or not retain the data whatsoever after the control signal has been derived. Of course it would be beneficial for commissioning purposes to retain the data.

The most substantial functional limitation is identifying a feasible location for the sensor. Since sensors cannot be located close to a seated occupant's eye position, an alternate location must be found. Possible alternate locations include the top of the monitor, workstation partition, ceiling or back wall. The top of the monitor is a strong candidate for either illuminance- or luminance-based sensors as has been demonstrated by this dissertation. Locating a sensor at the top of the monitor is likely to keep it free from clutter. In private offices or open office spaces with low office partitions this location is likely to be free of shadowing. It is very close in proximity to seated occupants' eye position and can be positioned to share nearly the same FOV as illustrated in Figure 121. However, additional research is required to determine the extent of the differences between the images captured and analyzed in this dissertation from the Canon camera at the participants' eye position versus the images captured from the top of the monitor.

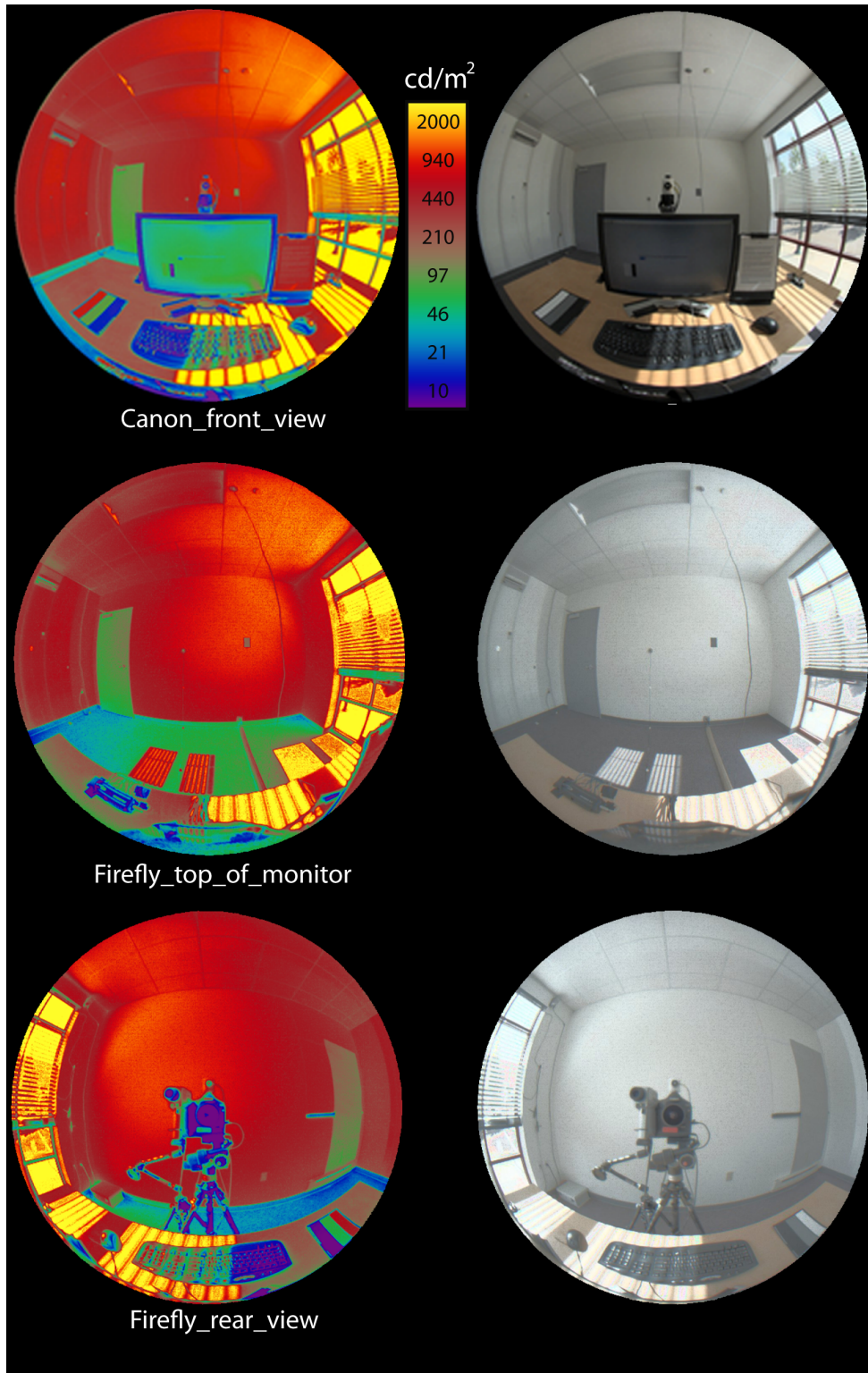


Figure 121 – Comparing FOV of Canon camera versus Firefly cameras from top of monitor

Previous research has demonstrated the ability of cameras to accomplish multiple functions (Newsham & Arsenault 2009; Sarkar et al. 2008) as outlined above; however, several limitations remain. For any of the functions (with the exception of vacancy sensing), data capture and refresh rate are critical to their success. Further research is needed to address how few exposures can be used to generate an accurate HDR. Also, sensitivity analysis must be conducted to determine the minimum required resolution to maintain the usefulness of luminance-based metrics for environmental control, as well as any of the secondary functions (occupancy/vacancy, fire, security).

Several other factors remain to be addressed. Additional research is needed to determine the resolution of sensors required in an open-plan office environment and how to prioritize competing control signals from multiple locations and view directions within a single space. Another limitation is the cost of using cameras as sensors. Full-frame digital sensors capable of capturing a full 180° by 180° FOV with circular fisheye lenses are still expensive.

A strategy that could minimize both of these concerns is utilization of simulation-based luminance-based control. It is possible to capture HDR luminance maps of real sky conditions and feed these data to simulated environments (Inanici 2010) as a daylight source that can, in turn, create accurate luminance representations of the physical space using only the simulated environment. If this could be accomplished in near-real-time fashion, it could minimize the need for sensors in the physical space, and the required number of sensors could be located precisely where they are needed (replete with full fisheye FOV) within the simulated environment with little capital cost. There are, of course, a host of other challenges with this approach, including

ensuring that the simulated environment replicates the physical environment as closely as possible, accounting for changes to interior furnishes and real-time blind position.

5.5.2 Benefit of scene-independent masks, X20

The benefit of using scene-independent masks has already been established (0) with regard to design criteria and design analysis, and they hold true for environmental control as well. There are two general categories of masks used in this dissertation; scene-dependent and scene-independent masks. Scene-independent masks have the benefit of not needing to be reconfigured for each new space or position within a space. Six different metrics based upon the X20 mask ranked in the top 20 squared correlation coefficients for right_scene whereas X01 did not have any. Preliminary recommended criteria for X01-based metrics were similar to criteria for X20-based metrics, but X20 metrics generally had higher squared correlation coefficients with right_scene. For example X20_mean preliminary recommended criteria were (bounded-BCD $500 > x < 700 \text{ cd/m}^2$) with an $\text{adj}r^2=0.31$ for right_scene, whereas X01_mean produced performance criteria with a similar range but with lower values (bounded-BCD $350 > x < 550 \text{ cd/m}^2$) and had a notably lower squared correlation coefficient ($\text{adj}r^2=0.21$ with right_scene). In other cases, the masks produced nearly identical results for the same metrics. For example, standard deviation of luminance between X01 and X20 produced essentially identical results (X01_standard_deviation, bounded-BCD $1250 > x < 2000$, $\text{adj}r^2=0.26$ with right_scene; X20_standard_deviation, bounded-BCD $1250 > x < 2000$, $\text{adj}r^2=0.25$ with right_scene).

Examining the luminance values in the X20 region is no more complicated than examining the entire scene because each requires one mask. Examining the entire scene requires X01 be applied to eliminate the lens barrel from the analysis region. X20 has the added benefit of being applicable to inexpensive digital cameras with small image sensors that cannot capture

the 180° by 180° FOV. See X20 versus X01 applied to the same image captured with an inexpensive fisheye lens adaptor (Olloclip n.d.) on a cell phone camera (Figure 122, Figure 117). There are clearly fewer missing data using X20 than for X01 as is marked in yellow.



Figure 122 - X01 (left), X20 (right) overlaid on photo from inexpensive fisheye lens and cell phone camera



Figure 123 - Olloclip fisheye lens adapter for iPhone camera

5.6 *Sensitivity to brightness*

There was an unexpected, although not necessarily surprising, finding that participants were statistically more sensitive to glare from a standard electric light source in a windowless chamber during the fall than during the summer. This appears to be yet another nuance to human visual perception of comfort that could have implications to recommended practices for daylighting design if supported by further research. This result is interpreted to be attributable to seasonal effects but could be in part, or in whole, due to the duration (hours and minutes) of post-waking sunlight availability. Of course the constructs of post-awake sunlight availability and seasonal effects are connected. At 8:30 in summer, participants were more likely to have had a greater duration of post-waking sunlight availability as compared to the same clock time in fall. A similar phenomenon could occur over the course of a single day, and may not be directly related to season. Therefore, this phenomenon needs to be clarified with additional research. A similar study should be conducted, both in summer and in fall or winter, but retested multiple times over the course of a single day. This would help to explain whether this phenomenon has more to do with short-term, post-awake sunlight availability or with long-term seasonal sunlight-availability.

There is another curious finding from the sensitivity to brightness test with regard to participant age. The loess lines in Figure 86 and the results in Table 51 and Table 52 reveal unexpected variations in sensitivity to brightness by age range. These data suggest that the middle age ranges (30-59 years) were generally less sensitive than both the younger age range (18-29) and the older age range (60-70 years). There is no known support for this finding in existing literature it and could be unique to this sample.

5.7 *Human factors lighting research*

This research built upon previous examples of laboratory-based lighting research to extend useful data collection practices as documented in Section 3. The sensitivity to brightness test provided a low-cost method to assess individuals' sensitivity to brightness. Having two identical rooms ensured a more natural environment for participants while providing high-quality data without participant disruption. The redundant illuminance- and luminance-based HDR calibration methods facilitated complete and accurate HDR data. The supplemental cameras located on the top of the monitor provided additional data for future analysis using a more feasible sensor location. The results documented in Section 4.9 further validate several of the subjective questionnaire items, and prioritize some for future application in laboratory or field studies.

In addition to these useful evolutions in human factors lighting data collection methods, several data analysis methods were developed that supported comprehension of the measured results. The most beneficial of these are the plots using color-coded subjective (Likert) responses ordered by the metric result (e.g. Figure 42). These plots clearly depicted the variability in human response and helped to establish the bounded-BCD criteria concept. This dissertation examined the bounded-BCD for excessiveness, but some evidence emerged for a sufficiency-based bounded-BCD. The plots showing the range of a metric's output using tone-mapped photography, luminance false color maps and subjective response data in a single layout is another innovation of this dissertation (e.g. Figure 107) that allows a reader to quickly comprehend a wide range of metric results for a given space. These plots proved useful for understanding how a metric reacted to a wide range of lighting conditions in a single space and provided a useful frame of reference for comparisons with future research in different settings.

5.8 *Generalizability*

As with any research, these findings must be understood within the context that they were developed. This investigation was conducted in a highly controlled daylighting laboratory, with daylight from one side and with participants in three age groups from 18-70 years of age. There was one solar orientation (southwest), one view direction (perpendicular to the window looking northeast, two if counting the pilot study looking northwest), and a single participant occupied the study space at a given time. Therefore, these findings apply most directly to private offices and do not address several effects unique to open-plan office environments. The most notable of these are the multiple concurrent viewpoints of occupants in open-plan office environments, the diversity in occupants' visual preference and acceptance levels, and the social psychological aspects that may influence occupant behavior with regard to environmental control.

6 Conclusions

This dissertation addressed three specific aims. It determined illuminance- and luminance-based lighting metrics and criteria associated with subjective measures of human visual preference and acceptance (Aim 1). It determined whether, and to what extent, human visual performance is statistically improved in an office space with environmental lighting conditions rated as “most preferred” compared to conditions rated as “just uncomfortable” (Aim 2). It provided guidance for the application of the lighting metrics that are most representative of human visual acceptance and preference in the context of integrated luminous environmental control systems (Aim 3).

Section 2 provided the necessary context of, and need for, this dissertation. Section 2.1 reviewed existing human visual performance literature and established the hypothesis that visual performance may follow a similar plateau and escarpment phenomenon at the upper bounds of visual comfort (“just uncomfortable” glare) as it does at very low levels of illuminance and contrast. Section 2.2 reviewed the best practices in daylight-sensing electric lighting control, motorized blind control and human acceptance of these practices. It provided an overview of patterns of occupant interaction with window blinds in commercial buildings. It also established the energy consumption implications associated with occupants’ use of lights and blinds and the effects of current best practices of automated lighting and blind control. Lastly, it summarized preliminary proof of concept research regarding luminance-based environmental control. Section 2.3 provided a detailed review of existing illuminance- and luminance-based lighting metrics and their associated recommended criteria. It established the need for rigorous human factors research under both daylight and integrated lighting conditions. It also demonstrated the

benefits and capabilities of HDR photography as a tool to support this pursuit. Finally, Section 2.4 summarized a two-day pilot study that was used to guide the research plan executed in the six-month laboratory study.

Sections 3.1 through 3.4 described the experimental design, research setting, participant recruitment, the study day procedures and conditions descriptions. Sections 3.5 described the location and frequency of the measured data and Section 3.6 described the data processing, cleaning and statistical analysis methods.

Section 4 documented the results. Section 4.1 provides results comparing MP and JU conditions illustrating that significant differences were found for many lighting metrics as well as subjective responses. Summary data are provided for several key metrics for these two condition groupings. Section 4.2 illustrated significant differences between MP daylit scenes and MP integrated light scenes. Section 4.3 provided detailed correlational results for metrics that best fit subjective responses or are otherwise commonly referenced lighting metrics. Section 4.4 provided similar results for a few multiple-regression models. Section 4.5 documented the findings for participants' sensitivity to brightness. Section 4.6 reported human visual performance results by comparing MP and JU scenes. Section 4.7 summarized participant choices in operating motorized blinds and dimming electric lights in MP and JU conditions. Section 4.8 outlined general participant feedback with regard to their opinions on the lighting and blind technologies, the general office setting, and their strategies with regard to controlling the visual environment. Section 4.9 documented the relationships between various questionnaire items to guide future research.

Finally, Section 5 discusses the results from Section 4 using a similar progression. Section 5.1 discusses the general difference between MP and JU conditions and also focused on

comparing MP daylight-only and MP integrated lighting conditions. Section 5.2 examines the capabilities and limitation of illuminance-based metrics with regard to subjective responses. Section 5.3 did the same for luminance-based metrics. Section 5.4 discussed the human visual performance results. Section 5.5 interpreted the results for occupant choice regarding the control of electric lights and motorized blinds and outlines a pathway forward for improved luminous environmental control. Section 5.6 qualified the findings of human sensitivity to brightness. Section 5.8 provided some general limitations to the application of the results given the context of the data collection.

6.1 Contributions of this dissertation

The following findings are reported here as the contributions of this dissertation to the body of human factors and lighting research:

6.1.1 Aim 1 – Lighting metrics, criteria and human visual acceptance and preference

- Luminance-based metrics were more capable than illuminance-based metrics for fitting the range of human subjective responses to visual preference questionnaire items. Therefore, establishing reliable luminance-based metrics and design criteria that can be referenced in design stages should lead to improved occupant satisfaction in spaces adhering to these criteria.
- The standard deviation of window luminance (X08_standard_deviation) was the metric that best fit human subjective responses to visual preference on seven of 12 questionnaire items. This metric consistently differentiated between MP and JU scenes and the recommended bounded-BCD was robust for two unique view

directions and room configurations (pilot study room and six-month study room).

This metric is easily understood; however, it requires a space- and position-specific mask to be created for each new space or position for which it is calculated.

- Luminance metrics calculated within the 40° horizontal band (X20) ranked in the top 20 squared correlation coefficients for almost all subjective visual preference questionnaire items. Metrics calculated within this masked region were highly ranked more frequently and more consistently than metrics derived from any other region of analysis, including the masked region representing the entire 180° by 180° FOV (X01). This is fortunate because this mask can be calculated with cameras incapable of capturing a full 180° by 180° FOV, thus reducing the cost of equipment for either purposes of research data collection or luminous environmental control.
- The strongest multiple regression model was for the semantic differential rating (too dim – too bright) of the window wall ($_{adj}R^2=0.49$) and was built upon three variables:
 - Standard deviation of window luminance (X08_standard_deviation)
 - 50th percentile luminance value from the lower window (X10_50th_percentile)
 - Mean luminance of the 40° horizontal band (X20_mean)

The strongest multiple regression model for the basic visual comfort question

(QU1) produced an $_{adj}R^2=0.36$ and was built upon four variables:

- Participants' measured sensitivity to brightness (SB_just_uncomfortable)

- Standard deviation of window luminance (X08_standard_deviation)
- 50th percentile luminance value from the lower window (X10_50th_percentile)
- Mean luminance of the 40° horizontal band (X20_mean)

These variables should be viewed as some of the most meaningful metrics to support future research and luminance-based environmental control. Because of the statistical significance of these multiple regressions, it can be said that these metrics represent unique constructs of the luminous environment. Given the improved predictive ability of the multiple regression models as compared to any single regression model, they will be beneficial to future research and luminance-based environmental control.

- The luminance ratio between the mean luminance of the daylight source (X08_mean) and the mean luminance of the circular task (X03_mean) did not yield squared correlation coefficients as high as (more than 400) other metrics with regard to the subjective visual comfort ratings. The borderline between comfort and discomfort suggested by this study (22:1) is higher than existing recommendations: the current IESNA recommendations are not supported by existing literature. Given these challenges, it would be reasonable to dismiss this metric entirely. However, the simplicity of this metric is its greatest strength and is a big reason it has persisted. There is sufficient evidence in this dissertation to suggest additional research is warranted, but it is critical that future research explicitly state the method used when calculating this metric. The current calculation definition is too loose and suffers from multiple interpretations, thus

making it nearly impossible to draw meaningful relationships between existing literature.

- Daylight Glare Probability performed better than Daylight Glare Index. However, only 1.5% of the 201 JU scenes that were rated as uncomfortable had DGP values that corresponded to “perceptible glare” or “disturbing glare.” The other 98.5% of the scenes rated as uncomfortable in this study had DGP values in the “imperceptible” portion of the glare scale. Therefore, as DGP is currently defined, it does not appear to be sensitive enough for use as a daylighting design guide or as part of an automated blind control algorithm as a singular input.
- While not as strong as luminance-based metrics, E_v measured at a seated occupant’s eye position or at the top of the monitor pointed in the same viewing direction as the occupant were both more capable than horizontal illuminance measures of fitting the range of human subjective responses to visual preference questionnaire items. Therefore, establishing reliable design criteria for E_v that can be referenced in design stages should lead to improved occupant satisfaction in spaces adhering to these criteria. Preliminary bounded-BCD criteria for E_v measured near occupants’ point of view from this study range from 1000-1500 lux.
- An upper horizontal illuminance comfort-based threshold, as required by Daylight Saturation Percentage or Useful Daylight Illuminance metrics, should be set between 2000-4300 lux, but must be applied with an understanding that some individuals may prefer values as high as 5000 lux (during some parts of the year), thus confidently identifying only the most extreme cases as uncomfortable.

- The capability of a particular metric to discern between MP and JU scenes was found to be an important consideration when evaluating their effectiveness. Furthermore, the range over which the metric could consistently differentiate between MP and JU scenes began to indicate the thresholds for the bounded-BCD. The bounded-BCD serves as preliminary recommended design criteria and can support both design analysis and environmental control.
- Participants were statistically more sensitive to glare from a standard electric light source in a windowless chamber during the fall than during the summer. The effect was substantial enough that it could have implications to recommended practices for daylighting design if it is confirmed. However, this result could be in part, or in whole, due to the duration (hours and minutes) of post-waking sunlight availability, rather than entirely due to seasonal effects.

6.1.2 Aim 2 – Visual performance in “most preferred” and “just uncomfortable” lighting conditions

- One out of four types of visual performance tests examined showed a decrement in visual performance for scenes rated as “just uncomfortable” as compared to scenes rated as “most preferred,” while the other three did not show statistical significant differences. The Stroop color-word matching tests showed a decrement in the range of 0.51-1.65% for “just uncomfortable” conditions.
- This dissertation examined visual performance between “most preferred” scenes and scenes at the borderline between comfort and discomfort, not extreme discomfort glare or disability glare scenarios. The findings for Stroop tests support the hypothesis that a similar plateau and escarpment as defined by the

RVP models for low light levels may exist for uncomfortably bright light levels. This could be explored further under a range of more extreme discomfort glare scenes.

- Participants perceived themselves as having approximately 10% higher productivity during “most preferred” as compared to paired “just uncomfortable” conditions.

6.1.3 Aim 3 – Improved integrated luminous environmental control systems

- Luminance-based metrics were far more capable of predicting participants’ electric lighting dimmer choice than illuminance metrics, and of predicting blind position than exterior vertical irradiance. Therefore, establishing reliable luminance-based metrics and design criteria that can be referenced in design stages and used within control algorithms should lead to improved occupant satisfaction in spaces adhering to these criteria.
- The ratio between the 25th and 75th percentile luminance values for the desk task mask (X05_25th_to_75th_percentile) was the metric that best fit participants’ electric lighting dimmer choice ($adjr^2=0.41$). Since an HDR sensor (camera) cannot be located near to the occupant’s eye position in an actual office space, an alternate location is required and the top of the monitor is a strong candidate.
- While not as strong as luminance-based metrics, horizontal illuminance measured at the top of the monitor was better able to fit participants’ electric lighting dimmer choice than $E_{ceiling}$ (ceiling, $adjr^2=0.05$; top of monitor = choice $adjr^2=0.28$). Therefore, until luminance-based control technologies become available, daylight-sensing lighting control systems should use this location, or a similar

location, whenever feasible in order to improve occupant acceptance of these systems.

- Providing personally controlled electric lighting to supplement available daylight was preferred to daylight alone, and resulted in an approximate 5% increase in satisfaction. However, the mean dimming choice in MP integrated lighting scenes was 73% dimmed, thus supplementing daylight with approximately 125-200 lux of electric light measured on the desktop.
- In the MP integrated lighting conditions, participants agreed or strongly agreed that dimming the electric light in accordance with the available daylight was important, and that it was possible for 60% of participants to perceive the space as too bright if electric lights were not dimmed in response to daylight available.
- Several luminance-based metrics were better able to fit participants' choice of blind position in "most preferred" scenes than exterior vertical irradiance ($adjr^2=0.05$). For example, the sum of the solid angles of the glare sources (X01_evalglare_mL0005_omega_sources, $adjr^2=0.45$) and the mean luminance of the window (X08_mean, $adjr^2=0.34$) both were far more capable. However, metrics that fit blind height data well do not necessarily correspond directly to subjective ratings of visual comfort. Thus, metrics that correlate well with subjective ratings of comfort should be prioritized over, and perhaps coupled with, metrics that fit chosen blind height or blind tilt data for MP conditions in future applications of luminance-based metrics to automatically control blind position.

6.2 *Future research*

Additional data analysis within the existing data set will address a range of methods for capturing HDR data in an accurate manner, determine how best to calculate luminance ratios in future research as discussed in Figure 105, examine the concept of the bounded-borderline between comfort and discomfort for the sufficiency range, explore metrics with respect to blind tilt patterns and document the feasibility of the top of the monitor location for luminance data acquisition. Beyond these additional analyses of the existing data, several new studies are suggested below.

6.2.1 Aim 1 – Lighting metrics, criteria and human visual acceptance and preference

Additional robustness testing should be conducted using the top performing metrics that emerged from this study. The goal is to understand how well the proposed luminance metrics and preliminary recommended criteria perform in a wide range of architectural settings. For example, does the standard deviation of window luminance work best near the window wall? Or, do metrics within the 40° horizontal band perform equally well in spaces with toplighting? There are a few avenues of inquiry that will produce useful results.

One approach is to conduct longitudinal field studies similar to Painter et al. (Painter et al. 2009; Painter et al. 2010). In fact, a few of these data sets exist and could be reexamined using the proposed metrics to determine if similar criteria emerge with regard to occupant comfort feedback. Of course, using similar data collection methods, calibration and data analysis techniques is essential. This avenue would provide data about the variability of the luminous environment from multiple viewpoints within one space under various sky conditions and across times of the day and year, but would not address the variability between different architectural daylighting strategies, except in accumulation. One challenge of conducting field studies is the

cost of data collection equipment. Fortunately, low cost data collection alternatives are emerging (K. S. Konis 2011) using inexpensive cameras with smaller sensors, and the success of the 40° horizontal band (X20) as presented in this dissertation makes these inexpensive methods more useful. Finally, future field or laboratory research in this area should incorporate a questionnaire item similar to “the scene to your right is: too dim – too bright,” as it yielded the highest overall squared correlation coefficients between subjective responses and physical lighting measures. A more generalizable version of the question is: “right now the windows and/or skylights in the space are: too-dim – too bright.”

A simulation-based approach can also be pursued, similar to the recent work of annualized DGP calculations (Reinhart & Wienold 2011; Wienold 2009). While simulation obviously lacks much of the realism of field or laboratory studies, it has several benefits as well. Annualized data collection and analysis can be conducted more quickly and less expensively using simulated environments than using real buildings; therefore, the annual performance of metrics from one or more viewpoints can be evaluated. If these studies are conducted within well-established and understood simulated architectural settings, the output should prove useful for evaluating the recommended performance criteria.

With the growing popularity of HDR luminance mapping techniques as a data collection method, a growing body of research is emerging. However, much of this work is focused on glare definition (Hirning et al. 2010; Painter et al. 2010). It is necessary to understand the range of human visual acceptance and preference of luminance conditions more broadly. Future visual comfort research should incorporate a wide range of visual conditions, not just focus on glare. This study demonstrated the importance of conducting human visual preference and acceptance research that is aimed at developing luminance-based metrics for design guidance or

environmental control by using a wide range of visual conditions. Developing metrics aimed at fitting the variability in subjective visual discomfort ratings while using visual conditions that are primarily extreme or glaring can lead to a false sense of confidence in the capabilities of the resultant metric or model. Any visual comfort lighting metric, whether it is illuminance-based or luminance-based, should not only be able to fit the subjective ratings on the glaring side of the spectrum, but must also be able to consistently differentiate between very comfortable and uncomfortable scenes. Future “glare” research should be characterized as “visual comfort” research and test the “fitting” capabilities of lighting metrics across very comfortable scenes as well as uncomfortable scenes.

Additionally, measured sensitivity to brightness appears to have a seasonal effect and additional research is needed to determine whether this phenomenon has more to do with short-term, post-awake sunlight availability or whether it has more to do with long-term seasonal sunlight-availability.

Finally, the wide degree of variability in subjective responses to lighting stimuli found in this study is likely to widen further as the suggested additional studies are conducted in multiple settings. These results will present challenges to organizations striving to establish luminance-based daylighting and integrated lighting design recommendations and standards. In fact, some may argue that it is a futile effort. Nonetheless, this dissertation suggests that some guidance for both sufficiency and excessiveness are possible to identify. However, with regard to controlling for excessive daylight brightness in particular, it seems reasonable to suggest that localized personal approaches to glare control may perform better than a one-size fits all approach because it may allow for window blinds to be open more often or controlled by thermal priorities rather than visual priorities. Therefore, future research should examine personalized glare control

alternatives at the occupant level (this could be thought of as “task shading”) and determine the resultant occupant (workstation) satisfaction and energy implications associated with these alternatives.

6.2.2 Aim 2 – Visual performance in “most preferred” and “just uncomfortable” lighting conditions

The findings for Stroop color-word matching tests reported in this dissertation support the hypothesis that a similar plateau and escarpment as defined by the RVP models for low light levels may exist for uncomfortably bright light levels. This should be explored further under a range of more extreme discomfort glare scenes, as this study focused primarily on the borderline between comfort and discomfort.

6.2.3 Aim 3 – Improved integrated luminous environmental control systems

As future research tests and refines the metrics and preliminary recommended criteria proposed herein, it is likely that the bounded-BCD criteria will vary under different daylighting configurations across spaces and for various viewpoints within a given space. That said, the general usefulness of the metric, and probably the general shape of the loess curve fit, are expected to hold true in future research, even if it is shifted along the metrics’ range. If this is the case, it is likely that these metrics can be used in the near term to reliably control automated electric lighting and blind systems by coupling the system with a learning mechanism (such as ANN, genetic and fuzzy algorithms) with model-training input from a specific user over a relatively short period of time (Inkarojrit 2005; Osterhaus et al. 2005; Guillemin & Morel 2002; Guillemin & Morel 2001; C. P. Kurian et al. 2005; C. Kurian et al. 2008). Given that a preliminary shape of the fit of the metric relative to subjective responses has been established, it

is conceivable that in the course of a single day an occupant could provide feedback to a luminance-based integrated lighting control system which could establish the absolute values of the bounded-BCD, essentially establishing the “the intercept” of the curve for that particular space, user and viewpoint. While the findings of this dissertation support this approach to control, future research is required to see how quickly the current bounded-BCD can be modified for new spaces and specific users. Also, the data set captured from the Firefly MV cameras in this study should be examined to determine if the data from the top of the monitor correlate adequately with the Canon HDR data captured from the seated occupant’s perspective.

Furthermore, if these control strategies are to be applied to open-plan offices, several additional factors must be addressed. There will be competing signals from multiple viewpoints within a given environment that need to be prioritized and combined into an integrated electric lighting and blind control hierarchy. Additionally, the number and location of HDR sensors across a space must be determined. It is necessary to examine these phenomena in field settings and via simulation prior to developing control strategies for open-plan office environments.

Finally, probably in the more distant future, it could prove interesting to consider near-real-time HDR sky capture to feed a Radiance simulation of interior lighting conditions (Inanici 2010), and ultimately control electric lights and blinds in a real building using simulated sensors from the Radiance model. There are obvious limitations, which include ensuring the simulated environment matches the physical environment (especially blind position), and having sufficient computational power so that control signals are available quickly.

7 References

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8 Appendices

8.1 Top 20 metrics for each subjective item

Table 63 - Top 20 metrics ranked by squared correlation coefficients for each subjective item individually

QU1		QU2		QU3		QU4		QU5		QU6		QU7	
X08_standard_deviation	0.2983	X08_standard_deviation	0.2543	X08_standard_deviation	0.1635	X08_standard_deviation	0.3019	X08_standard_deviation	0.1495	X08_25th_percentile	0.2877	X08_standard_deviation	0.2322
X10_25th_percentile	0.2713	X10_25th_percentile	0.2240	X08_25th_percentile	0.1590	X10_25th_percentile	0.2887	MD_irradiance	0.1356	MD_daq05_illumina nce_NEwall	0.2858	X10_25th_percentile	0.2178
X08_25th_percentile	0.2570	X08_25th_percentile	0.2233	X13_75th_percentile	0.1564	X08_25th_percentile	0.2874	X10_10th_percentile	0.1355	MD_daq02_illumina nce_topFF406	0.2833	X08_25th_percentile	0.2163
X10_50th_percentile	0.2447	X13_75th_percentile	0.2080	MD_daq02_illumina nce_topFF406	0.1500	MD_daq05_illumina nce_NEwall	0.2658	X10_25th_percentile	0.1334	X17_25th_percentile	0.2828	MD_daq02_illumina nce_topFF406	0.2132
X20_mean	0.2436	X10_10th_percentile	0.2066	X18_50th_percentile	0.1457	X13_75th_percentile	0.2630	X08_25th_percentile	0.1304	MD_daq06_illumina nce_SEwall	0.2817	X10_10th_percentile	0.2092
X13_75th_percentile	0.2421	X18_50th_percentile	0.2026	X18_75th_percentile	0.1450	MD_daq02_illumina nce_topFF406	0.2602	MD_daq08_illumina nce_desktop	0.1282	X08_standard_ deviation	0.2809	X13_75th_percentile	0.2070
X08_mean	0.2411	MD_daq02_illumina nce_topFF406	0.2004	X23_50th_percentile	0.1431	X10_10th_percentile	0.2573	MD_daq06_illumina nce_SEwall	0.1225	X22_25th_percentile	0.2789	X18_75th_percentile	0.2016
X10_10th_percentile	0.2406	X18_75th_percentile	0.1998	X10_25th_percentile	0.1410	X23_50th_percentile	0.2549	X13_75th_percentile	0.1224	X04_2nd_percentile	0.2757	MD_daq05_illumina nce_NEwall	0.2009
MD_daq02_illumina nce_topFF406	0.2389	X23_50th_percentile	0.1995	MD_daq05_illumina nce_NEwall	0.1410	MD_daq06_illumina nce_SEwall	0.2547	X08_10th_percentile	0.1200	X01_minimum	0.2748	X18_50th_percentile	0.1994
X18_50th_percentile	0.2311	X20_mean	0.1939	X13_mean	0.1401	X20_75th_percentile	0.2539	X09_standard_ deviation	0.1193	X01_25th_percentile	0.2747	X23_50th_percentile	0.1952
X23_50th_percentile	0.2306	X18_10th_percentile	0.1931	X18_10th_percentile	0.1366	X18_50th_percentile	0.2518	MD_daq02_illumina nce_topFF406	0.1182	X03_2nd_percentile	0.2724	X08_10th_percentile	0.1933
X18_75th_percentile	0.2301	X08_mean	0.1931	X01_25th_percentile	0.1348	X20_mean	0.2518	MD_daq07_illumina nce_ceiling	0.1181	X22_2nd_percentile	0.2724	X20_25th_percentile	0.1914
X20_75th_percentile	0.2299	X10_50th_percentile	0.1921	X20_75th_percentile	0.1348	X10_50th_percentile	0.2511	X08_mean	0.1165	X18_50th_percentile	0.2716	X18_10th_percentile	0.1909
X14_10th_percentile	0.2261	X01_minimum	0.1917	X14_10th_percentile	0.1347	X08_mean	0.2502	X18_75th_percentile	0.1154	X01_2nd_percentile	0.2713	X10_minimum	0.1907
X20_25th_percentile	0.2250	X14_10th_percentile	0.1916	X13_2nd_percentile	0.1345	X18_75th_percentile	0.2492	X10_50th_percentile	0.1149	X17_2nd_percentile	0.2706	X22_25th_percentile	0.1901
MD_daq05_illumina nce_NEwall	0.2234	X20_75th_percentile	0.1907	X13_50th_percentile	0.1339	X14_10th_percentile	0.2486	X20_mean	0.1130	X18_75th_percentile	0.2703	X20_75th_percentile	0.1898
X14_25th_percentile	0.2188	X01_25th_percentile	0.1894	X22_25th_percentile	0.1331	X20_25th_percentile	0.2474	X10_2nd_percentile	0.1123	X19_2nd_percentile	0.2700	X20_mean	0.1892
X01_minimum	0.2178	X19_25th_percentile	0.1889	X03_2nd_percentile	0.1329	X22_25th_percentile	0.2438	X18_50th_percentile	0.1118	X13_75th_percentile	0.2698	X01_25th_percentile	0.1889
X22_25th_percentile	0.2169	X22_25th_percentile	0.1885	MD_daq06_illumina nce_SEwall	0.1327	X19_25th_percentile	0.2420	X23_50th_percentile	0.1098	X19_25th_percentile	0.2695	X19_25th_percentile	0.1862
X18_10th_percentile	0.2167	X20_25th_percentile	0.1883	X19_25th_percentile	0.1326	X14_25th_percentile	0.2417	MD_daq05_illumina nce_NEwall	0.1096	X10_25th_percentile	0.2690	X04_2nd_percentile	0.1860

Likert_all		front_scene		left_scene		right_scene		ceiling		light_in_scene	
X08 standard deviation	0.2875	X20 90th percentile	0.1516	X13 mean	0.1786	X08 standard deviation	0.4252	X18 minimum	0.1291	X20 percent above 2000 cd	0.1149
X08 25th percentile	0.2662	X10 50th percentile	0.1452	X13 75th percentile	0.1715	X10 25th percentile	0.3890	X18 25th percentile	0.1186	X20 percent below 1000 cd	0.1140
X10 25th percentile	0.2636	X08 50th percentile	0.1365	MD_daq05_illuminance NEwall	0.1525	X10 50th percentile	0.3697	X18 2nd percentile	0.1179	X20 percent above 1500 cd	0.1134
X13 75th percentile	0.2506	X20_percent_below_1000_cd	0.1341	X13 50th percentile	0.1465	X08 25th percentile	0.3589	MD_daq01_illuminance topcanon	0.1175	X14 10th percentile	0.1051
MD_daq02_illuminance topFF406	0.2496	X20_percent_above_1500_cd	0.1264	X14 10th percentile	0.1444	X08 mean	0.3401	X23 25th percentile	0.1165	X18 98th percentile	0.1025
X10 10th percentile	0.2431	X20_percent_above_2000_cd	0.1257	MD_daq07_illuminance ceiling	0.1428	X20 mean	0.3312	X04 10th percentile	0.1161	X14 2nd percentile	0.1025
X18 50th percentile	0.2407	X20_mean	0.1247	X20 50th percentile	0.1415	X13 75th percentile	0.3242	X04 minimum	0.1142	X20_percent_above_2500_cd	0.1003
X18 75th percentile	0.2405	X10 25th percentile	0.1243	X20 75th percentile	0.1399	X14 10th percentile	0.3214	X08 standard deviation	0.1133	X20_percent_below_10_cd_to_percent_above_1500_cd	0.0974
MD_daq05_illuminance NEwall	0.2403	X13 75th percentile	0.1233	X14 25th percentile	0.1399	X10 10th percentile	0.3199	X23 minimum	0.1126	X13 10th percentile	0.0938
X23 50th percentile	0.2384	X20 75th percentile	0.1189	X17 50th percentile	0.1394	X20_percent_below_1000_cd	0.3185	X19 25th percentile	0.1126	X13 75th percentile	0.0934
X20 75th percentile	0.2336	X14 10th percentile	0.1177	X13 90th percentile	0.1388	X23 50th percentile	0.3147	MD_daq05_illuminance NEwall	0.1110	X20_percent_below_50_cd_to_percent_above_2000_cd	0.0920
X20 mean	0.2315	X20_percent_above_2500_cd	0.1162	X21_standard_deviation	0.1374	X20 75th percentile	0.3135	X19 minimum	0.1108	X12 25th percentile	0.0916
X20 25th percentile	0.2307	MD_daq06_illuminance SEwall	0.1147	X19 50th percentile	0.1370	X14 25th percentile	0.3097	X17 minimum	0.1100	X20_percent_above_3000_cd	0.0911
MD_daq06_illuminance SEwall	0.2305	X13 50th percentile	0.1145	X22 75th percentile	0.1362	X20 25th percentile	0.3084	X13 2nd percentile	0.1094	X21 standard deviation	0.0909
X22 25th percentile	0.2299	X08 mean	0.1132	X14 2nd percentile	0.1361	X14 2nd percentile	0.3073	X22 25th percentile	0.1073	X20 50th percentile	0.0907
X14 10th percentile	0.2293	X08 25th percentile	0.1130	X23 50th percentile	0.1356	X20 90th percentile	0.3052	X09 standard deviation	0.1069	X20_percent_below_250_cd_to_percent_above_1500_cd	0.0898
X08 mean	0.2291	X14 2nd percentile	0.1116	MD_daq06_illuminance SEwall	0.1356	X18 50th percentile	0.3043	X22 minimum	0.1068	X13 50th percentile	0.0883
X01 25th percentile	0.2289	X20 50th percentile	0.1107	X01 50th percentile	0.1354	X20 50th percentile	0.2999	X03 minimum	0.1067	X01_evalglare_mL0010_dgp	0.0876
X10 50th percentile	0.2283	X01_evalglare_th5000_lum_backg	0.1104	X22 50th percentile	0.1343	X19 25th percentile	0.2993	X03 2nd percentile	0.1065	X20_percent_below_30_cd_to_percent_above_2000_cd	0.0872
X18 10th percentile	0.2276	X13 10th percentile	0.1103	X01_evalglare_th5000_lum_backg	0.1339	X08 50th percentile	0.2991	X18 10th percentile	0.1064	X01_findglare_dgi_th1000	0.0868

8.2 Appendix A – Participant Recruitment Email



To: Anyone between the ages of 18-70 with basic computer skills

RE: Participating in a Study at the University of Idaho Integrated Design Lab

Currently, a study is being conducted at the University of Idaho Integrated Design Lab in Boise in conjunction with the University of Washington to examine the effects of various electric lighting and daylighting conditions on users' visual preference and acceptance ranges and lighting energy consumption among office workers in a mock office space with daylight and view in Boise, ID. We would like to give you the opportunity to participate in the study. The study will take place over two days (8:30AM – 4:00 PM), one day in June-August 2011 and one day in September-December 2011. If you do decide to participate, you can choose to be compensated in one of two ways. You can elect to be entered into a raffle with a chance to win an Apple I-Pad valued at approximately \$500, or you can elect to be paid \$10.00 per hour (up to \$75.00 per day).

During this study, you will be asked to assess lighting conditions in a 12'x12' office space on the southwest façade of a commercial office building in Boise, Idaho. You will experience several combinations of electric lighting and daylighting conditions and assess the conditions by completing questionnaires. You will also complete several visual performance tasks under each condition. These data will facilitate assessment of relative visual performance and user preference under the various lighting conditions. Participants will complete a sensitivity to brightness test in order to determine whether there are any moderating effects due to a potential vision sensitivity.

If you are between 18 and 70 years of age, have basic computer skills, and are interested in participating in the study, please contact us by phone or e-mail. Please be careful with information sent via e-mail because we cannot assure confidentiality of information e-mailed to us. Contact information is provided below.

Thank You,
Kevin Van Den Wymelenberg

Kevin Van Den Wymelenberg – Assistant Professor – Director
University of Idaho – Integrated Design Lab

Please Contact:
Julia Day - Research Assistant
University of Idaho – Integrated Design Lab
306 S 6th Street, Boise, Idaho, 83702
e-mail: juliad@uidaho.edu Phone: 208.401.0646

8.3 Appendix B – Internal Review Board Approvals

The University of Idaho Internal Review Board (IRB) has approved that this study was in compliance with all Human Subject guidelines (project # 10-187) and the University of Washington has an Authorization Agreement for this project with the University of Idaho IRDB. (HSD 40217).

University of Idaho

Office of Research Assurances Institutional Review Board

PO Box 443010
Moscow ID 83844-3010

Phone: 208-885-6162
Fax: 208-885-5752
hac@uidaho.edu

To: Kevin G. Van Den Wymelenberg

From: Traci Craig, PhD
Chair, University of Idaho Institutional Review Board
University Research Office
Moscow, Idaho 83844-3010

IRB No.: IRB00000843

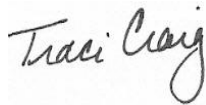
FWA: FWA00005639

Date: March 25, 2011

Project: "Luminance-based Daylighting Controls for Improved Building Energy Efficiency and Increased Occupant Comfort"
Project No.: 10-187
Approved: March 25, 2011
Expires: March 24, 2012

On behalf of the Institutional Review Board at the University of Idaho, I am pleased to inform you that the protocol for the above-named research project is approved as offering no significant risk to human subjects.

This approval is valid for one year from the date of this memo. Should there be significant changes in the protocol for this project, it will be necessary for you to resubmit the protocol for review by the Committee.



Traci Craig

University of Idaho

Office of Research Assurances Institutional Review Board

PO Box 443010
Moscow ID 83844-3010

Phone: 208-885-6162
Fax: 208-885-5752
irb@uidaho.edu

To: Kevin G. Van Den Wymelenberg

From: Traci Craig, PhD
Chair, University of Idaho Institutional Review Board
University Research Office
Moscow, ID 83844-3010

IRB No.: IRB00000843

FWA: FWA00005639

Date: July 12, 2011

Title: 'Luminance-based Daylighting Controls for Improved Building Energy Efficiency and Increased Occupant Comfort'

Your modification request has been approved.
Modification Requested: 06/29/11

Please note that this does not change your approval period.

On behalf of the Institutional Review Board at the University of Idaho, I am pleased to inform you that the proposed protocol modification for the above-named research project has been approved as offering no significant risk to human subjects.

The approval for this project is valid for one year from the date of the original approval, a modification **does not** change your approval period. Should there be significant changes in the protocol for this project, it will be necessary for you to resubmit the protocol for review by the Committee.

Thank you for submitting your extension request.



Traci Craig

Authorization Agreement

Name of Institution or Organization Providing IRB Review (Institution/Organization A):

University of Idaho IRB

IRB Registration #: 00000843 Federalwide Assurance (FWA) #, if any: 00005639 exp. 10-22-2015

Name of Institution Relying on the Designated IRB (Institution B):

University of Washington IRB

FWA #: ~~000004341~~ 00006878 expires 3-24-2014 6-7-2014 LRB
JKM

The Officials signing below agree that Univ. of Washington may rely on the designated IRB for review and continuing oversight of its human subjects research described below: (check one)

This agreement applies to all human subjects research covered by Institution B's FWA.

This agreement is limited to the following specific protocol(s):
Luminance-Based Daylighting Controls for Improved

Name of Research Project: Building Energy Efficiency and Increased Occupant Comfort (10-187) HSD 40217

Name of Principal Investigator: Kevin G. Van Den Wymelenberg
College of Art & Architecture, Assistant Professor, University of Idaho - Boise

Sponsor or Funding Agency: NO FUNDING Award Number, if any: N/A
ASSOCIATED WITH THIS PROJECT

Other (describe): _____

The review performed by the designated IRB will meet the human subject protection requirements of Institution B's OHRP-approved FWA. The IRB at Institution/Organization A will follow written procedures for reporting its findings and actions to appropriate officials at Institution B. Relevant minutes of IRB meetings will be made available to Institution B upon request. Institution B remains responsible for ensuring compliance with the IRB's determinations and with the Terms of its OHRP-approved FWA. This document must be kept on file by both parties and provided to OHRP upon request.

Signature of Signatory Official (Institution/Organization A):
[Signature] Date: 20 April 2011

Print Full Name: John K. McIver Institutional Title: Vice President of Research & Economic Development

Signature of Signatory Official (Institution B):
[Signature] Date: 6-14-11

Print Full Name: WENDY S. BROWN Institutional Title: ASSISTANT DIRECTOR FOR QUALITY & COMPLIANCE
UW Human Subjects Division

8.4 Appendix C – Participant Consent Form

UNIVERSITY OF IDAHO

CONSENT FORM

Lighting and Daylighting Preference Study

Department of Architecture, Box 355720

Investigators:

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Investigators' statement

The University of Idaho and University Institutional Review Board has approved this project. We are asking you to be in a research study. The purpose of this consent form is to give you the information you will need to help you decide whether or not to be in the study. Please read the form carefully. You may ask questions about the purpose of the research, what we would ask you to do, the possible risks and benefits, your rights as a participant, and anything else about the research or this form that is not clear. When all your questions have been answered, you can decide if you want to be in the study or not. This process is called 'informed consent.'

PURPOSE

The purpose of this study is to determine the effect that aspects of the lighting environment have on visual comfort and productivity across a group of participants in an office space with electric lighting and daylighting. By recording several types of lighting data under a variety of blinds positions and electric lighting settings and comparing them to visual comfort data, we hope better understand human preference for luminance distribution patterns.

PROCEDURES

If you choose to be in this study, you will be asked to assess lighting conditions in a 12'x12' office space on the southwest façade of a commercial office building in Boise, Idaho. You will experience several combinations of electric lighting and daylighting conditions and assess the conditions by completing questionnaires. You will also complete several visual performance tasks under each condition. These data will facilitate assessment of relative visual performance and user preference under the various lighting conditions. You will complete a sensitivity to brightness test in order to determine whether there are any moderating effects due to a potential vision sensitivity. As the study participant, you may refuse to answer any question or item in any test or questionnaire.

The study procedures will take about 8 hours. You will be given a 10 minute break in the morning, a 60 minute lunch break at noon and a 20 minute break in the afternoon. During the experiment you will be welcome to take any breaks as needed.

RISKS, STRESS, OR DISCOMFORT

The degree of possible injury, stress, or discomfort is minimal. There will be one occasion during the study where you will be asked to create 'just intolerable glare' in a controlled sensitivity to brightness test for a few seconds. You will have complete control over the intensity and duration of this test. There will be several occasions during the study that ask you to rate lighting conditions, some of which may be glaring, however these conditions are similar to those normally found in an office with daylight. Furthermore, they will be only for a brief period and you will be allowed to shade your eyes with your hand if necessary. If at any time you become uncomfortable or tired during the measurement procedures, you can take a break from the testing or stop. If you choose to end participation early, you will be compensated for the amount of time engaged in the study.

8.5 Appendix D – Participant questionnaire

Demographics:

(The following questions will be answered by selecting the single correct answer.)

What is your gender?

- Female
- Male

What is your age?

- 18-29 years
- 30-39 years
- 40-49 years
- 50-59 years
- 60-70 years

What type of vision correction do you normally require?

- I do not need vision correction
- Contact lenses
- Reading glasses
- Distance Glasses
- Bi or Trifocals
- Multi-focals or Gradual

What type of vision correction do you have today?

- I have no vision correction today

- Contact lenses
- Reading glasses
- Distance Glasses
- Bi or Trifocals
- Multi-focals or Gradual

Do you have any type of color blindness?

- I do not have any color blindness
- Yes, total color blindness
- Yes, red/green colorblindness
- Yes, blue/yellow colorblindness

(The following questions will be answered by selecting the single correct answer.)

What is your eye color?

- Blue
- Blue-green
- Brown
- Green
- Hazel

Conditions:

Condition 1 - By adjusting the blind height and louver rotation only, please set the room to a condition you determine is the most preferable for office work. Be sure you have the blinds adjusted to your most preferred setting from your seated position. Readjust blinds as necessary

until you have created your most preferred setting. Then, select the appropriate response for each item from the list below.

(Assessments made on a 7 point Likert Scale or from Very Strongly Disagree – Very Strongly Agree.)

This is a visually comfortable environment for office work.

I am pleased with the visual appearance of the office.

I like the vertical surface brightness.

I am satisfied with the amount of light for computer work.

I am satisfied with the amount of light for paper-based reading work.

The computer screen is legible and does not have reflections.

The lighting is distributed well.

(Assessments will be made on a Semantic Differential Scale from Too Dim - Too Bright)

When I look up from my desk the scene I see in front of me seems:

When I look to my left the scene that I see seems:

When I look to my right the scene that I see seems:

I find the ceiling to be:

(Complete selected objective visual performance tests – See Table 7)

(The following question will be answered by selecting the single correct answer.)

Please click on the button to estimate how you think your personal productivity increased or decreased working under the present lighting conditions.

-30% -20% -10% 0% +10% +20% +30%

(The following question will be answered using a BORG CR-10 Scale.)

Rate your level of fatigue.

Condition 2 - Be sure that the blinds are still adjusted to your most preferred setting from your seated position. Readjust blinds as necessary until you have created your most preferred setting. Now adjust the electric lighting to try to improve the visual conditions for office work. Then, select the appropriate response for each item from the list below.

- Repeat seven typical Likert items
- “I was able to improve the visual conditions with electric lighting”
- Repeat four typical semantic differential items
- Complete selected objective visual performance tests – See Table 7
- Repeat typical personal productivity and fatigue items

Condition 3 - Be sure that the blinds are still adjusted to your most preferred setting from your seated position. Readjust blinds as necessary until you have created your most preferred setting. Now adjust the electric lighting to try to worsen the visual conditions for office work. Then, select the appropriate response for each item from the list below.

- Repeat seven typical Likert items
- “I was able to worsen the visual conditions with electric lighting”
- Repeat four typical semantic differential items
- Complete selected objective visual performance tests – See Table 7
- Repeat typical personal productivity and fatigue items

Condition 4 - By adjusting the blind height and louver rotation only, please set the room to a condition you determine to be "Just Disturbing" (“Just Uncomfortable”) glare for office work.

'Just Disturbing' glare is more severe than glare that is 'Just Noticeable' and less severe than glare that is 'Just Intolerable'. It is the visual environment under which you would normally correct a blind position because of disturbing glare from daylight/sunlight. Be sure you have the blinds adjusted so that glare is 'Just Disturbing' from your seated position. Readjust blinds as necessary until you have created a 'Just Disturbing' setting. Then, select the appropriate response for each item from the list below.

- Repeat seven typical Likert items.
- Repeat four typical semantic differential items.

(The following question will be answered by selecting up to three choices that apply.)

When you set the office so there was 'just disturbing' glare, what caused the scene to be disturbing? Check up to three that apply and indicate where each occurred by outlining the area on the image provided.

The disc of the sun

Sun patches in the space

Brightness from the sky (other than the sun)

Brightness from the hardscape out the window

Brightness of the blinds themselves

Reflections on the computer screen

Computer screen washed out by daylight or sunlight

Brightness from window mullions

Brightness from interior vertical surfaces

Brightness from interior horizontal surfaces

Other: (write in)

- Complete selected objective visual performance tests – See Table 7
- Repeat typical personal productivity and fatigue items.

Condition 5 - Be sure that the blinds are still adjusted to create a setting with ‘just disturbing’ glare from your seated position. Readjust blinds as necessary until you have created a ‘just disturbing’ setting. Now adjust the electric lighting to try to improve the visual conditions for office work. Then, select the appropriate response for each item from the list below.

- Repeat seven typical Likert items.
- Repeat four typical semantic differential items.
- Complete selected objective visual performance tests – See Table 7
- Repeat typical personal productivity and fatigue items.

Condition 6 - Be sure that the blinds are still adjusted to create a setting with ‘just disturbing’ glare from your seated position. Readjust blinds as necessary until you have created a ‘just disturbing’ setting. Now adjust the electric lighting to try to worsen the visual conditions for office work. Then, select the appropriate response for each item from the list below.

- Repeat seven typical Likert items.
- Repeat four typical semantic differential items.
- Complete selected objective visual performance tests – See Table 7
- Repeat typical personal productivity and fatigue items.

Condition 7 - By adjusting the blind height, louver rotation, and electric lighting, please set the room to a condition you determine is the most preferable for office work. Be sure you have the

blinds and electric lights adjusted to your most preferred setting from your seated position.

Readjust the blinds and electric lights as necessary until you have created your most preferred setting. Then, select the appropriate response for each item from the list below.

- Repeat seven typical Likert items.
- Repeat four typical semantic differential items.
- Complete selected objective visual performance tests – See Table 7
- Repeat typical personal productivity and fatigue items.

Condition 8 - By adjusting the blind height and louver rotation only, please set the room to a condition you determine is the most preferable for office work. Be sure you have the blinds adjusted to your most preferred setting from your seated position. Readjust blinds as necessary until you have created your most preferred setting. Then, select the appropriate response for each item from the list below.

- Repeat seven typical Likert items.
- Repeat four typical semantic differential items.
- Complete selected objective visual performance tests – See Table 7
- Repeat typical personal productivity and fatigue items.

Condition 9 – Researcher lowers and closes blinds all the way, electric lights off.

- Repeat seven typical Likert items.
- Repeat four typical semantic differential items.
- Complete selected objective visual performance tests – See Table 7
- Repeat typical personal productivity and fatigue items.

Condition 10 - By adjusting the blind height and louver rotation only, please set the room to a condition you determine to be "Just Disturbing" glare for office work. 'Just Disturbing' glare is more severe than glare that is 'Just Noticeable' and less severe than glare that is 'Just Intolerable'. It is the visual environment under which you would normally correct a blind position because of disturbing glare from daylight/sunlight. Be sure you have the blinds adjusted so that glare is 'Just Disturbing' from your seated position. Readjust blinds as necessary until you have created a 'Just Disturbing' setting. Then, select the appropriate response for each item from the list below.

- Repeat seven typical Likert items.
- Repeat four typical semantic differential items.
- Complete selected objective visual performance tests – See Table 7
- Repeat typical personal productivity and fatigue items.

Condition 11 - By adjusting the blind height, louver rotation, and electric lighting, please set the room to a condition you determine is the most preferable for office work. Be sure you have the blinds and electric lights adjusted to your most preferred setting from your seated position. Readjust the blinds and electric lights as necessary until you have created your most preferred setting. Then, select the appropriate response for each item from the list below.

- Repeat seven typical Likert items.
- Repeat four typical semantic differential items.
- Complete selected objective visual performance tests – See Table 7
- Repeat typical personal productivity and fatigue items.

Condition 12 – Researcher lowers and closes blinds all the way, leaving electric lights as they were set for most preferred Condition 11.

- Repeat seven typical Likert items.
- Repeat four typical semantic differential items.
- Complete selected objective visual performance tests – See Table 7
- Repeat typical personal productivity and fatigue items.

Condition 13 - Leaving electric lights as they were set for most preferred Condition 11, adjust the blind height and louver rotation only, please set the room to a condition you determine to be "Just Disturbing" glare for office work. 'Just Disturbing' glare is more severe than glare that is 'Just Noticeable' and less severe than glare that is 'Just Intolerable'. It is the visual environment under which you would normally correct a blind position because of disturbing glare from daylight/sunlight. Be sure you have the blinds adjusted so that glare is 'Just Disturbing' from your seated position. Readjust blinds as necessary until you have created a 'Just Disturbing' setting. Then, select the appropriate response for each item from the list below.

- Repeat seven typical Likert items.
- Repeat four typical semantic differential items.
- Complete selected objective visual performance tests – See Table 7
- Repeat typical personal productivity and fatigue items.

Condition 14 - By adjusting the blind height, louver rotation, and electric lighting, please set the room to a condition you determine is the most preferable for office work. Be sure you have the blinds and electric lights adjusted to your most preferred setting from your seated position.

Readjust the blinds and electric lights as necessary until you have created your most preferred setting. Then, select the appropriate response for each item from the list below.

- Repeat seven typical Likert items.
- Repeat four typical semantic differential items.
- Complete selected objective visual performance tests – See Table 7
- Repeat typical personal productivity and fatigue items.

Condition 15 – Leaving the blinds as they were set for most preferred Condition 14 (or readjusting them as necessary to ensure that the condition is still without glare) decrease the amount of electric lighting until you feel the overall environment is “just too dim” , if after dimming the electric lights all the way the environment still does not feel “just too dim”, feel free to turn the electric lights completely off.

- Repeat seven typical Likert items.
- Repeat four typical semantic differential items.
- Complete selected objective visual performance tests – See Table 7
- Repeat typical personal productivity and fatigue items.

Condition 16 - Leaving the blinds as they were set for most preferred Condition 14 (or readjusting them as necessary to ensure that the condition is still without glare), increase the amount of electric lighting until you feel the overall environment is “just too bright”.

- Repeat seven typical Likert items.
- Repeat four typical semantic differential items.
- Complete selected objective visual performance tests – See Table 7

- Repeat typical personal productivity and fatigue items.

End of day items:

(Assessments will be made by providing an open answer text field.)

What was your strategy when using the electric lighting control?

What was your strategy when using the motorized blind control?

Were you trying to light a particular part of the room?

If yes, which parts of the room were you trying to light?

(Assessments made on a 7 point Likert Scale or from Very Strongly Disagree – Very Strongly Agree.)

I am satisfied with the control of the electric lights

I am satisfied with the control of the motorized blinds

I would like these electric lights in my office

I would like these motorized blinds in my office

(Open ended comments)

Please describe any changes you would make to the office set up to make it more comfortable.

For example, would you move the desk location or direction? Would you change anything about the electric lights, blinds, walls or windows? Please explain.

Vita

Kevin G. Van Den Wymelenberg earned a Bachelor of Sciences in Architectural Studies from the University of Wisconsin at Milwaukee in 2000, a Master of Architecture from the University of Washington in 2002, and a Doctor of Philosophy from the University of Washington in the Built Environment in 2012. He has taught at the University of Idaho Boise campus since 2004 and directs the activities of the University of Idaho Integrated Design Lab in Boise.