

1 A color graphic informing on the impact of electric lighting and 2 coated glazing in complex architectural scenes

3 Coralie Cauwerts PhD^{1*}, Sophie Jost PhD²

4 ¹ Architecture & Climat, Université catholique de Louvain (UCL), 1348 Louvain-la-Neuve, Belgium, email:
5 coralie.cauwerts@uclouvain.be

6 ² Ecole Nationale des Travaux Publics de l'Etat (ENTPE), Université de Lyon, 69120 Vaulx-en-Velin, France,
7 email: sophie.jost@entpe.fr

8 *Corresponding author: Coralie Cauwerts, email: coralie.cauwerts@uclouvain.be

9 **Abstract.** *The present work proposes a graphical indicator that provides descriptive information*
10 *about the color content of architectural environments, and shows color shifts due to illuminant*
11 *or glazing changes. This color graphic is in accord with representations recently developed in*
12 *electric lighting to provide information on color rendering. Its originality lies in (1) including*
13 *contextualization, (2) dividing the color space based on color naming and (3) giving the user*
14 *the opportunity to compare scenes with different correlated color temperatures. After*
15 *describing the development steps of the color graphic, two case studies and three validation*
16 *experiments are presented. While the application of the graphic highlights its interest in a*
17 *building design process, the validation experiments identified potential improvements.*

18 **Keywords:** *Lighting research, color rendering, color shift, tinted glazing, complex stimuli.*

19 1. Introduction

20 The need to reduce energy consumption in buildings has, among other things, encouraged
21 the development of smart glazing and LED lighting. Regrettably, both can affect the color
22 appearance of indoor spaces¹⁻⁴.

23 In lighting practice, and for about six decades, the color rendering properties of electric light
24 sources have been evaluated through the calculation of the CIE General Color Rendering
25 Index Ra (CRI Ra)⁵. This index assesses the ability of a light source to render color faithfully. It is
26 calculated from the average color shift of eight test color samples illuminated by the test
27 source, or by a reference illuminant. The reference illuminant is set at the same Correlated Color
28 Temperature (CCT) as the test source. Below 5000K, it is a Planckian radiator and above 5000K,
29 a daylight illuminant. The color rendering properties of glazing in transmission can be expressed
30 by an amended CIE Ra (CRI Ra_D65)⁶. The reference illuminant is the CIE standard illuminant
31 D65 and the test illuminant is the Spectral Power Distribution (SPD) of the same illuminant
32 transmitted through the glazing.

33 Over the past 20 years, CRI Ra limitations have been largely documented (see Technical
34 Report CIE 177:2007⁷ for a review). Particular criticism concerns its single number output and its
35 failure to consider all dimensions of color quality⁸⁻¹³. To deal with this issue, additional or
36 alternative indices of color quality have been proposed^{8,14-16}. Graphical representations were
37 developed assuming that lightness has little influence on color shifts: color appearance
38 differences are projected in the chromatic plane^{8,13,15}.

39 Graphical tools have been used since the Fifties to present chromatic-adaptation effects¹⁷ and
40 color shifts^{18,19}. They came back into use about ten years ago for color rendering
41 characterization. For instance, the color rendering vectors of van der Burgt et al.¹³ represent, in

1 the a^*b^* plane of CIELAB, the color shifts of 215 color samples produced by a test source in
2 comparison to a reference illuminant at the same CCT (Fig.1a). Color shifts are symbolized by
3 vectors. The starting point represents the color under the reference SPD and the end point, the
4 color under the test SPD. The length of the arrow represents the magnitude of the color shift
5 and its direction gives an estimate of the type of distortion. Pointing toward the origin means
6 that the color has less chroma (with no change in hue) under the test source than under the
7 reference, pointing outward indicates the opposite. Radial deviations signify shifts in hue. In
8 their paper, van der Burgt et al.¹³ also introduced a color-rendering polar diagram. This graph
9 provides information on the average shifts in hue and relative chroma for 36 hue segments of
10 10 degrees each (Fig.1b). In this figure, the starting point of each vector is positioned on a circle
11 representative of the hue under the reference illuminant (the values are normalized).

12 Based on the same principles, Davis and Ohno⁸ proposed a CIELAB a^*b^* plot of color shifts for
13 the 15 samples of the Color Quality Scale CQS (Fig.2a) and a color icon (Fig.2b). In the color
14 icon, the colored surface represents the color shift introduced by the test source in comparison
15 to the reference illuminant symbolized by the white circle. A colored surface inside the white
16 circle means a loss of chroma, a surface outside means a gain in chroma. This graphic has
17 proved to be useful to interpret the results of scientific papers^{9,10,20-24}.

18 More recently, IES proposed, in IES TM-30¹⁵, a new color fidelity index to replace CIE Ra, as well
19 as a color gamut index and a set of graphical representations including a color vector graphic
20 and a color distortion graphic (see Fig.3a and Fig.3b respectively). These graphs show, in the
21 a^*b^* plane of CAM02-UCS, the average color shifts of 99 samples divided into 16 hue bins (22.5
22 degrees each). Since their publication, they have become the reference to test the hypothesis
23 of psychophysical experiments and to illustrate experimental results²⁵⁻²⁸.

24 All these graphical representations provide information on the magnitude of the color shift for
25 a pre-defined set of samples, similar to the CIE special color rendering indices (CRI Ri). They also
26 show the direction of the color shifts. In particular, they provide information on potential hue
27 changes and indicate if the test source leads to a loss or gain in chroma (the latter often seems
28 to be preferred by people). While these graphical representations are very useful to visualize
29 and understand color rendering properties, they are not calculated based on a specific color
30 content and might not provide a reliable prediction of the effect of light source SPD over real
31 scenes.

32 Based on these developments and because color preference varies with lighting
33 applications^{24,29}, the present work aims to develop a color indicator that includes
34 contextualization. Rather than being based on a pre-defined set of color samples, our color
35 graphic provides descriptive information about color shifts (in hue and chroma) due to
36 illuminant and/or glazing changes based on spectral photographs or spectral simulated
37 renderings of architectural environments. This graphic aims to serve the decision-making
38 process in building design. It must be easily understandable and should provide lighting
39 designers and other building professionals intuitive information on expected color distortions.
40 The ultimate goal of this work is to develop an indicator predicting preference of people for
41 color shifts, in building design.

42

43

2. Development of the color graphic

The main steps of the development of the color graphic are illustrated in Fig.4 and described below.

As input, the color graphic requires absolute CIE XYZ tristimulus values of both the original and the color distorted scenes. Such data can be generated by simulation or acquired by a camera. When data are generated by spectral simulation^a or captured with a hyperspectral camera, the distorted scene can be generated from the original scene by applying a spectral transformation. CIE XYZ tristimulus values are then derived from spectral radiances using CIE color matching functions. Hyperspectral databases of indoor, outdoor, natural and man-made scenes, with various types of illumination (daylight, artificial, mixed) exist³⁰⁻³⁶. On request, the authors can provide images from their own database, mainly composed of large field-of-view scenes. Images produced with a digital camera can also be used after colorimetric and radiometric calibration^{37,38}.

2.1. iCAM06

Tristimulus values of traditional colorimetry do not provide information on the perceived appearance of color stimuli. In modeling appearance phenomena such as chromatic adaptation and nonlinear visual responses, color appearance models extend traditional colorimetry to three-dimensional spaces. Their dimensions correspond to perceived lightness, chroma and hue (which can be considered as the three main attributes of color^b).

Beyond color appearance models, image appearance models include spatial and temporal phenomena typical of complex scenes. To the best of our knowledge, iCAM06³⁹ is the only color appearance model developed for complex scenes. Its aim is to "accurately predict human visual attributes of complex images in a large range of luminance levels"³⁹. iCAM06 uses IPT opponent color space⁴⁰. The I channel corresponds to the intensity; the P channel to the red-green color opponency (P stands for protan) and the T channel to the blue-yellow color opponency (T stands for tritan). IPT space has the particularity to present very good hue uniformity (hue is independent of lightness and chroma)⁴⁰.

In the present work, the iCAM06 algorithm was slightly modified to accept tristimulus values based on cone fundamentals⁴¹ $X_{F,10}$, $Y_{F,10}$, $Z_{F,10}$ instead of CIE XYZ 1931 values. This modification is consistent with recent developments in colorimetry and in line with both the future update of the CIE publication on colorimetry⁴² by CIE Technical Committee TC1-85 (*Update CIE publication 15:2004 Colorimetry*) and the ongoing work of CIE Joint Technical Committee JTC09 (*CIE system for Metrology of ipRGC influenced light response*). iCAM06 also requires some user-controllable parameters: the maximum luminance, max_L was set to 0 (the values of the scene are absolute luminance units), the overall contrast, p was set to 0.75 as in Kuang et al.³⁹ and the surround factor parameter, $gamma_value$ was set to 1 (average surround). The degree-of-adaptation factor, D was set to 0.9 (quasi-complete adaptation) as in Smet et al.¹⁶.

^a While Radiance (<https://www.radiance-online.org/>), a popular lighting simulation software in lighting research, only produces XYZ data, Ocean (<http://www.eclat-digital.com/>) also makes it possible to produce spectral data.

^b It is known that three dimensions are not sufficient to completely specify the appearance of a color. Brightness and colorfulness - which describe the environment - as well as brilliance are other useful attributes of colors.

1 In the present work, iCAM06 is used both for tone-mapping the scene and calculating IPT
2 coordinates. The Bartleson surround adjustment is not applied for calculating IPT coordinates
3 represented in the color graphic but is only used for creating the tone-mapped images.

4 **2.2. Division of the color space in color categories**

5 IPT coordinates calculated in the previous step are then projected in the P-T plane of IPT
6 opponent color space. To facilitate the interpretation of the color content of the scene, the
7 plane is divided into bins in which hue and chroma are averaged. Rather than dividing the
8 plane in equal parts, as in previously developed graphical representations, the P-T plane is
9 divided based on color naming. That seems reasonable for communication purposes: in
10 everyday life, and for many practical situations, colors are identified by their names.
11 Dissatisfaction can be experienced when the same object is sorted into different color
12 categories under different illuminants. Color rendering based on color categorization has been
13 previously investigated, in the context of simple stimuli^{43,44}. The present study brings together
14 categorical color rendering and graphical representation. The number and names of the color
15 bins were chosen with reference to historical primaries and their associated secondary colors.
16 Six bins were defined: yellow, red, blue, orange, green and purple. This set of six colors also
17 corresponds to the Munsell primary names (red, purple, blue, green, and yellow) plus orange.
18 The boundaries of our six color bins were set based on the work by Hansen et al.⁴⁵ who observed
19 a high agreement between color categorization by people and the Munsell color system. The
20 boundary between the red and orange categories was fixed to 5R, between orange and
21 yellow to 10YR, between yellow and green to 10Y, between green and blue to 5BG, between
22 blue and purple to 5PB, and between purple and red to 10P. IPT coordinates of the Munsell
23 color chips of these boundary hues were determined from the reflectance spectra^c of matt
24 Munsell color chips under D65. Linear regressions of PT coordinates were used to determine the
25 boundaries in the P-T plane (Fig.5).

26 For better accuracy, each of the six color bins was finally subdivided into three equal parts
27 (equal angle). The resulting 18 sub-bins represent the following colors: orange-red, orange,
28 orange-yellow, yellow-orange, yellow, yellow-green, green-yellow, green, green-blue, blue-
29 green, blue, blue-purple, purple-blue, purple, purple-red, red-purple, red, red-orange.

30 **2.3. Color content**

31 The color content of a scene can be represented either by color category or by element. For
32 color category analysis, a color bin (among the 18 sub-bins) is first assigned to each pixel of the
33 image of the scene based on its PT coordinates. Mean chroma and mean hue are then
34 calculated for each bin and plotted in the graphic (Fig.6a). In order to give the user information
35 on the color distribution of the scene, a histogram supplements the graphic. The histogram
36 represents the proportion of the pixels assigned to each color bin. The scene represented in
37 Fig.6a is mainly composed of orange-yellow and blue-purple having a moderately high
38 chroma in comparison to other colors, which are less present in the scene. In addition to this
39 color category analysis, the scene can be analyzed by elements (Fig.6b). For natural scenes,
40 elements could be sky, buildings and vegetation. For indoor spaces, walls, ceiling, floor and

^c Database link: <http://www.uef.fi/es/web/spectral/munsell-colors-matt-spectrofotometer-measured>

1 furniture could be analyzed as separate elements. For element analysis, mean chroma and
2 mean hue are calculated by element rather than by color bin.

3 **2.4. Color shift**

4 Similarly to color content (Section 2.3), the color shift can be represented by color category or
5 by element (Fig.7). As illustrated in Fig.7a, the color shift is represented by a vector beginning
6 with an empty point (mean hue and chroma by bin for the reference scene) and ending with
7 a full point (mean hue and chroma of the same pixels for the distorted scene). Pixels belonging
8 to each bin or each element are identical in the original and distorted scenes, only the PT
9 coordinates differ (consequently a vector can shift toward another color bin). Two histograms
10 supplement the graphic to give the user the opportunity to evaluate whether the color shifts
11 impact a lot of pixels or not, and to determine which colors appear in or disappear from the
12 scene (blank histograms represent the original distribution while gray histograms are for the
13 distorted scene). In Fig.7a, the scene after distortion is still composed of orange–yellow and
14 blue–purple but the yellow–orange content is increased. The orange–yellow content shifted in
15 hue (toward yellow) without modification of chroma. It results in a decrease of the orange–
16 yellow content to the benefit of yellow–orange. A high increase of chroma of the blue–purple
17 content is observed in the distorted scene in comparison with the original scene.

18 The color vector graphics presented in Section 1 aim to provide information about the color
19 rendering properties of the light source and to promote the comparison of a test source with a
20 reference illuminant at the same CCT. The graphical indicator we propose aims to predict color
21 shifts in context. In addition, it can be used to compare the effect of SPDs (light source or
22 glazing) with different CCTs.

23 **3. Application**

24 **3.1. Influence of coated glazing**

25 One application of the color graphic is the study of the color appearance of views through
26 coated glazing. Indeed, such glazing affects both the colors of the indoor space and the view
27 on the outside, even after complete adaptation.

28 Fig.8 represents the view of a city (Lyon, France) from a tall building through clear glazing and
29 two tinted examples. The reference scene (clear glazing) was photographed with a calibrated
30 VNIR4 SPECIM hyperspectral camera (sCMOS-50-V10E model) attached to a SPECIM rotating
31 scanner mounted on a MANFROTTO tripod. The camera was controlled by the LUMO Software
32 Suite distributed by the camera manufacturer. Blue-tinted and bronze-tinted scenes were
33 obtained by virtually applying the spectral transmittance of colored filters (LEE 061 and LEE 763
34 respectively) to the reference scene. Tristimulus values calculated from original and distorted
35 hyperspectral images were used as input to the color graphics.

36 The color graphic representing the color content of the reference scene shows that the original
37 scene is mainly composed of blue–purple, purple–blue, orange–red, orange and orange–yellow
38 (Fig.8a). The other colors have little presence in the scene: the gray points mean that the scene
39 is composed of less than 5% of this color. The large unsaturated bluish component in the
40 reference scene is the sky and the more saturated orange component represents the buildings.

1 With the blue-tinted glass (Fig.8b), the sky appears more bluish and more saturated. Buildings
2 shift toward less saturated orange and red (buildings become pinkish). The bronze-tinted glass
3 (Fig.8c) increases the chroma of the orange component of the scene, while the bluish
4 component disappears in favor of low chroma green-yellow.

5 **3.2. Color rendition of electric light sources**

6 Another application of the color graphic is the characterization of the color rendition properties
7 of electric light sources, in context. This second application is illustrated by computer-
8 generated images (simulated with Ocean version 2017 R4). The rendering and the color
9 graphic of relevant elements of the reference scene (a scene lit by indoor daylight illuminant
10 ID65⁴⁶ to mimic a daylight source) is presented in Fig.9a. The same scene lit by a fluorescent
11 source and by an LED source is presented in Fig.9b and Fig.9c respectively. These two SPDs
12 were used in a previous study by Jost et al.⁴⁷ and have similar fidelity indices.

13 The histogram of the reference scene (Fig.9a) shows that the original scene is mainly composed
14 of orange and, in a smaller amount, of blue. Other colors have little presence in the scene.
15 With the fluorescent SPD, colored elements have small color shifts. Nevertheless, the histogram
16 indicates a slight increase of orange-yellow content (shifts toward yellow). With the LED SPD,
17 there is a large increase of chroma for red and orange elements and a loss of chroma for
18 element #8 (yellow book).

19 **4. Validation**

20 To test the division of the P-T plane into six categories, and their associated color names, three
21 experiments were conducted: an objective analysis of typical colored objects, a color listing
22 experiment and a color content experiment.

23 **4.1. Objective analysis of typical colored objects**

24 The aim of this analysis was to determine the relevance of the limits proposed between the six
25 color categories. A Macbeth Color Checker (MCC) chart, some fruits, vegetables and well
26 known soda cans were illuminated with a spectrally tunable luminaire (ETC Source Four LED
27 Lustr+) to obtain an LED source with a very high CIE Ra (95) and on the Planckian locus at
28 3000 K. The scene was captured with the hyperspectral camera described in Section 3.1.

29 The scene was analysed by elements (Fig.10). Squares represent the colors of MCC chart,
30 diamonds the cans and circles the fruits and vegetables. The colors of the points are
31 approximate colors (achromatic elements are plotted in gray, the pear is the khaki point and
32 the potato, onion and kiwi are plotted in brown). The main concern in this analysis comes from
33 red elements which are not in the red principal color bin but at the limit between the red and
34 orange bins. The strong blue of the MCC chart is in the purple bin and the magenta is in the
35 red bin. These observations question our division of the color space.

36 **4.2. Color listing experiment**

37 The objective of the color listing experiment was to evaluate whether the six color bins, and
38 their associated names, are basic color terms for French people.

39

1 4.2.1. Procedure

2 Twenty-four French participants aged between 22 and 40 years (mean 26 +/- 5 years) were
3 asked to write down at least eleven color names^d. There was no restriction on the type of color
4 terms and no time limit was given. All the participants had normal or corrected-to-normal visual
5 acuity and normal color vision, as assessed with a simplified Ishihara test for color-deficiency
6 (plates 1, 2, 6, 10, 14, 18 were used). None of the participants was a color professional. The room
7 in which the task was organized was dim and as neutral as possible (black wall, black seats
8 and black carpet to partially cover the dark brown floor). The instructor wore a white lab coat,
9 neutral shoes and no jewelry.

10 4.2.2. Results

11 Before analyzing the results, the data were cleaned following the Taft and Sivik method⁴⁸:

- 12 - terms listed by less than 10% of respondents were considered as idiosyncratic and not
13 counted;
- 14 - terms modified by a color qualifier such as light or dark were only counted once;
- 15 - color terms modified by other qualifiers (lemon yellow, blue sky...) were counted as
16 specific colors; it was considered that people used these modifiers in the absence of a
17 specific term in their language.

18 Table 1 lists the 31 color names given by the 24 participants, after data cleaning. All the
19 participants listed at least 11 color names, as requested. A maximum number of 28 terms was
20 listed by one participant and on average, people named 16 color terms (+/- 4.4).

21 The 11 most frequently listed terms were Berlin and Kay basic color terms⁴⁹. Among these terms,
22 the six color bins were at the top of the ranking.

23 Contrary to what was expected, no participant listed the three primary colors first (neither
24 subtractive, nor additive). Only two participants first listed the six color bins (RGB primaries and
25 associated secondary colors). Three listed the four unique hues first (red, blue, green, yellow).
26 Red was listed first by nine participants, blue and orange by four, yellow by two and green by
27 only one. Only blue and yellow were listed by all the participants.

28 The six color bins used in the graphic are at the top of the ranking, but there is also a high
29 frequency of other basic color terms such as *marron*, *rose*, *blanc*, *noir* and *gris*. These results by
30 French people corroborate the original Berlin and Kay hypothesis on the existence of 11 basic
31 color terms.

32 4.3. Color content experiment

33 The objective of the color content experiment was to check the consistency of the color
34 graphic (in terms of content and distribution) with the perception of the participants.

35

^d Instructions in French were: Citez un maximum de couleurs dans l'ordre dans lequel elles vous viennent à l'esprit (minimum 11 couleurs).

1 4.3.1. Procedure

2 Twelve people aged between 23 and 62 (mean 37 +/- 14 years) participated in the
3 experiment. They had normal or corrected-to-normal vision and normal color vision. Six images
4 (five natural and one urban scene) were displayed full screen on a 27-inch calibrated monitor
5 (Eizo ColorEdge CG277) in a dark room to favor immersion. Two 6-order Latin squares were
6 used to balance the presentation order of the images. Participants were first asked to list (with
7 their own words) the dominant colors of each scene and to give them a proportion to quantify
8 their amount in the scene^e. They were then asked to allocate one of the graphic color
9 categories to each color they listed (yellow, orange, red, purple, blue, green) or one of the
10 following achromatic colors: white, black or gray^f.

11 4.3.2. Results

12 The same method as in Section 4.2.2. was applied for data cleaning. Two terms referring to
13 objects (without a clear reference to a specific color name) were removed from the analysis:
14 *ciel* (sky) and *béton* (concrete).

15 As shown in Table 2, in addition to the names of the six color bins, participants used the following
16 terms to describe the color content of natural scenes: *ocre* – ocher, *rose* – pink, *marron* – brown,
17 *bleu électrique* – electric blue, *mauve* – mauve, *bordeaux* – bordeaux. The six color categories
18 were listed more frequently (between 11 and 63 times) than the other terms (between two and
19 nine times).

20 It can also be observed in Table 2 that *gris* – gray and *blanc* – white (terms referring to
21 achromatic colors) were frequently used by respondents to describe the color content of the
22 six natural scenes.

23 The distribution of chromatic and achromatic content is defined by the sum of yellow, orange,
24 red, purple, blue and green, and the sum of white, gray and black, respectively. Fig.11 shows
25 that while scene F was perceived by people as totally chromatic, the achromatic content was
26 quite large in scenes A and C (up to about 40%).

27 Fig.12 illustrates the category to which people allocated the listed non-basic colors. *Ocre* was
28 overwhelmingly allocated to the orange bin. As expected *bleu électrique* was allocated to
29 the blue bin. *Bordeaux* and *mauve* were allocated to red and violet bins respectively. *Marron*
30 was considered as an achromatic color (either gray or black). *Rose*, was mostly allocated to
31 the purple category. Consensus between people was high even though the number of
32 respondents was low.

33 The color content estimated by the participants was compared to the color content provided
34 by the color graphic. A high consistency was observed between distributions produced by the
35 color graphic and the human judgments except for achromatic colors and the green bin.

^e Instructions in French were: Citez les couleurs que vous trouvez dominantes dans l'image et associez leur une proportion (la moitié de l'image, un quart, 70%, un petit peu...).

^f Instructions in French were: Associez une catégorie (jaune, orange, rouge, violet, bleu, vert, blanc, noir, gris) à chaque couleur citée.

1 For instance, in scene A (Fig.13a), a large difference is observed between the color graphic
2 and the human judgment for the orange bin and the achromatic bin (about 40% of the scene
3 was perceived as achromatic by the participants). An analysis by element reveals that the
4 ground, in the absence of achromatic bins, was allocated by the color graphic to the orange
5 bin (with a low chroma). If elements identified as achromatic by the participants (gray ground,
6 white cars and white façades) are now allocated to the achromatic bin (represented by the
7 orange arrow and bold hatched bars), a higher consistency is obtained between the color
8 graphic and the human judgments.

9 Beside this orange/gray inversion, Fig.13b illustrates that, in natural scenes with vegetation, part
10 of green detected by participants is analyzed as yellow by the color graphic. If the surplus in
11 yellow is moved toward the green bar (represented by the green arrow and the bold hatched
12 bars) a higher match is observed between the color graphic and people's judgment.

13 **5. Discussion**

14 **5.1. Interest of the color graphic**

15 The present study investigates color appearance in built environments and contextualizes the
16 analysis of color shifts due to lighting or glazing changes. Rather than assessing color differences
17 on a predefined set of color samples (simple stimuli), as traditionally done in electric lighting,
18 we propose to analyze complex stimuli (computer-generated images or pictures of built
19 environments). The ultimate goal of the work was to develop a graphical indicator that could
20 predict preference of people for color shifts and this contextualization is essential as it is well
21 known that the application (and the colors present in the scene) influences preference of
22 people regarding color rendering. Like recent experiments in electric lighting, our indicator
23 favors a graphical representation of color shifts. The chromatic plane however, is divided up
24 based on color naming instead of equal parts. Another advantage of our graphic is to give
25 the user the opportunity to choose the reference scene and to enable the comparison of
26 scenes with different CCTs. Hence, it becomes possible for designers to compare, for instance,
27 a scene under daylight at daytime and under electric light at nighttime. While that is not the
28 aim of traditional color rendering metrics, it could be of interest in building design.

29 In the first application (Section 3.1), the reference scene was a city viewed through clear
30 glazing. The color shifts analyzed were due to coated glass having CRI Ra_D65 values of 82
31 (blue-tinted glass) and 90 (bronze-tinted glass). From this standard index, the bronze glazing
32 was expected to have less impact on the scene than blue glazing and would probably have
33 been selected. The color graphics (Fig.8) illustrate that the magnitudes of the color shifts are
34 similar for both glasses but that the directions differ. With the blue-tinted glass, blue content
35 remains blue, with a higher chroma. Orange content shifts to pinkish colors. With the bronze-
36 tinted glass, an increase of chroma and a shift toward yellow is observed for orange content.
37 Blue content turns to green-yellow. The renderings suggest that the blue-tinted glass might be
38 preferred because of the increase in chroma of blue sky.

39 In the second application (Section 3.2), the reference scene is lit by an ID65 SPD (to simulate
40 the colors of the room during daytime). Color shifts due to either a fluorescent source or an LED
41 source were analyzed. These two light sources have similar IES-Rf values (77 and 78 respectively)
42 and slightly different IES color vector graphics as illustrated in Fig.14. When lit by the LED source,
43 one could expect, from the IES indicators, orange and green contents with a higher chroma

1 and yellow with a lower chroma than when lit by a fluorescent source. The difference with the
2 "daylight" reference scene cannot be assessed with such metrics.

3 The proposed color graphics (Fig.9) indicate that the fluorescent source introduces fewer
4 distortions than the LED source in comparison to the "daylight" reference scene. If the objective
5 is to render colors faithfully to daylight, the fluorescent source must be selected. But the scene
6 lit by the LED source could be preferred by people due to the increase in chroma of some
7 architectural and decorative elements.

8 These two case studies point out that contextualizing color shifts can lead to a different decision
9 from that based on existing indicators. Moreover, our graphic facilitates the identification of
10 the elements of a scene influenced by a change of SPD (glazing or illuminant).

11 **5.2. Improvements**

12 While the application of the color graphic in two case studies proves its usefulness in a building
13 design process, validation experiments questioned:

- 14 - the inclusion in the analysis of the scene's achromatic color content without including
- 15 achromatic bins in the color graphic;
- 16 - the number of color bins, and more particularly, the addition of a pink and a brown bin;
- 17 - the definition of the boundaries between color bins.

18 In response, some improvements to the graphic are considered.

19 *5.2.1. Achromatic colors*

20 In postmodern architecture, achromatic colors are largely present. Surprisingly, validation
21 experiment #3 highlights that, even in natural scenes, a large part of the color content (up to
22 40% as illustrated in Fig.13a) is identified by people as achromatic. Moreover, among the 11
23 Berlin and Kay basic color terms (identified in validation experiment #2), only black was not
24 listed by the respondents to describe the color content of the rated scenes.

25 These observations support the need to distinguish chromatic and achromatic content in the
26 analysis. And, as achromatic colors are little influenced by color shifts, in further development
27 of the graphic, pixels with low chroma could be removed from the analysis similarly, as was
28 done by van der Burgt et al.¹³ (for their color rendering polar diagram, they excluded colors
29 having chroma less than 15 for the reference illuminant). To make a similar approximation, CIE
30 XYZ tristimulus values taken as color graphic input should be relative instead of absolute. And
31 thus a reference white needs to be defined. While in a laboratory context the reference white
32 is easily defined, in a real scene it is less obvious. Indeed, the non-uniformity of the lighting (in
33 the field of view of the observer) and the presence of emitting sources (that should also be
34 deleted from the analysis) make the determination of this reference white more complex.

35 *5.2.2. Number of color categories*

36 Part of the success of a building depends on the exchange of information between people
37 from different backgrounds (architects, engineers, owners...). For a matter of communication,
38 it was decided to divide the color space, as a function of hue, into six categories based on
39 color naming. In validation experiment #2, in addition to these six categories and three
40 achromatic colors, participants identified pink and brown as basic color terms.

1 Given the high consensus of people who allocated pink and brown to one of the six principal
2 bins (validation experiment #3), we assume that for communication purposes, the six color bins
3 are relevant enough. Moreover, adding pink and brown would reduce the simplicity and the
4 readability of the graphic.

5 *5.2.3. Boundaries between color categories*

6 An inadequate determination of the red and blue bin boundaries was identified in validation
7 experiment #1. Indeed, the strong red of the MCC chart, the red Coca-Cola can and other
8 red elements, are on the boundary between the red and orange bins. The strong blue of the
9 MCC chart is in the purple bin. Validation experiment #3 also highlighted the inadequate
10 definition of the yellow-green boundary (in several scenes, grass and trees are perceived green
11 while the icon categorizes them yellow).

12 In the present work, color category boundaries were determined based on a study by Hansen
13 et al.⁴⁵ in which a high agreement between color categorization by people and the Munsell
14 color system was observed. The center of their yellow category matched with Munsell 5Y,
15 orange with 5YR, purple with 5P, blue with 5B. Differences were observed for red and green
16 categories (red matched with 5RP instead of with the expected 5R and green was halfway
17 between 5G and 5GY). Determining new boundaries based on the Munsell color system will
18 probably improve the categorization of red elements. The divergence observed for green
19 would probably remain because it is linked to memory colors (grass is green as illustrated in
20 Fig.13b). When the grass is zoomed and the texture is removed (Fig.15), it will probably be
21 perceived yellow as calculated by the color graphic.

22 Concerning blue categorization, using the Munsell color system to determine boundaries
23 between color bins will not permit the strong blue of the MCC chart to be in the appropriate
24 category. An alternative method could be to use the Swedish Natural Color system (NCS).
25 While, in the NCS system, elementary yellow, green and red match Munsell 5Y, 5G and 5R
26 respectively, elementary blue in NCS does not match Munsell 5B but is between Munsell 5B and
27 5P. The work of Kuehni on unique hues⁵⁰ could also be used to establish boundaries between
28 color categories.

29 **6. Conclusion and further work**

30 The present work proposes a graphical indicator providing descriptive information about color
31 content and color shift due to illuminant or glazing changes in architectural environments. This
32 indicator is in accord with graphical representations used to describe the color rendering
33 properties of light sources. Its originality lies in:

- 34 - a concern to contextualize;
- 35 - a division of the color space based on color naming;
- 36 - the possible comparison of SPDs with different CCTs.

37 The present work validates the interest of an analysis of color shifts in context and identifies first
38 points of improvement (removal of achromatic content, redefinition of color bin boundaries).
39 Plotting memory color regions in the color graphic (for example for sky or grass) and adding
40 houseplants and skin tones could further improve the graphic.

41

1 Validation work will continue in:

- 2 - pursuing the comparison between existing indicators and the developed color graphic
- 3 in order to clearly identify their specific interests;
- 4 - determining preference of people for color shifts in different contexts, using the
- 5 developed color graphic.

6 Finally, this work highlights the need to pursue fundamental research on color naming, unique
7 hues and color appearance models for complex scenes (including memory colors, color
8 constancy, etc.).

9 **Acknowledgments**

10 This work was partially supported by the Belgian Fund for Scientific Research (FNRS) through the
11 postdoctoral fellowship of Coralie Cauwerts. The authors thank Pascale Avouac who provided help for
12 image editing and data collection of validation experiment #3.

13 **ORCID**

14 Coralie Cauwerts <https://orcid.org/0000-0001-9107-0810>

15 **References**

- 16 1. Dangol R, Krusselbrink T, Rosemann A. Effect of window glazing on colour quality of transmitted
17 daylight. *Journal of Daylighting*. 2017;4(2):37-47.
- 18 2. Arsenault H, Hébert M, Dubois M-C. Effects of glazing colour type on perception of daylight
19 quality, arousal, and switch-on patterns of electric light in office rooms. *Building and Environment*.
20 2012;56:223-231.
- 21 3. Smet KAG, Whitehead L, Schanda J, Luo RM. Toward a Replacement of the CIE Color Rendering
22 Index for White Light Sources. *LEUKOS*. 2016;12(1-2):61-69.
- 23 4. Pimpitkar S, Speck JS, DenBaars SP, Nakamura S. Prospects for LED lighting. *Nature photonics*.
24 2009;3(4):180.
- 25 5. *CIE 13.3-1995 Method of Measuring and Specifying Colour Rendering Properties of Light Sources*.
26 Vienna: Commission Internationale de l'Eclairage;1995.
- 27 6. *NF. EN 410:2011 Glass in building — Determination of luminous and solar characteristics of glazing*.
28 2011.
- 29 7. *CIE 177:2007 Colour Rendering of White LED Light Sources*. Vienna: Commission Internationale de
30 l'Eclairage;2007.
- 31 8. Davis W, Ohno Y. Color quality scale. *Optical Engineering*. 2010;49(3):1-16.
- 32 9. Jost-Boissard S, Avouac P, Fontoynt M. Preferred Color Rendition of Skin under LED Sources.
33 *LEUKOS*. 2016;12(1-2):79-93.
- 34 10. Jost-Boissard S, Avouac P, Fontoynt M. Assessing the colour quality of LED sources: Naturalness,
35 attractiveness, colourfulness and colour difference. *Lighting Research and Technology*.
36 2015;47(7):769-794.
- 37 11. Rea MS, Freyssinier-Nova JP. Color rendering: A tale of two metrics. *Color Research & Application*.
38 2008;33(3):192-202.
- 39 12. Smet KAG, Ryckaert WR, Pointer MR, Deconinck G, Hanselaer P. Memory colours and colour
40 quality evaluation of conventional and solid-state lamps. *Optics Express*. 2010;18(25):26229-26244.
- 41 13. van der Burgt P, van Kemenade J. About color rendition of light sources: The balance between
42 simplicity and accuracy. *Color Research & Application*. 2010;35(2):85-93.
- 43 14. Hashimoto K, Yano T, Shimizu M, Nayatani Y. A new method for specifying color rendering
44 properties of light sources based on feeling of contrast. *Color Research & Application*.
45 2007;32(5):361-371.
- 46 15. IES. *IES TM-30-15: Method for evaluating light source color rendition*. 2015.
- 47 16. Smet KAG, Ryckaert WR, Pointer MR, Deconinck G, Hanselaer P. A memory colour quality metric
48 for white light sources. *Energy and Buildings*. 2012;49:216-225.
- 49 17. Sobagaki H, Yamanaka T, Takahama K, Nayatani Y. Chromatic-adaptation study by subjective-
50 estimation method. *Journal of the Optical Society of America*. 1974;64(6):743-749.
- 51 18. Helson H, Judd D, Wilson M. Color rendition with fluorescent sources of illumination. *Illuminating
52 Engineering*. 1956;51:329-346.
- 53 19. Hunt RWG. Measurement of Color Appearance. *Journal of the Optical Society of America*.
54 1965;55(11):1540-1551.

- 1 20. Dangol R, Bhusal P, Halonen L. Performance of colour fidelity metrics. *Lighting Research & Technology*. 2015;47(8):897-908.
- 2 21. Feng XF, Xu W, Han QY, Zhang SD. Colour-enhanced light emitting diode light with high gamut area for retail lighting. *Lighting Research & Technology*. 2017;49(3):329-342.
- 3 22. Jost-Boissard S, Fontoyntont M, Blanc-Gonnet J. Perceived lighting quality of LED sources for the presentation of fruit and vegetables. *Journal of Modern Optics*. 2009;56(13):1420-1432.
- 4 23. Wei M, Houser KW, Allen GR, Beers WW. Color Preference under LEDs with Diminished Yellow Emission. *LEUKOS*. 2014;10(3):119-131.
- 5 24. Lin Y, Wei M, Smet K, Tsukitani A, Bodrogi P, Khanh TQ. Colour preference varies with lighting application. *Lighting Research & Technology*. 2017;49(3):316-328.
- 6 25. Khanh T, Bodrogi P, Vinh Q, Stojanovic D. Colour preference, naturalness, vividness and colour quality metrics, Part 1: Experiments in a room. *Lighting Research & Technology*. 2017;49(6):697-713.
- 7 26. Royer M, Wilkerson A, Wei M, Houser K, Davis R. Human perceptions of colour rendition vary with average fidelity, average gamut, and gamut shape. *Lighting Research and Technology*. 2017;49(8):966-991.
- 8 27. Royer MP. Comparing Measures of Average Color Fidelity. *LEUKOS*. 2018;14(2):16-85.
- 9 28. Wei M, Houser K, David A, Krames M. Colour gamut size and shape influence colour preference. *Lighting Research & Technology*. 2017;49(8):992-1014.
- 10 29. Wei M, Houser K, David A, Krames M. Colour gamut size and shape influence colour preference. *Lighting Research and Technology*. 2016.
- 11 30. Chakrabarti A, Zickler T. Statistics of real-world hyperspectral images. Paper presented at: IEEE Conference on Computer Vision and Pattern Recognition (CVPR) 2011.
- 12 31. Le Moan S, George ST, Pedersen M, Blahová J, Hardeberg JY. A database for spectral image quality. Paper presented at: Image Quality and System Performance XII 2015.
- 13 32. Hirvonen T, Orava J, Penttinen N, et al. Spectral image database for observing the quality of Nordic sawn timbers. *Wood science and technology*. 2014;48(5):995-1003.
- 14 33. Yasuma F, Mitsunaga T, Iso D, S.K. Nayar. *Generalized Assorted Pixel Camera: Post-Capture Control of Resolution, Dynamic Range and Spectrum, Technical Report, Department of Computer Science, Columbia University*. 2008.
- 15 34. Finlayson GD, Hordley SD, Morovic P. Using the spectracube to build a multispectral image database. Paper presented at: Conference on Colour in Graphics, Imaging, and Vision 2004.
- 16 35. Hordley S, Findlyson G, Morovic P. A multi-spectral image database and its application to image rendering across illumination. Paper presented at: Third International Conference on Image and Graphics (ICIG'04) 2004.
- 17 36. Laparra V, Jiménez S, Camps-Valls G, Malo J. Nonlinearities and adaptation of color vision from sequential principal curves analysis. *Neural Computation*. 2012;24(10):2751-2788.
- 18 37. Kim MH, Kautz J. Characterization for high dynamic range imaging. Paper presented at: Computer Graphics Forum 2008.
- 19 38. Varghese D, Wanat R, Mantiuk R. Colorimetric calibration of high dynamic range images with a ColorChecker chart. Paper presented at: HDRi 2014 Second International Conference and SME Workshop on HDR imaging 2014.
- 20 39. Kuang J, Johnson GM, Fairchild MD. iCAM06: A refined image appearance model for HDR image rendering. *Journal of Visual Communication and Image Representation*. 2007;18(5):406-414.
- 21 40. Ebner F, Fairchild MD. Development and testing of a color space (IPT) with improved hue uniformity. Paper presented at: Color and Imaging Conference 1998.
- 22 41. *CIE 170-1:2006 Fundamental chromaticity diagram with physiological axes - part 1*. Vienna: Commission Internationale de l'Eclairage; 2006.
- 23 42. CIE. *CIE 15-1986 Colorimetry*. Vienna: CIE: Commission Internationale de l'Eclairage; 1986 1986.
- 24 43. Boynton RM, Fargo L, Collins BL. Categorical color rendering of four common light sources. *Color Research & Application*. 1990;15(4):222-230.
- 25 44. Yaguchi H, Endoh N, Moriyama T, Shioiri S. Categorical Color Rendering of LED Light Sources. Paper presented at: CIE Expert Symposium on LED Light Sources 2004.
- 26 45. Hansen T, Walter S, Gegenfurtner KR. Effects of spatial and temporal context on color categories and color constancy. *Journal of Vision*. 2007;7(4):2-2.
- 27 46. *CIE 204:2013 Methods for redefining CIE D illuminants* Vienna: Commission Internationale de l'Eclairage;2013.
- 28 47. Jost S, Cauwerts C, Avouac P. CIE 2017 color fidelity index Rf: a better index to predict perceived color difference? *Journal of the Optical Society of America A*. 2018;35(4):B202-B213.
- 29 48. Taft C, Sivik L. Salient color terms in four languages. *Scandinavian journal of psychology*. 1997;38(1):29-34.

- 1 49. Berlin B, Kay P. *Basic color terms: Their universality and evolution*. Univ of California Press; 1991.
2 50. Kuehni RG. Determination of unique hues using Munsell color chips. *Color Research & Application*.
3 2001;26(1):61-66.

4

5 **Authors' biographies**

6 *Coralie Cauwerts* received her Ph.D degree in Engineering Sciences from the Université catholique de
7 Louvain, Belgium in 2013. She is currently an FNRS post-doctoral researcher at the Faculty of Architecture
8 of the same University. Her research interests include color vision, environmental psychology, atmosphere,
9 (day)lighting simulations, HDR techniques.

10 *Sophie Jost* obtained her Ph.D in Civil Engineering from Lyon University, France in 2010. Since 2012 she is a
11 researcher at the Civil Engineering and Building laboratory of ENTPE in Lyon University. Her research
12 interests are lighting, lighting quality, color rendering, color science, colorimetry, color appearance and
13 psychophysics.

14

1 Table 1. Color terms resulting from the color listing experiment.

Color terms (FRENCH term – English equivalent)	Occurrence	
	–	(%)
BLEU – blue (4)	24	100%
JAUNE – yellow (2)	24	100%
ORANGE – orange (4)	23	96%
VERT – green (1)	23	96%
VIOLET – purple (1)	23	96%
ROUGE – red (9)	22	92%
MARRON – brown	22	92%
ROSE – pink (1)	21	88%
BLANC – white	20	83%
NOIR – black (1)	20	83%
GRIS – gray	18	75%
Cyan – cyan	15	63%
Mauve – mauve	11	46%
Turquoise – turquoise	11	46%
Magenta – magenta	10	42%
Beige – beige	9	38%
Pourpre – purple	8	33%
Bordeaux – bordeaux	7	29%
Taupe – mole gray	7	29%
Bleu marine – navy blue (1)	6	25%
Argent – silver	5	21%
Fuchsia – fuchsia	5	21%
Kaki – khaki	5	21%
Saumon – salmon	5	21%
Corail – coral	4	17%
Indigo – indigo	4	17%
Bleu ciel – sky blue	3	13%
Jaune citron – yellow lemon	3	13%
Ocre – ocher	3	13%
Or – gold	3	13%
Vert pomme – green apple	3	13%

Note: The number in parentheses is the number of times the term is listed in the first position by the respondents. Bold names are Berlin and Kay's basic color terms; underlined names are the six bins of the color graphic.

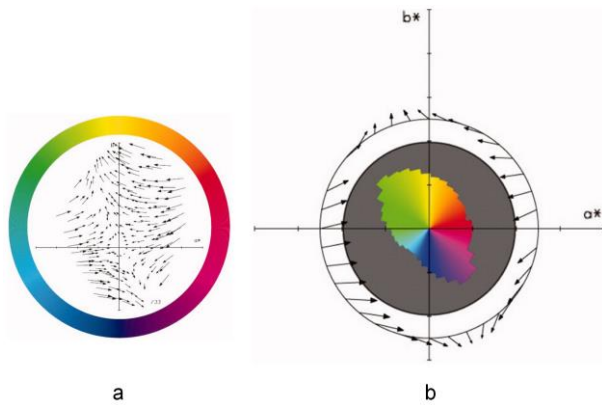
2

1 Table 2. Frequency of terms used by people to describe the color content of the scenes.

Color terms	Scene						Total	Nb_scenes
	A	B	C	D	E	F		
<u>VERT</u> – green	6	<u>12</u>	<u>9</u>	<u>12</u>	<u>12</u>	<u>12</u>	63	6
<u>BLEU</u> – blue	<u>11</u>	<u>10</u>		6	<u>12</u>	<u>12</u>	51	5
<u>GRIS</u> – gray	<u>12</u>	6	<u>10</u>	<u>11</u>	5	5	49	6
<u>JAUNE</u> – yellow	<u>8</u>	6	<u>12</u>	<u>10</u>	4		40	5
<u>BLANC</u> – white	<u>11</u>	<u>11</u>		3	5		30	4
<u>ORANGE</u> – orange	6		<u>12</u>			6	24	3
<u>ROUGE</u> – red	3	<u>11</u>	6				20	3
<u>VIOLET</u> – purple			<u>11</u>				11	1
OCRE – ocher	3					6	9	2
<u>ROSE</u> – pink		8					8	1
<u>MARRON</u> – brown		3			2		5	2
BLEU_ELECTRIQUE – electric_blue	3						3	1
MAUVE – mauve			2				2	1
BORDEAUX – bordeaux			2				2	1
<u>NOIR</u> – black							0	0

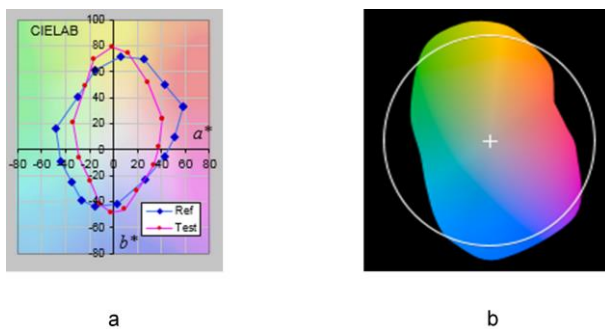
Note. Bold names are Berlin and Kay's basic color terms; underlined names are the six bins of the color graphic.

2



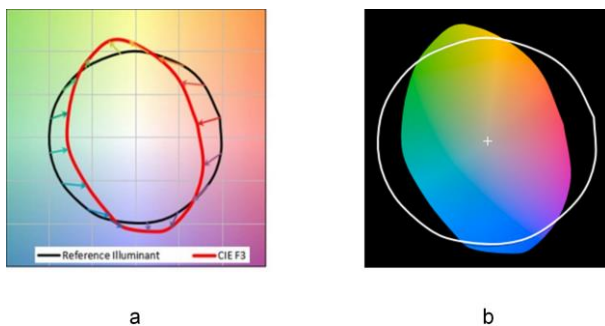
1
2 Figure 1. Color-rendering vectors (a) and color-rendering polar diagram (b) for a standard
3 halophosphate fluorescent lamp. From "About colour rendition of light sources: The balance
4 between simplicity and accuracy", by P. van der Burgt and J. van Kemenade, 2010, Color
5 Research & Application, 35(2), p.87 and p.90. Copyright 2010 by John Wiley and Sons.
6 Reprinted with permission.

7
8



9
10 Figure 2. CIELAB a^*b^* plot (a) and color icon (b) computed from CQsv9.0.2 for CIE illuminant
11 F3.

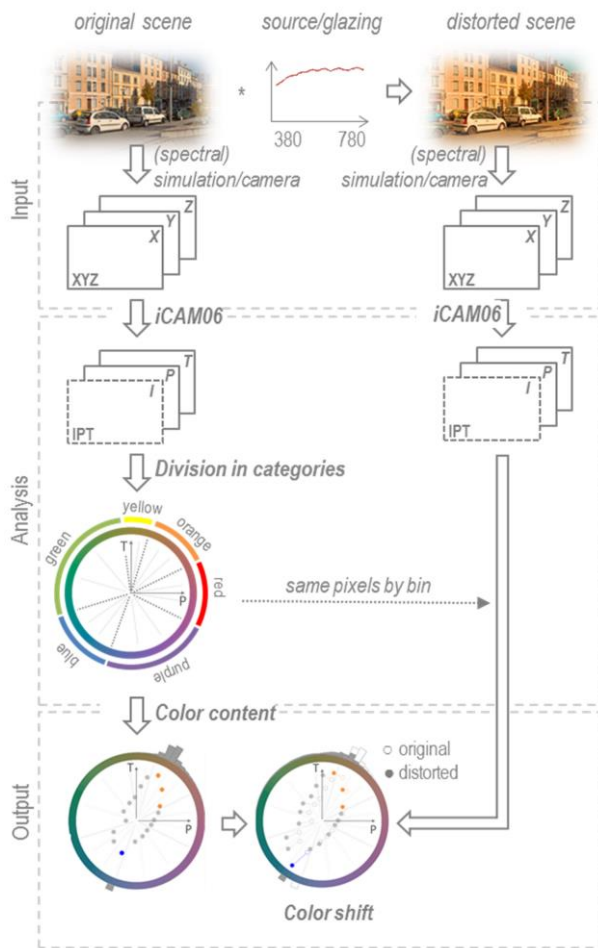
12
13



14
15 Figure 3. Color vector graphic (a) and color distortion graphic (b) computed from IESTM30-15
16 Advanced Calculation Tool v1.01 for CIE illuminant F3.

1

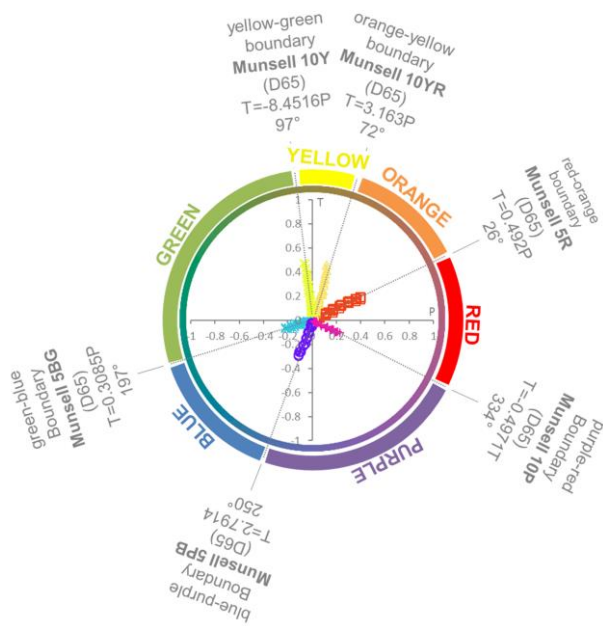
2



3

4 Figure 4. From data acquisition to color graphics.

5



1

2 Figure 5. Determination of the boundaries between the six principal color categories of the
3 color graphic.

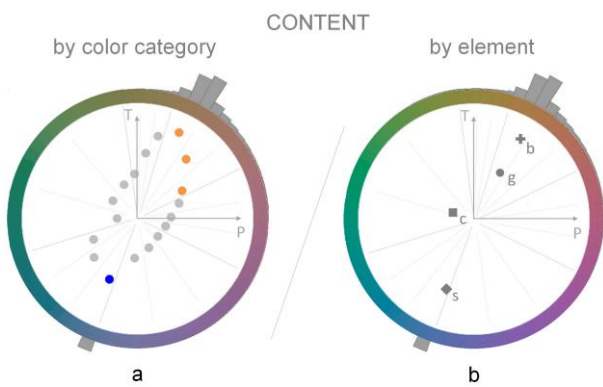
4

5

6

7

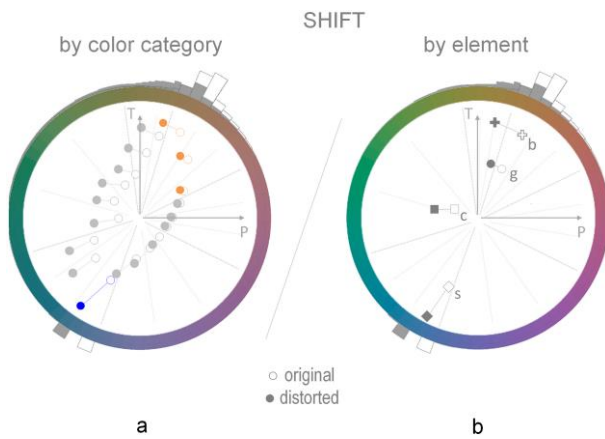
8



9

10 Figure 6. The two representations of the color content of a scene, a) by color category (gray
11 points mean that the scene is composed by less than 5% of this color) and b) by element (b, g,
12 c and s stand respectively for buildings, ground, green car and sky).

13



1

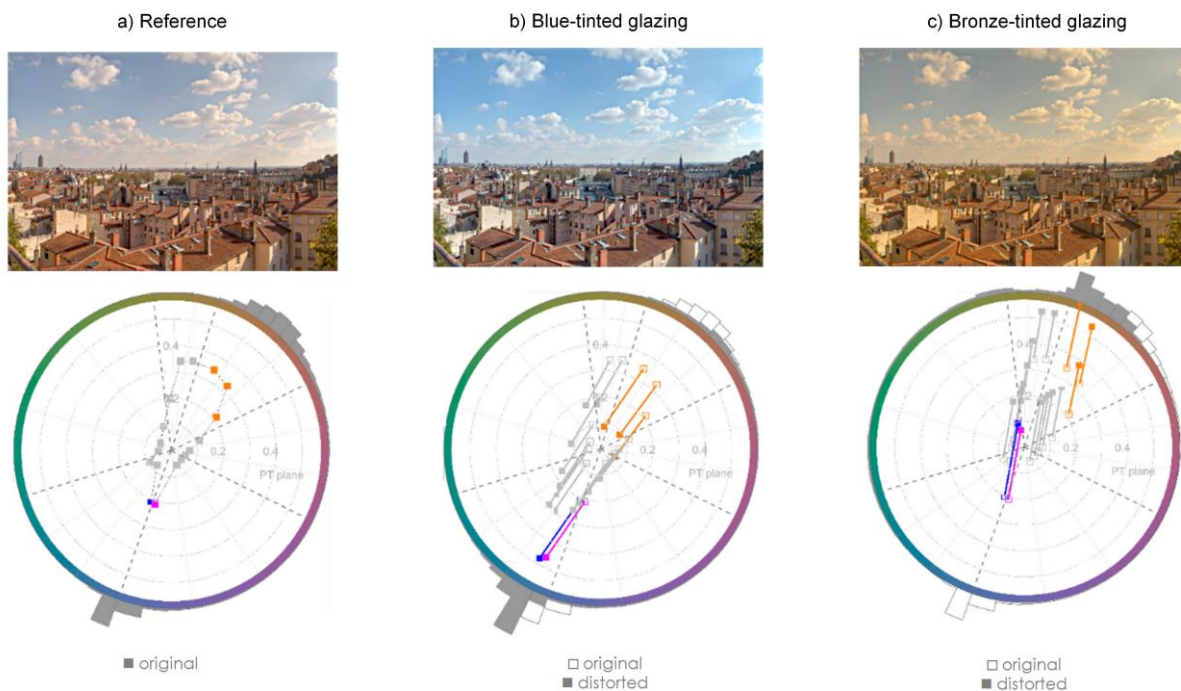
2 Figure 7. Representation of the color shift, a) by color category (gray points mean that the
3 scene is composed by less than 5% of this color) and b) by element (b, g, c and s stand
4 respectively for buildings, ground, green car and sky).

5

6

7

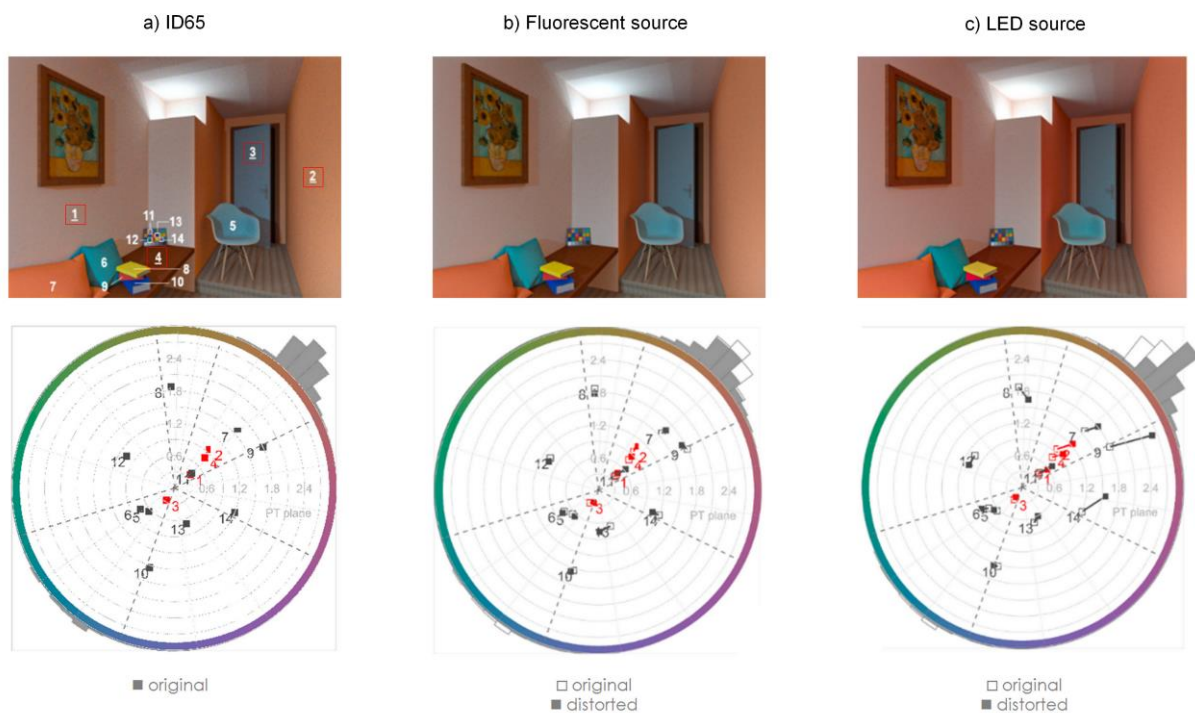
8



9

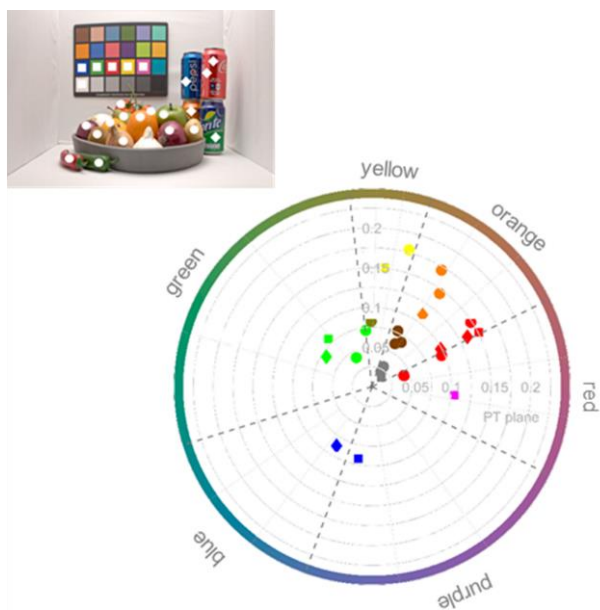
10 Figure 8. Renderings and color graphics for a) a clear glazing (reference) b) a blue-tinted
11 glazing (LEE filter 061) and c) a bronze-tinted glazing (LEE filter 763).

12



1
2
3
4
5
6

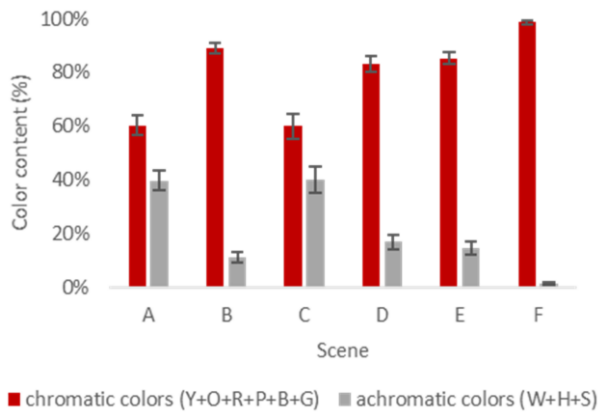
Figure 9. Renderings and color graphics (by element) for a scene illuminated a) with ID65 b) a fluorescent source c) a LED source. Red points are for architectural elements and black points for furniture.



7

Figure 10. Rendering and color graphic of a scene lit by a 3000K LED source, CIE Ra = 95 (■ MCC chart, ◆ cans, ● fruits/vegetables).

1



2

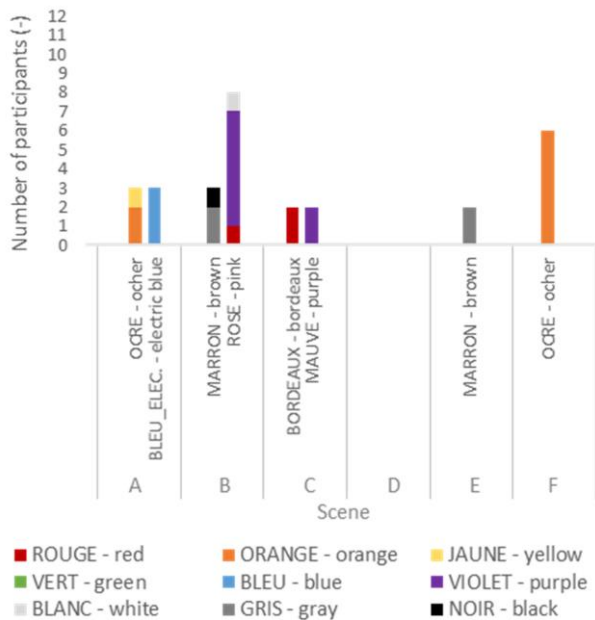
3 Figure 11. Distribution of chromatic and achromatic content in each scene. Color content by
 4 scene is calculated as the mean judgement given by the 12 participants. Chromatic content
 5 is the sum of yellow (Y), orange (O), red (R), purple (P), blue (B) and green (G) categories.
 6 Achromatic content is the sum of white (W), gray (H) and black (S) categories. Error bars are
 7 standard error of the mean.

8

9

10

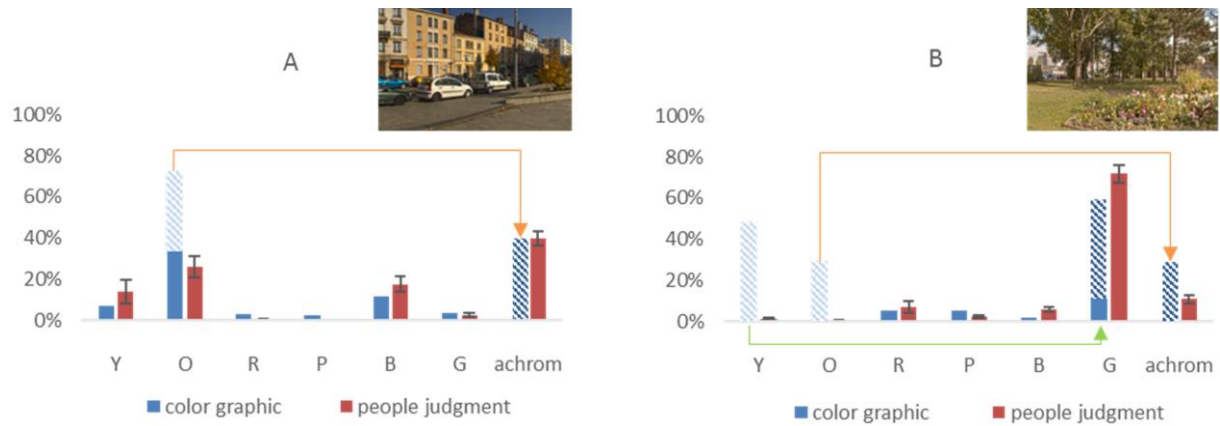
11



12

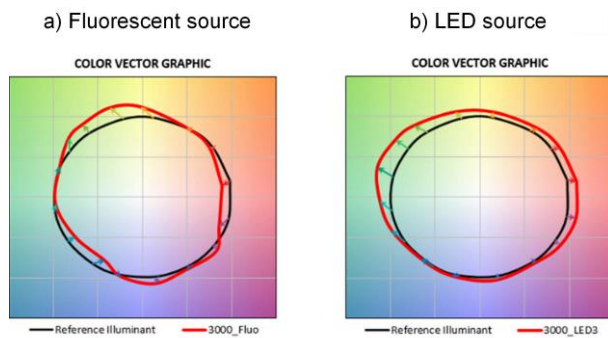
13 Figure 1. Allocation of listed non-basic colors to predefined color categories.

14



1
 2 Figure 2. Comparison between color content of a) scene A and b) scene B, as described by
 3 people and by the color graphic (Y, O, R, P, B and G stands respectively for yellow, orange,
 4 red, purple, blue and green bins, achrom is for achromatic content). Error bars are standard
 5 error of the mean.

6
 7
 8



9
 10 Figure 3. Color vector graphic calculated for (a) fluorescent source and (b) LED source.

11
 12
 13



14
 15 Figure 4. Illustration of real colors versus memory colors.