Chroma Shift and Gamut Shape: Going Beyond Average Color Fidelity and Gamut Area

Michael P Royer[1]
Kevin Houser[2]
Aurélien David[3]

[1]Pacific Northwest National Laboratory
620 SW 5th Avenue, Suite 810
Portland, OR 97204
michael.royer@pnnl.gov

[2] Department of Architectural Engineering, The Pennsylvania State University, University Park, Pennsylvania, USA

[3] Soraa, Inc., Fremont, California, USA

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Abstract

Though sometimes referred to as a two-measure system for evaluating color rendition, IES TM-30-15 includes key components that go beyond the two high-level average values, Fidelity Index (IES R_f) and Gamut Index (IES R_g). This article focuses on the Color Vector Graphic and Local Chroma Shift (IES $R_{cs,hj}$), discussing the calculation methods for these evaluation tools and providing context for the interpretation of the values. We illustrate why and how the Color Vector Graphic and Local Chroma Shift values capture information about color rendition that is impossible to describe with average measures (such as CIE R_a, IES R_f, or IES R_g), but that is pertinent to more completely quantifying color rendition, and to understanding human evaluations of color quality in the built environment. We also present alternatives for quantifying the Color Vector Graphic and Local Chroma Shift values, which can inform the development of future measures.

1 Introduction

The familiar CIE General Color Rendering Index R_a (CRI) [CIE 1995; Houser and others 2016] is a measure of average color fidelity, which means that it is intended to characterize the overall similarity of object color appearance between a test source and reference illuminant. However, subsequent research and published standards have documented the limitations and inaccuracies of the measure [CIE 2017; Davis and Ohno 2010; Houser and others 2016; Ohno 2005; Royer and others 2016; Smet and others 2015; Xu and others 2016]. Today, more accurate measures of average color fidelity are available [CIE 2017; IES 2015]. Regardless of these improvements, average color fidelity is only one aspect of color rendition. When considered alone, average color fidelity has been shown to be poorly correlated with human perceptions of color naturalness, normalness (the opposite of shifted [Royer and others 2016]), preference, and saturation [Islam and others 2013; Jost-Boissard and others 2014; Jost-Boissard and others 2009; Khanh and Bodrogi 2016; Khanh and others 2016a; 2016b; Khanh and others 2016c; Liu and others 2013; Ohno and others 2015; Royer and others 2016; Smet and Hanselaer 2015; Smet and others 2011; Szabó and others 2009; Szabo and others 2014; Teunissen and others 2016; Vick and Allen 2014; Wei and others 2014; Wei and Houser 2017; Zukauskas and others 2012]. That is, regardless of the specifics of the color fidelity measure, a single-number quantification of average color difference is insufficient for characterizing human perceptions of object color appearance in architectural environments [David and others 2015; de Beer and others 2015; Houser and others 2013; Rea and Freyssinier-Nova 2008]. Despite this knowledge, regulatory and energy efficiency agencies exclusively use color fidelity—specifically CIE R_a—as part of minimum specifications for color quality, sometimes supplementing average color fidelity with CIE R_9, a measure of red color fidelity.

Over the past 50 years, numerous measures of color rendition have been proposed that focus on a characteristic other than color fidelity. As outlined by Guo and Houser [2004], Rea and Freyssinier-Nova [2008], and Houser and colleagues [2013], gamut area has been considered an important complement to average color fidelity, and numerous iterations of gamut area measures have been proposed [Boyce and Simons 1977; David and others 2015; Davis and Ohno 2010; IES 2015; Rea and Freyssinier-Nova 2008; Teunissen and others 2016; Thornton 1972]. Like average color fidelity, however, gamut area is a limited characterization of color quality, providing no information about the rendition of objects having specific hues. Two light sources with equal average color fidelity *and* equal gamut area may be perceived differently because they distort different hues in different ways [Royer and others 2016].

IES TM-30-15 formalized a method for characterizing color rendition beyond average color fidelity (IES TM-30-15 R_f) and gamut area (IES TM-30-15 R_g), allowing for a multi-faceted comparison of color rendition across hues. The IES TM-30-15 Color Vector Graphic (CVG) is a visual representation of the average hue and chroma shifts within 16 defined hue-angle bins. Like all the measures included in IES TM-30-15, the representation is for a given light source in comparison to a reference illuminant of the same correlated color temperature (CCT). Complementing this visual information are Local Chroma Shift values (IES TM-30-15 $R_{cs,hj}$), which quantify the average relative chroma shift for the samples in each of the 16 hue-angle bins (j). Unlike measures of average color fidelity and gamut area, the CVG and Local Chroma Shift are relatively new and unfamiliar concepts with no directly-comparable historical counterparts—although they did evolve from previous work.

This article discusses *gamut shape*—defined as the average pattern of color shifts across different hues—and how it is characterized in IES TM-30-15 with the CVG and Local Chroma Shift (IES $R_{cs,hj}$). Specifically, it documents the formulas used to calculate IES $R_{cs,hj}$, which are not written in IES TM-30-15, but were included in the accompanying calculator tools. This article contrasts IES $R_{cs,hj}$ with hue-specific color fidelity (IES TM-

30-15 $R_{f,hj}$) and gamut area (IES R_g) to highlight important differences in derivation and meaning and explores how Local Chroma Shift measures, and gamut shape in general, can be used in practice. The article begins with a brief review of gamut area (specifically focused on IES R_g), because the topic is an important backdrop for understanding gamut shape; it does not include direct comparisons of various gamut area measures.

2 Review of Gamut Area

As it pertains to color rendition, gamut area is defined as the area enclosed by a set of test color samples illuminated by a light source, in a two-dimensional chromaticity diagram or a plane of color space. Gamut area is often converted to an index by dividing the area enclosed under a test light source by the area enclosed under a reference illuminant, then multiplying by 100. As such, values greater than 100 indicate an average increase in gamut area, whereas values less than 100 indicate an average decrease in gamut area. For some gamut area measures, the reference condition is a fixed illuminant (for example, CIE Illuminant C, CIE Illuminant E), whereas for others it is a specified illuminant at the same CCT as the test source.

This definition of gamut area is different from how the term is used in the printing and display industries, potentially sowing confusion. In those industries, gamut refers to the number or range of colors than can be created from a given set of primaries (for example, inks, color filters in liquid crystal cells). In architectural lighting, gamut may refer to the colors of light that can be created with a color-tunable fixture. The context is different for color rendition, however, which is the study of how the apparent color of an object changes based on the interaction of the spectral power distribution (SPD) and an object's spectral reflectance function for a standard observer and adaptation condition.

Gamut area is typically thought of as a measure of object color saturation (or chroma, or colorfulness), although to a small extent hue shifts can also contribute to changes in gamut area. A common tenet of measures of gamut area is that they treat changes to all the specified color samples equally. Gamut area measures are an average across all hues, meaning some colors may be desaturated while others are saturated. Gamut area has been linked to color preference in two known studies when used in conjunction with average color fidelity [Rea and Freyssinier-Nova 2008; Teunissen and others 2016], but both relied on 8 or fewer SPDs, which is not enough to sufficiently vary average color fidelity, gamut area, and gamut shape. Gamut area has also been linked to color preference in conjunction with gamut shape [for example, Wei and others 2016a, Wei and Houser 2017, Esposito 2016].

Gamut area measures date back to the early 1970s, with the Color Discrimination Index (CDI) proposed by Thornton [1972; 1973]. CDI—based on the eight test color samples used to calculate CIE R_a, like several measures to follow—received some attention in the research community [Boyce 1977], but did not become a mainstay of the broader lighting industry. The idea was revisited in 2008, when Rea and Freysinnier-Nova [Rea and Freyssinier-Nova 2008] proposed the Gamut Area Index (GAI). Note that these measures rely on non-uniform chromaticity diagrams intended for the specification of light sources—rather than modern object color spaces that account for chromatic adaptation—and use a fixed reference illuminant. This combination is particularly problematic for off-Planckian and low-CCT light sources, for which gamut area may be overstated or understated, respectively. The recently proposed G_a and Relative Gamut Area Index (RGAI) [Teunissen and others 2016] fix some of the limitations of these earlier measures by using a relative reference, but both still rely on a limited number of test color samples and G_a still relies on the CIE U*V*W* (1964) color space, which is nonuniform and has been superseded by several improved color spaces suited for describing object colors, including CIELUV (1976), CIELAB (1976), and CIECAM (1997, 2002).

Gamut area measures not based on the eight test color samples of CIE R_a have also been studied. Boyce and Simons [1977] proposed a gamut area measure based on the samples of the Farnsworth-Munsell 100 Hue Test. Davis and Ohno [2010] developed the Color Quality Scale (CQS), which includes the gamut measure Q_g that uses a set of 14 color samples with calculations performed in an object color space (CIELAB). Despite the availability of these gamut area measures for many years, they have seen limited use in the lighting industry and none was ever accepted by a national or international standardization body.

2.1 IES TM-30-15 R_g

IES TM-30-15's Gamut Index (IES R_g) is the only measure of gamut area that is currently formalized by an institutional authority. During the development process, a measure of gamut area was conceptualized as an important complement to the IES TM-30-15 measure of average color fidelity (IES R_f). However, the color evaluation samples (CES) used to calculate IES R_f—and all other measures documented in IES TM-30-15—do not form a polygon with approximately equal lightness, as they do for CIE R_a and its related gamut measures or CQS. Instead, they were carefully selected fill a three-dimensional volume related to the range of common colors, as described by David and colleagues [2015]. Thus, calculating an area enclosed by the samples required additional consideration.

IES TM-30-15 utilizes a modern, uniform color space, CAM02-UCS [Luo and others 2006]. CAM02-UCS is an extension of CIECAM02 [Fairchild 2013], built on the J (lightness), M (colorfulness), and h (hue) correlates of the latter. The first step toward calculating IES R_g is discarding the *J*' dimension of the CAM02-UCS color space. The calculation of IES R_g only considers shifts in the *a*'-*b*' plane, as motivated by the expectation that these shifts have a strong correlation to perceptions of saturation and preference in polychromatic environments. Strictly, the *a*' and *b*' dimension of CAM02-UCS form a plane based on M' (modified CIECAM02 colorfulness) and h (CIECAM02 hue angle). However, in the case of IES TM-30-15, the luminance level adaptation factor (F_L) is constant, meaning that M and C of CIECAM02 are direct linear correlates. For convenience of language, radial changes in the *a*'-*b*' plane are referred to as chroma shifts in IES TM-30-15 and its defined measures. Note also that in both CAM02-UCS and CIECAM02, chroma (or colorfulness or saturation), is not entirely independent of lightness, although hue, chroma, and lightness are typically used to describe the dimensions of color space.

To address the large number of samples with varying chroma, the *a*'-*b*' plane of CAM02-UCS was divided into 16 equally-sized bins based on hue angle [David and others 2015]. The intent of this procedure is to determine typical (average) shifts that occur for subsets of the 99 CES having similar hue angles (that is, 16 nominal colors), such that the values are easily interpreted and can be used to predict the performance of a light source when it is used in a real built environment. The developers believed that such average values are more useful than knowledge of the shift for any particular standardized color sample.

The number 16 was decided by consensus as a reasonable compromise between detail and simplicity, with enough CES in each bin to provide representative average color coordinates for the test and reference conditions. The binning protocol discards the shifts for individual CES, which may vary considerably among the small number of samples within each bin. However, it is important to remember that the 99 CES were selected to closely match the calculated terms (IES R_f, IES R_g, CVG) using a reference set of approximately 4,900 color samples [David and others 2015], which in theory represent all possible shifts in each hue-angle bin. The bins are numbered from 1 through 16 going counterclockwise from the positive *a*' axis. Hue-angle bin 1 is nominally red, 5 nominally yellow, 8 nominally green, and 12 nominally blue.

The averaged *a*' and *b*' coordinates of the samples in each hue-angle bin for the test and reference conditions constitute two polygons (**Figure 1**), the areas of which can be compared as done in earlier measures of gamut area. Complete equations are specified in IES TM-30-15, and discussed by David and colleagues [2015].

2.2 AlternativeGamut Area Measures

Since color spaces are three dimensional, a measure of change in color coordinates can in general be averaged along one, two, or three dimensions (corresponding to integration over a curve, an area, or a

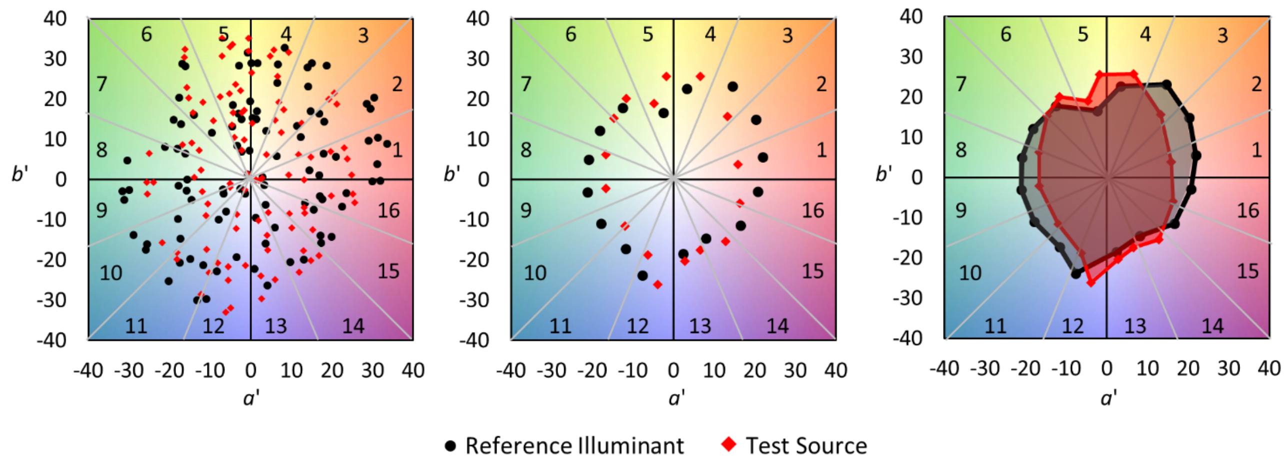


Figure 1. **Schematic of the calculation of IES R_g. First (left), the 99 Color Evaluation Samples (CES) are divided among 16 hue-angle bins based on the (a', b') coordinates of the sample under the reference illuminant. Next (center), the average a' and b' coordinates are calculated for both the reference and test condition in each hue-angle bin. Finally (right), the average coordinates are used to create two polygons, the areas of which are compared in the calculation of IES R_g.**

volume). All options were considered during the development of IES TM-30-15. The two-dimensional case, averaging in the a'-b' plane, corresponds to past iterations of gamut area and was deemed the likeliest to account for perception of integrated chroma or saturation level.

An example of a one-dimensional case is Change in Chroma (ΔC), a method under which change in chroma is averaged across color samples. This method was recently proposed by Khanh and colleagues using various sets of samples [Khanh and Bodrogi 2016; Khanh and others 2016a; 2016b]. Though seemingly similar, ΔC is not equivalent to a gamut area measure. As an extreme example, consider four color samples with equal reference chroma, where under a hypothetical test source two samples see their chroma doubled and the other two see their chroma reduced to zero, as shown in **Figure 2**. One would expect this test source to offer very poor color discrimination and contrast, since all color information along the b' (yellow-blue) axis is lost. Accordingly, the resulting gamut area of the samples is reduced to zero. However, the average chroma of this light source is equal to that of the reference illuminant—an inaccurate characterization of the light source's properties. Although this is an extreme example, it demonstrates why area-averaging is preferable. Moreover, hue shifts have some effect on gamut area, but are ignored by ΔC.

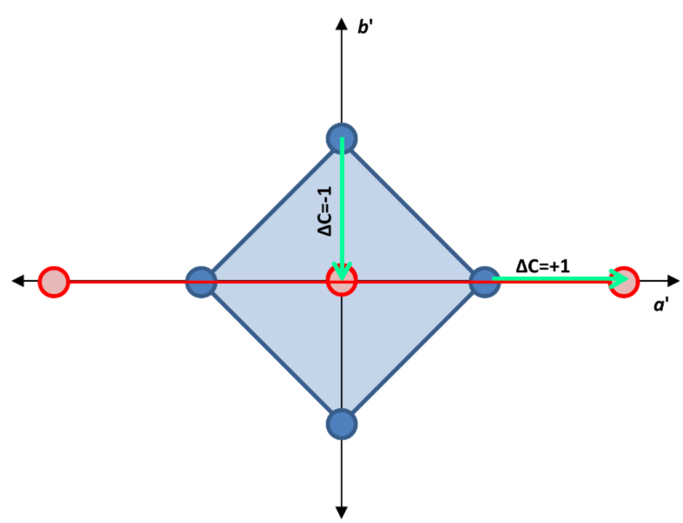


Figure 2. **Conceptual diagram of the differences between gamut area and average change in chroma. If all four samples have a change in chroma of 1 unit (two positive, two negative), there is no average change in chroma, but the gamut area becomes zero. This possibility is theoretical, and not expected to occur for any real light sources.**

For further illustration, **Figure 3** compares IES TM-30-15 R_g with ΔC_{CES}, a measure based on the change in chroma for the 99 CES of IES TM-30-15, using the chroma

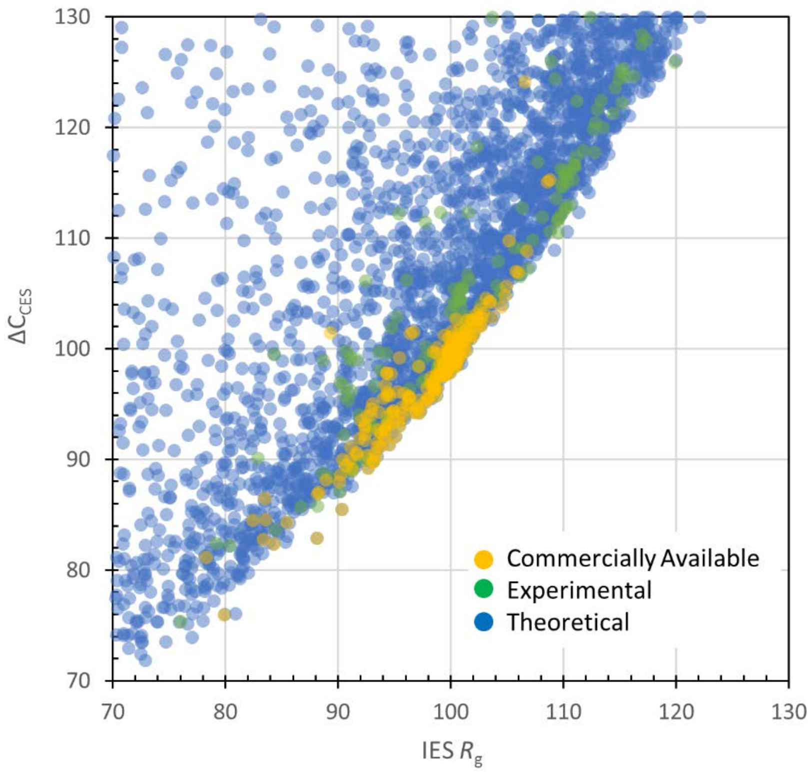


Figure 3. **Average change in chroma (ΔC_{CES}) versus gamut area (IES R_g) for a set of 211 commercially-available light sources, 152 experimental light sources, and 4,582 theoretical light sources. For most common light sources, the differences between the two measures is small, but for sources that induce large hue shifts, the differences can be substantial.**

correlate (C) of CIECAM02. ΔC_{CES} is calculated according to **Equation 1**, as described by Royer and Wei [2017].

$$\Delta C_{\mathrm{CES}} = 100 + 6.82\frac{\sum_1^{99} C_{i_{test}} - C_{i_{ref}}}{99}$$ **Equation 1**

The scaling factor of 6.82 was established so that the average ΔC_{CES} of a set of 344 SPDs was equal to the average IES R_g value for the same set of SPDs. The 344 SPDs are those from the IES TM-30-15 Advanced Calculator Tool library plus 26 from Royer and colleagues [2017]. As **Figure 3** illustrates, for most commercially available light sources, the values are similar, but especially for theoretical light sources, the values can be very different—in almost all cases, IES R_g is lower than ΔC_{CES}. When the difference between IES R_g and ΔC_{CES} was greater than 10 points for commercially available products, the SPDs were all highly structured with sharp peaks and valleys (for example, mercury vapor, color-mixed LED, theoretical tri-band illuminant) with low average color fidelity (IES $R_f \leq 74$). These light sources induce large hue shifts.

A two-dimensional alternative to IES R_g could be calculated based on the (a', b') coordinates of the 99 individual CES. That is, dividing the samples into hue-angle bins is not explicitly necessary for calculating of a gamut area measure. However, the 99 CES were not selected from the 4,900 sample reference set with this protocol in mind, and there are notable limitations to this approach. For example, the hue-angle order of the 99 CES can vary between the test source and reference illuminant, so that the polygon vertices would not be continuous (if the same sample order was used) or different polygons would be compared (if the samples were ordered independently).

An example of three-dimensional averaging would be comparing the volume defined by the IES TM-30-15 CES to that of the reference. This was deemed less desirable than a formula based on enclosed area. First, it would include direct contributions from changes in lightness, but there is no solid experimental knowledge relating lightness shifts to color preference or perception of saturation/chroma. Second, the calculation of a valid volume was fraught with conjecture: should one consider the convex hull of the samples (thus ignoring lower-chroma samples) or define some effective volume? Here again, no experimental knowledge was available to guide such a choice. Recently, the computation of a gamut volume and its relationship to color preference was explored by Liu and colleagues [2017], outside of the IES TM-30-15 system.

Some of these alternatives to IES R_g are still being examined by researchers and standards organizations. Additional work on methodologies for calculating gamut area or similar measures is warranted. All of the approaches described here—whether one-, two-, or three-dimensional—have one common attribute: they are an average representation. That kind of simplification can be useful for specifications and ease-of-communication, but it discards important information about hue-specific changes.

3 Gamut Shape and Hue-Specific Chroma Changes

Gamut area and related measures are an average of color shifts across all hues, meaning some colors may be desaturated while others are saturated. As a result, they may not always be aligned with perceptions of saturation or preference in polychromatic environments, because certain hues, most notably red, tend to influence psychology and perception more than others [Elliot and Maier 2014]. Specifically, two light sources with equal gamut area and average color fidelity can be perceived as different in terms of normalness, saturation, or preference [Royer and others 2016]. A number of studies have found similar results, with average color fidelity and gamut area not always capable of describing perceived differences in illuminated scenes [Esposito 2016; Royer and others 2016; Teunissen and others 2016; Wei and others 2016a; 2016b; Wei and Houser 2017].

One way to counter this problem is by considering *gamut shape*, which is the pattern of hue and chroma shifts for different nominal hues. Gamut shape especially highlights increases and decreases in chroma versus the reference. The pattern tends to be continuous across hue angle. The concept of gamut shape can be traced back to color rendering vectors [de Beer and others 2015; van der Burgt and van Kemenade 2010; Van Kemenade and Van der Burgt 1988; 1995], extended via the graphics associated with the Color Quality Scale [Davis and Ohno 2010], and further established in the graphics and measures of IES TM-30-15.

3.1 IES TM-30-15 Color Vector Graphic

The CVG is a special representation of the polygons used to calculate IES R_g (**Figure 1**), where the polygons are formed by connecting the average (a', b') coordinates of the samples in each of the 16 hue-angle bins. Instead of comparing the area of the two polygons, the CVG is used to examine the color rendition of different hues. To facilitate this, the polygon for the reference illuminant of the IES R_g calculation is normalized to a circle with a radius of 1. The shift of the average coordinates in each hue-angle bin is then transferred to the normalized circle; the shape resulting from connecting the ends of the individual vectors indicates relative color shifts under the test source. By design, the CVG discards information about the shifts for individual color samples within each hue-angle bin, which can vary but are not exactly independent [David 2013].

Figure 4 shows IES TM-30-15 CVGs for two light sources with approximately-equal average color fidelity and gamut area but different gamut shapes. Both light sources feature a nominally continuous gamut shape, visible in the oval shape of the red line compared to the circular black line representing the reference condition. The CVG is interpreted as follows:

- Arrows show the average shift in each hue-angle bin and are used to determine the vertices of the red shape, which is smoothed to improve the visual appearance of the graphic.
- Arrows projecting outward from the black reference circle indicate an average increase in chroma for the samples in that hue-angle bin.
- Arrows projecting inward from the black reference circle indicate an average decrease in chroma for the samples in that hue-angle bin.
- Arrows that are not purely radial indicate hue shift. An arrow that is tangential to the reference circle indicates that the average sample in the specific hue-angle bin only shifts in hue, not chroma.

In **Figure 4**, the CVG on the left represents a light source that increases red and green chroma compared to the reference, simultaneously shifting oranges toward red. The CVG on the right provides the opposite pattern of distortion, increasing nominally blue and yellow chroma compared to the reference, while shifting oranges toward yellow and purples toward blue. This latter pattern is typical of most tri-phosphor

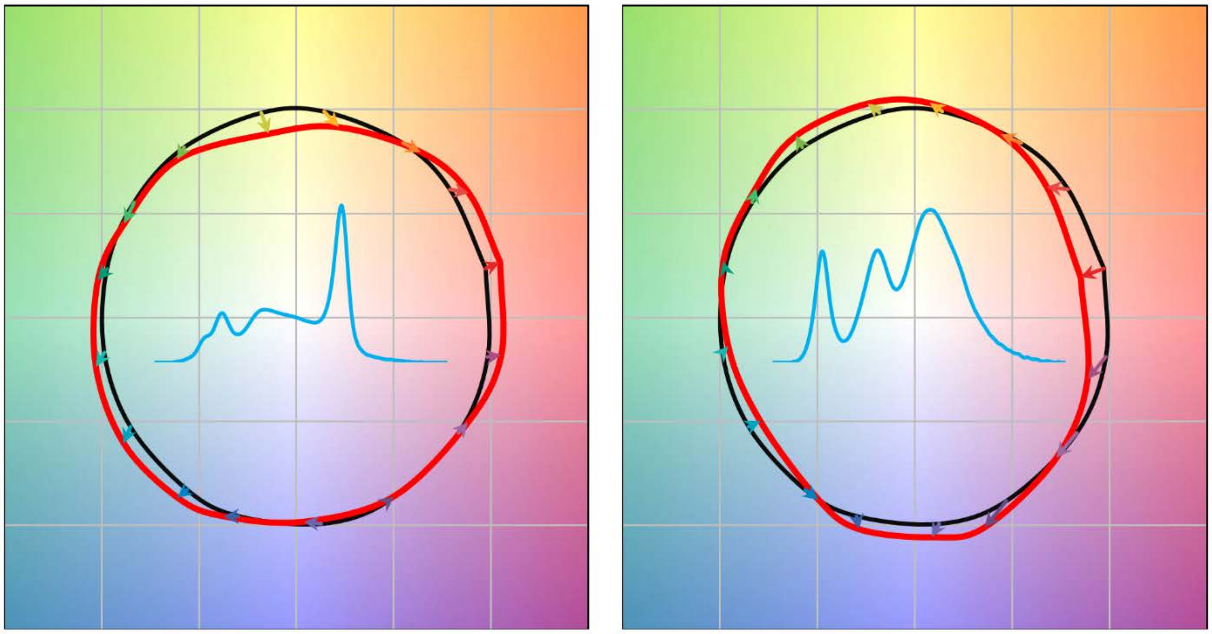


Figure 4. IES TM-30-15 Color Vector Graphics (CVGs) for two light sources used in a recent experiment [Royer and others 2016]. Despite very similar average color fidelity (~84), gamut area (~100), chromaticity, and delivered illuminance values, the light sources were rated statistically different in terms of saturation. Added to the center of each CVG is the SPD.

fluorescent lamps and phosphor-converted white LEDs that were designed to have a minimum CIE R_a value (for example, 80) while maximizing luminous efficacy. In a recent experiment, the lighting conditions corresponding to these two CVGs were perceived differently [Royer and others 2016], with the one on the left preferred to the one on the right. **Figure 5** shows a variety of CVGs for real (commercially available or experimental) light sources.

Exact specifications for formatting the CVG are not provided in IES TM-30-15, although an example graphic is included. Refinements in formatting may help improve future versions of the CVG. For example, instead of rectangular gridlines, it may be better to show radial gridlines representing the hue-angle bins. Further extending this approach to include concentric circles and complete polar axes is also a possibility.

Compared to the original proposal of color rendering vectors by Van Kemenade and Van der Burgt [1988] nearly 30 years ago, the use of 16 vectors for the CVG is a simplification that helps clarify trends in hue and chroma shifts, making the characterization more accessible. Information about individual sample shifts, which was maintained in conceptual precursors, is discarded. Sample-specific shifts are calculated as part of the IES TM-30-15 procedure, although specific hue and chroma components were not formalized as an identified measure. The importance of such values to applied lighting has not yet been demonstrated, but it would be possible to create an additional set of formalized measures or a graphic in a future revision.

Averaging the color samples in each hue-angle bin helps the CVG to display a continuous gamut shape, since the specific interaction of a narrow spectral feature with a change in a single objects' reflection is balanced against the broader set. However, the individual color shifts within a hue-angle bin can vary in magnitude and direction with absolute chroma, as depicted in **Figure 1** and as further illustrated by David [2013]. The differences among individual vectors for each CES should be put into context with the limitation of using standardized samples to predict the appearance of a real architectural environment. The individual vectors were considered too detailed and unhelpful for this graphical display—although this does not discount the

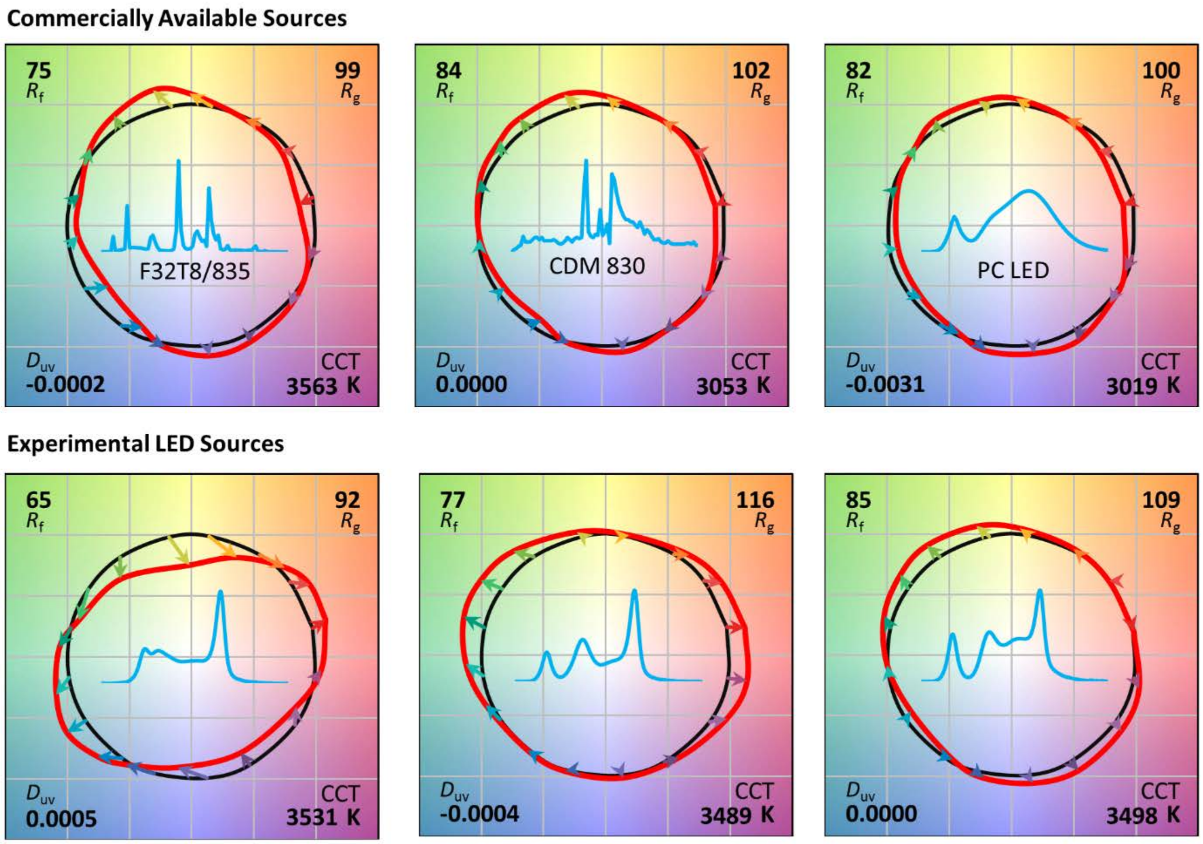


Figure 5. IES TM-30-15 Color Vector Graphics (CVGs) showing currently-available and select experimental gamut shapes. The SPD at the center and numerical data in the corners are added to the CVG exemplified in IES TM-30-15.

value of an added number of samples for calculating numerical measures. The variation in shifts for color samples of similar hue angles is a different concept that is not intended to be presented in the CVG, nor has it been the intended focus of any color rendition measure or perceptual experiment.

The exact number of averaged samples varies by hue-angle bin and depends on the CCT of the reference illuminant (**Figure 6**). In other words, while the 99 CES are uniformly distributed in color and wavelength space [David and others 2015], they are not uniformly distributed across the 16 hue-angle bins. The variation in quantity per hue-angle bin at any given CCT occurs because (1) the color volume itself is not uniformly distributed across hue angle, (2) the binning used to select the 99 CES was based on rectangular coordinates that do not match the polar specification of the hue-angle bins, and (3) some of the rectangular bins span more than one hue-angle bin. The variation in the number of CES per bin as a function of CCT occurs because there are differences in the color volume as a function of CCT. Over the CCT range of 2500 to 7500 K, the mean number of CES is as small as 2.96 (bin 14) and as large as 9.27 (bin 5). The range of CES-per-bin over the CCT range is as small as 2 (bin 14 has 2 to 4 CES) and as large as 7 (bin 6 has 4 to 11 CES). At any given CCT, the greatest number of CES in any one bin is between 9 and 11 (within one or more of bins 1, 3, 4, 5, 6, 9, 11) and as small as 2 or 3 (within one or more of bins 7, 8, 12, 14, and 15). As explained by David and colleagues [2015], the CES selection process used the 5000 K reference illuminant of IES TM-30-15; a different illuminant would likely have resulted in a different distribution of samples within each hue-angle bin.

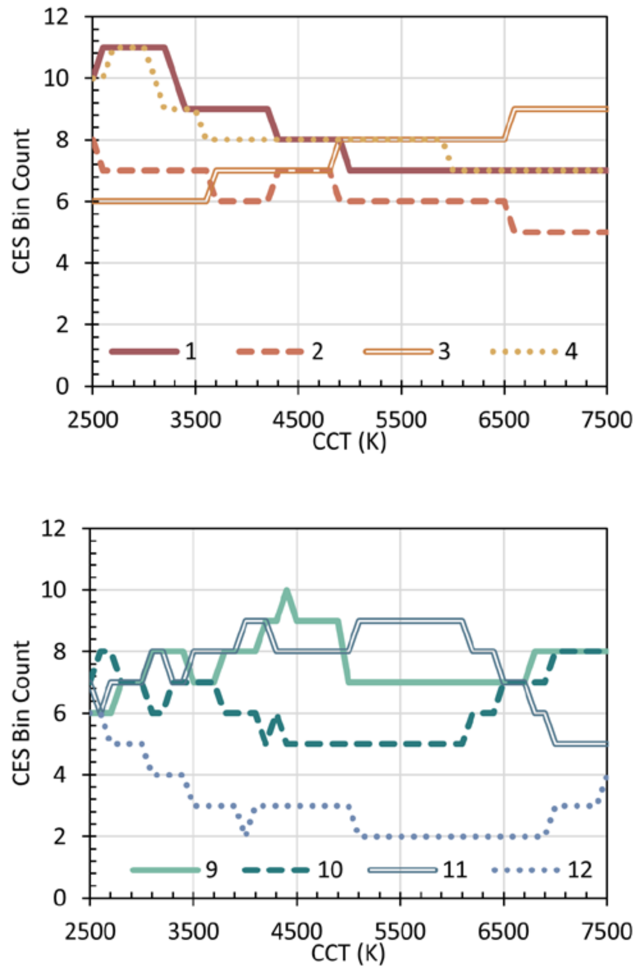


Figure 6. The number of CES in each hue-angle bin depends on the reference illuminant.

One might worry that such variations may strongly impact the CVG and other IES TM-30-15 measures for light sources of different CCTs. However, the 99 CES were designed to replicate the numerical predictions of an initial reference set of about 4,900 samples [David et al 2015]; this reference set has hundreds of samples per hue-angle bin and does not suffer from large swings in populations with CCT. For most light sources, the two sample sets offer very similar CVGs, as shown in Figure 7 for a typical linear fluorescent lamp and a phosphor-coated white LED. The CVGs on the left were calculated according to IES TM-30-15, whereas the CVGs on the right were calculated by replacing the 99 CES with the 4,900-sample reference set.

In some extreme cases, however, the lower sample count retained in TM-30-15 does produce deviations from CVGs determined using the reference set. **Figure 7** also shows two pairs of CVGs for theoretical SPDs that include very narrow, laser-like spectral components. Discontinuities, or abrupt changes, in the path of the test source seen in the two standard CVGs are the result of the limited number of color samples in each hue-angle bin. They do not appear when the CVG is generated using the reference set. The 99 CES were selected so that IES R_f and IES R_g were highly correlated between the 99 and 4,900 color sample sets; maintaining the CVG shape was an additional criterion weighted with lower importance. This artifact—whereby the CVG is an imperfect representation of gamut shape in extreme circumstances—is expected to have little practical impact on light source engineering, but does suggest a potential benefit of increasing the number of color samples used to calculate the CVG.

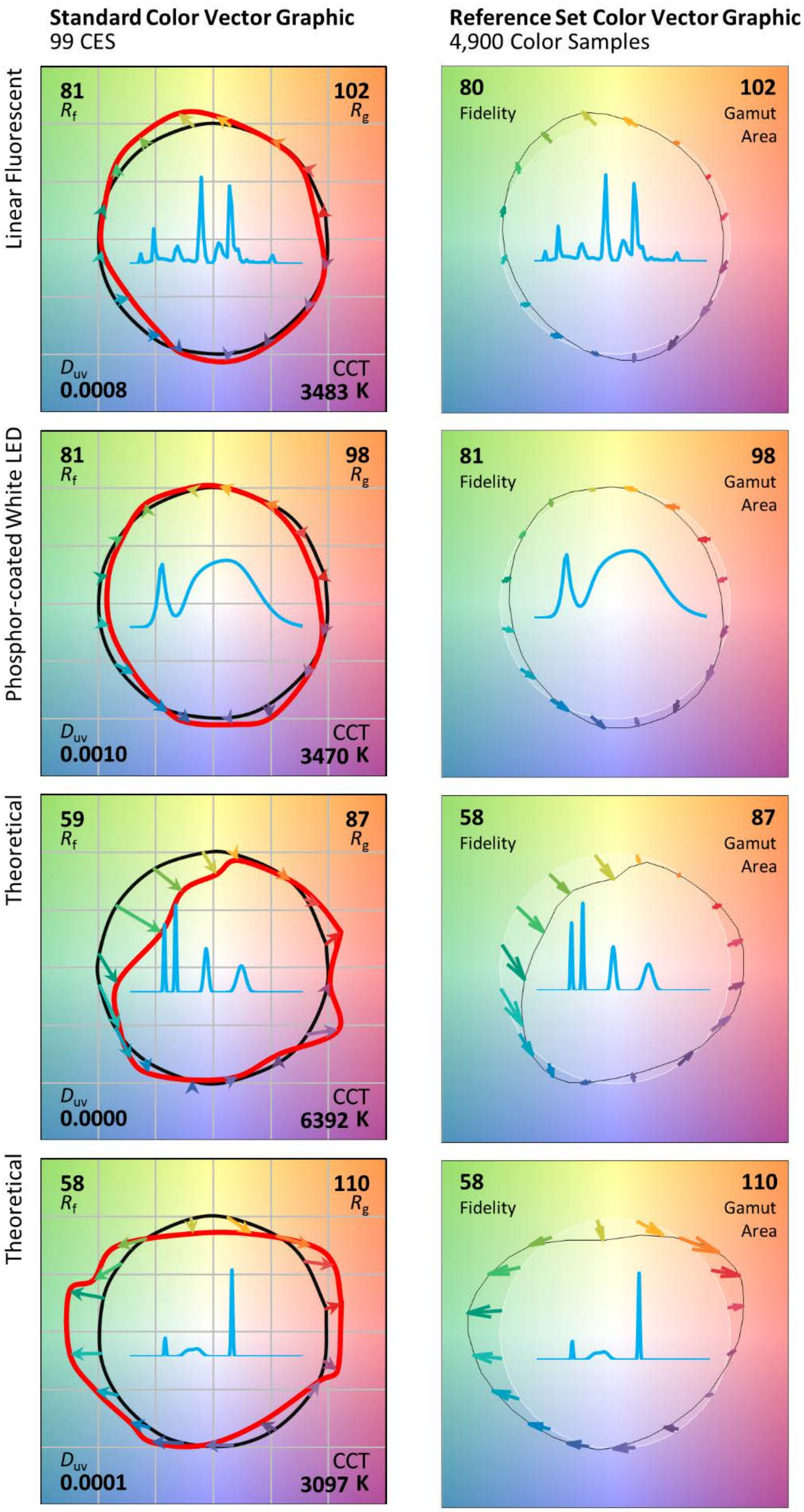


Figure 7. **Standard IES TM-30-15 CVGs (left) versus graphics calculated with a set of 4,900 color samples instead of the 99 CES (right), for fluorescent, LED, and two theoretical SPDs.**

To derive a simplified numerical system for quantifying gamut shape, Esposito [2016] used a method based on a best-fit ellipse, specifying length of the semi-major axis, length of the semi-minor axis, and angle of rotation. Further investigation of such methods is warranted.

One downside of the TM-30-15 CVGs is that they do not provide an easy way to compare small differences between products, or evaluate the magnitude of a difference. Likewise, they cannot easily be incorporated into a specification. To address this, the numerical analog IES $R_{cs,hj}$ was established, with one value for each of the hue-angle bins. The 16 values are collectively referred to in this manuscript as Local Chroma Shift—but were referred to in some previous literature as Hue-Angle Bin Chroma Shift.

3.2 IES TM-30-15 Local Chroma Shift (IES $R_{cs,hj}$)

The CVG was considered a key element of IES TM-30-15 by the committee that developed the method, precisely because it provides detailed information that goes beyond average color fidelity and gamut area. To address some of the limitations of the CVG, IES TM-30-15 Local Chroma Shift values (IES $R_{cs,hj}$) were established in the calculator tools accompanying IES TM-30-15. The intent of these values was to quantify the purely radial shift associated with each of the 16 vectors comprising the CVG; thus, a vector projection method was used. The calculation is as follows, with further information in **Figure 8**:

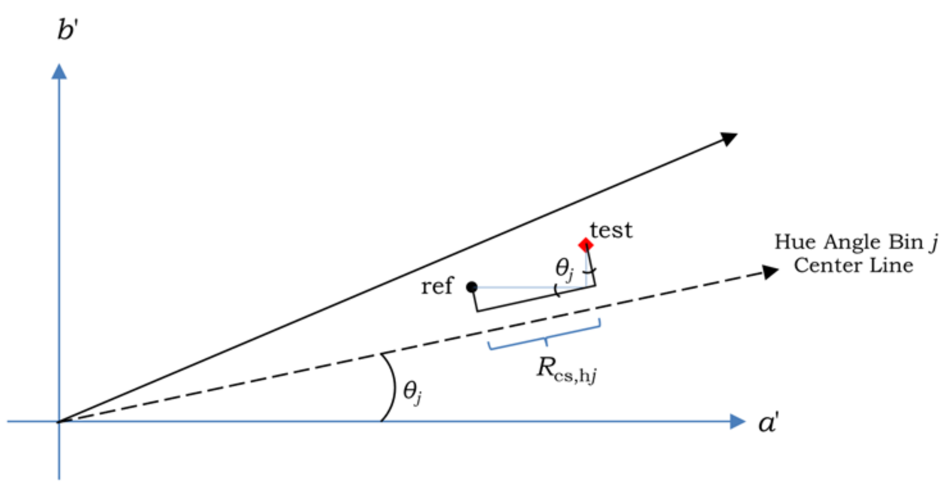
$$R_{\mathrm{cs,h}j} = \frac{(a'_{test} - a'_{ref})}{\sqrt{({a'_{ref}}^2 + {b'_{ref}}^2)}} \cos\theta_j + \frac{(b'_{test} - b'_{ref})}{\sqrt{({a'_{ref}}^2 + {b'_{ref}}^2)}} \sin\theta_j \qquad \textbf{Equation 2}$$

Where:

- a' and b' are the average CAM02-UCS coordinates for the CES in the hue-angle bin under the test and reference (ref) conditions, as indicated.
- θ_j is the angle of the vector bisecting each hue-angle bin, as measured from the positive a' axis (the division between hue-angle bins 1 and 16).

Local Chroma Shift values are based directly on the vectors shown in the CVG, where the reference coordinates are normalized to a circle with a radius of 1. Accordingly, the IES $R_{cs,hj}$ values represent a *relative* chroma shift and can easily be represented as a percentage. Since the *absolute* chroma shift (and total shift) of a sample roughly scales with the absolute value of the initial chroma (that is, high-chroma samples undergo a larger shift) [David 2013; Royer and Wei 2017], the relative shift is a well-defined quantity that

Figure 8. Schematic of calculation for IES $R_{cs,hj}$.



can be used to estimate the effect of the SPD on all samples of a given hue, from very low to very high chroma.

A key to interpreting the set of 16 measures, which are derived from the same 16 vectors as the CVG, is that negative values represent decreases in chroma and positive values represent increases in chroma. This is analogous to how gamut area values are interpreted above and below 100, although IES R_g values are based on absolute changes, whereas Local Chroma Shift values are based on relative changes. When presented as a group (**Figure 9**), it can be observed that the pattern of numerical values correspond with the relative position of the test and reference shapes in the CVG (**Figure 4**). While they provide the same information, IES TM-30-15 Local Chroma Shift values are important because they provide a numerical characterization of gamut shape that can be incorporated in a specification or implemented as an engineering target.

The bi-directionality of Local Chroma Shift values is a departure from the traditional way hue-specific information has been delivered as fidelity values (for example, CIE Special Color Rendering Indices R_9

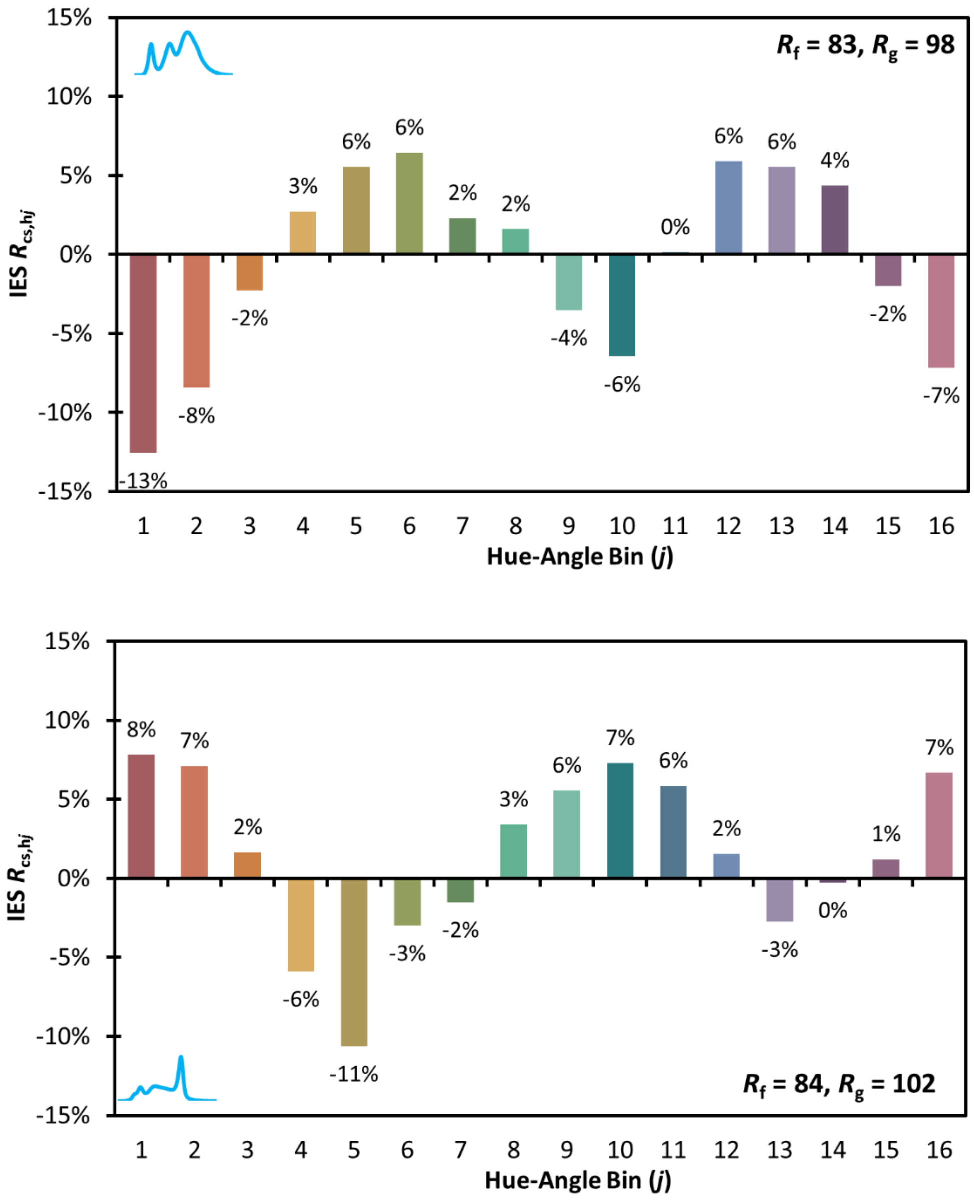


Figure 9. Local Chroma Shift (IES $R_{cs,hj}$) values for the two light sources shown in Figure 4.

through R_{14}). As shown in **Figure 10**, light sources with a given hue-specific fidelity value may either increase, decrease, or have no effect on the chroma of objects with the given hue. This leads to another important point of interpretation: a Local Chroma Shift value of 0% does not indicate that no color shift is occurring, because hue (and lightness) shifts are still possible. It is also relevant that Local Chroma Shift values are independent of average color fidelity and gamut area.

Figure 10 also demonstrates key differences between IES $R_{f,h1}$ and CIE R_9. Although they are both measures of red color fidelity, the use of CIE U*V*W*, a non-uniform color space, to calculate CIE R_9 means increases in red chroma lowers the CIE R_9 value more than decreases in red chroma. This does not happen with IES $R_{f,h1}$. While increasing luminous efficacy of radiation (LER) is likely the primary driver of commercially-

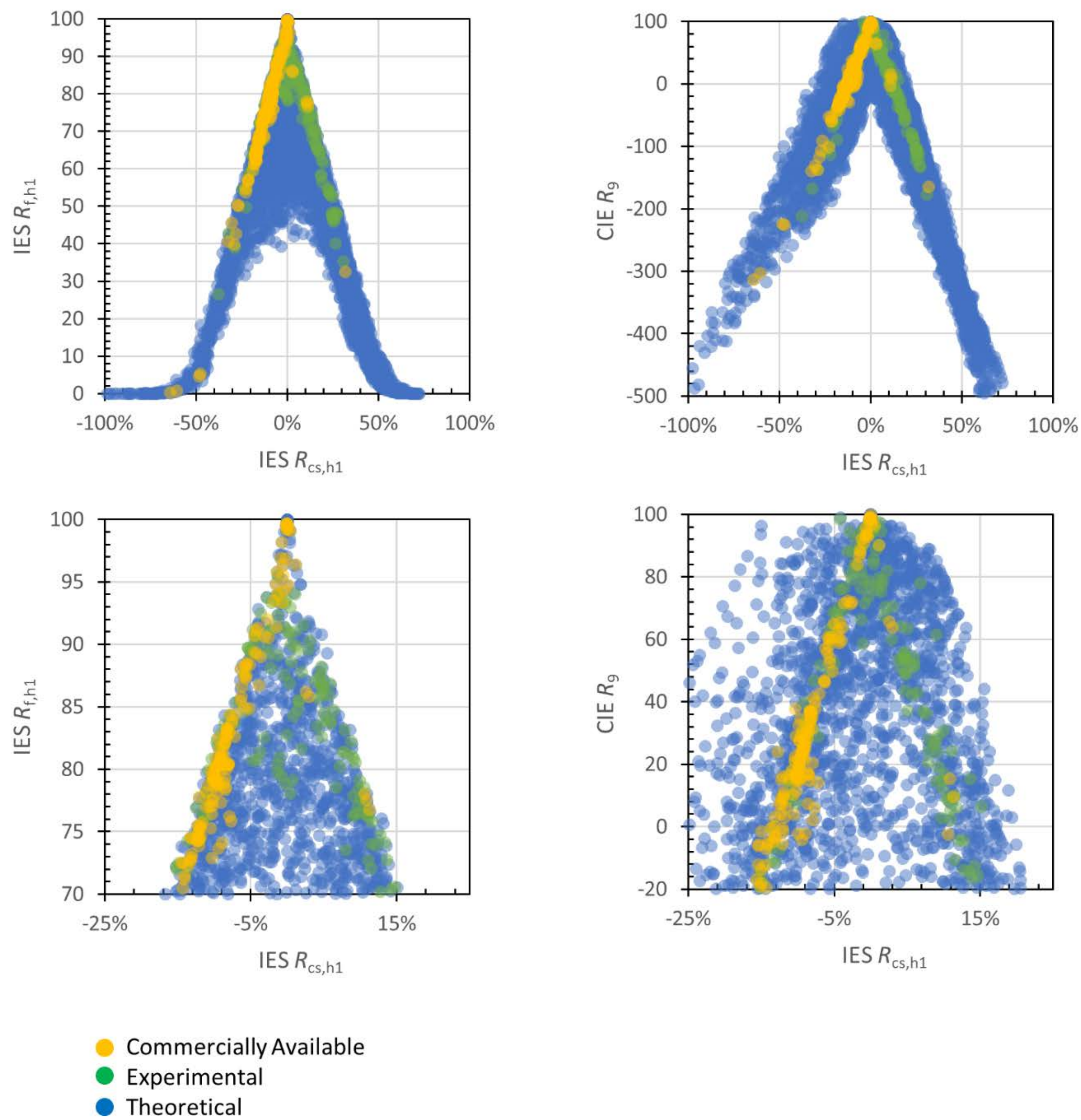


Figure 10. **Comparison of IES $R_{f,h1}$ (left) and CIE R_9 (right) versus IES $R_{cs,h1}$. Both comparisons show that a given value of red fidelity can mean very different chroma for red objects. Both comparisons also show that current commercially-available light sources almost unanimously reduce the chroma of nominally red objects. Together, the charts demonstrate how a decrease in chroma of reds (IES $R_{cs,h1}$) is penalized less by CIE R_9 than an increase in chroma of equal magnitude, and that the performance of one sample is not always representative of similar-hued samples.**

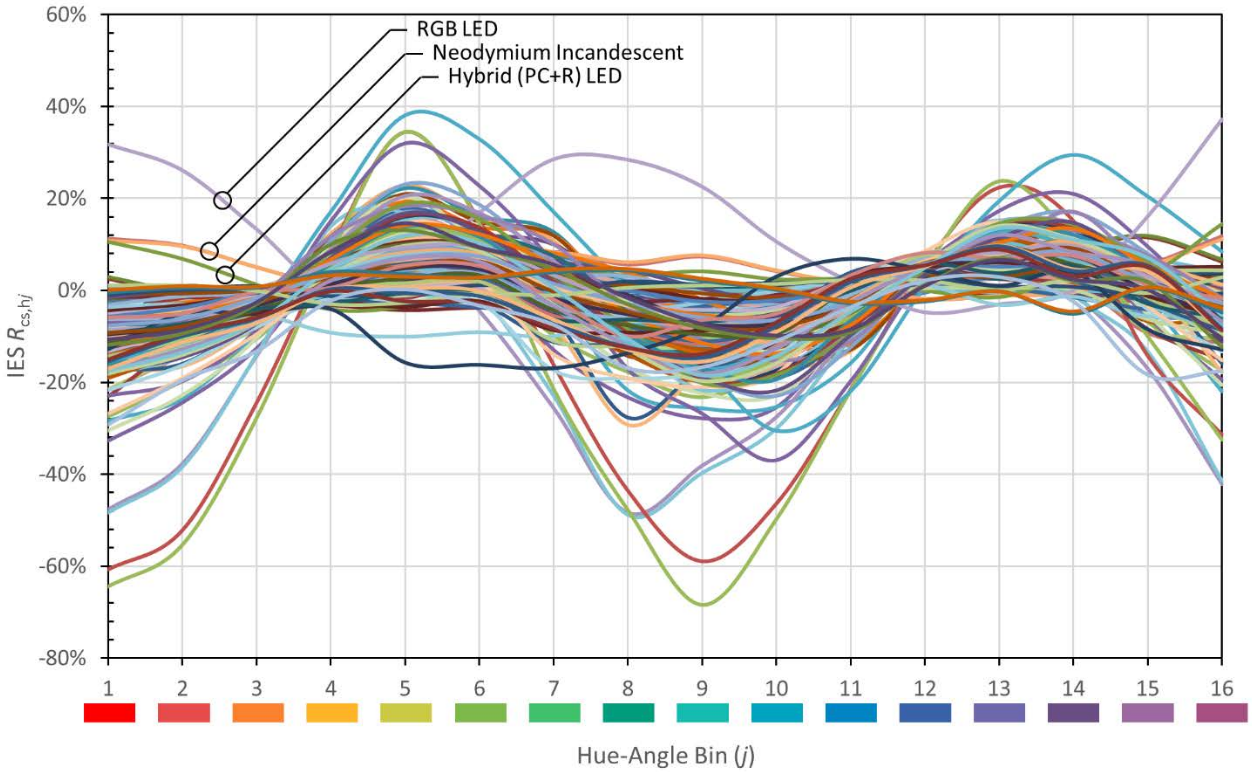


Figure 11. Local Chroma Shift patterns for commercially-available light sources listed in the IES TM-30-15 Calculator Tool Library. Note that this set of light sources is not representative of the present lighting market, but does include many LED, fluorescent, and HID sources that were available prior to 2015.

available light sources most often decreasing red chroma compared to the reference (**Figure 11**), this limitation of the CIE test color method further discourages increasing red chroma compared to the reference. As a secondary effect, measures of red fidelity (for example, CIE R_9, IES $R_{f,h1}$) are reasonably effective for conveying red color rendition for most currently-available lighting products. That does not hold true, however, if a broader set of light sources with more variety in gamut shape is considered.

The possible ranges of IES $R_{cs,hj}$ can be probed by examining a large set of SPDs. **Figure 12** shows the range in possible values for each hue-angle bin for a set of 211 commercially-available and 152 real but experimental SPDs, as well as a set of 4,582 randomly-generated theoretical SPDs (comprised of up to four Gaussian primaries of varying full-width-half-maximum, with the resulting SPD between approximately 2500 and 6500 K on the Planckian locus). For both datasets, the range across hue-angle bins varies, with nominally red and green hue-angle bins having a greater range in possible values than blue and yellow hue-angle bins. For example, in hue-angle bin 1, the theoretical range is -99% to +72%. For commercially-available and experimental light sources, the range is -64% to +32%. If only light sources with IES $R_f \geq 70$ are considered, the ranges become considerably smaller. For commercially-available and experimental light sources, the range for IES $R_{cs,h1}$ is -29% to +19%. Of the included commercially-available light sources, only neodymium incandescent, one hybrid LED (phosphor plus direct red), one phosphor-based LED, and Super High-Pressure Sodium (HPS) sources have IES $R_{cs,h1}$ values greater than zero. As is the nature of averages, the relative chroma shift for any individual CES—or any real object—may exceed the ranges shown for Local Chroma Shift values.

In contrast to the features of commercial availability light sources, several research studies have found that increases in red chroma are preferred [Davis and Ohno 2010; Esposito 2016; Ohno and others 2015; Royer

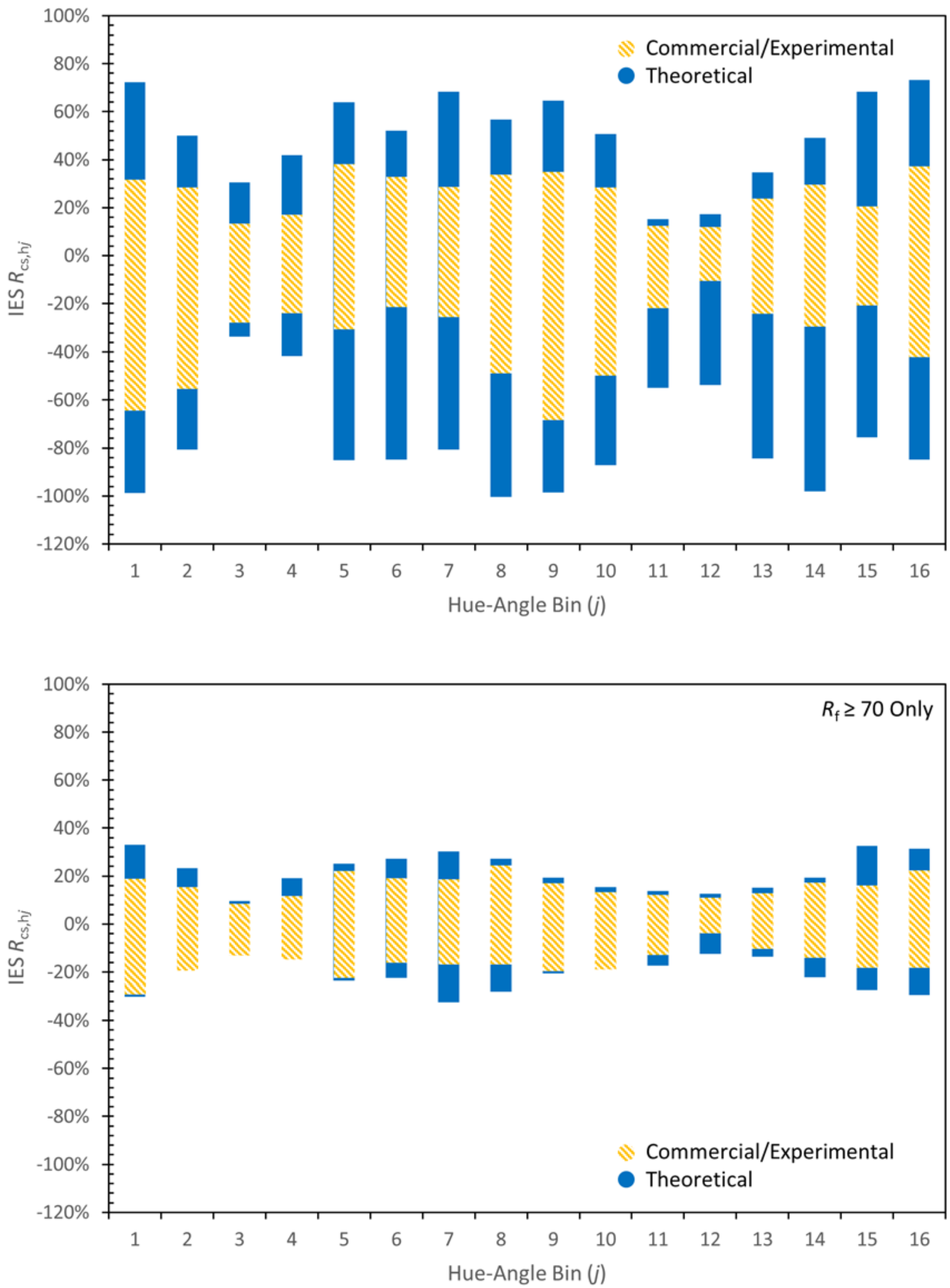


Figure 12. Approximate range of potential values for each Local Chroma Shift value. The bottom graph is limited to only SPDs with IES $R_f \geq 70$, which also limits the range of potential values.

and others 2017; Royer and others 2016; Wei and others 2016a; 2016b], including several studies that have examined IES TM-30-15 Local Chroma Shift values. One study [Royer and others 2017] found that acceptable ranges for IES $R_{cs,h1}$, when paired with a threshold for IES R_f (75), were -7% to 15%, with the most preferred light sources between -1% and 15%. In at least three recent experiments on perceptions of color rendition,[Esposito 2016; Royer and others 2017; Royer and others 2016] Local Chroma Shift values have been extremely well correlated ($r^2 > 0.90$) with perceptions of saturation, and integral components of models strongly correlated with perceptions of normalness and preference.

As more research on gamut shape emerges, new guidelines and recommendations should be generated. This should include application-specific material, as a key benefit of using Local Chroma Shift values is that they allow for consideration of objects with specific hues in a space. Red chroma shift may be important in generic, polychromatic environments, but other colors may be important in specific applications. For example, green chroma shift is likely most relevant for lighting foliage. Further, tunable systems could allow consideration of the specific hues within a specific piece of art.

Like all measures of color rendition, Local Chroma Shift values simplify the complex interaction of an SPD and spectral reflectance functions. Accordingly, they do have limitations. Local Chroma Shift values ignore hue shifts, and they are the average of several standardized color samples. As with any average, the relative chroma difference between test and reference for individual color samples can vary, but it is important to remember that individual sample color shifts are not likely to be more predictive of performance in a real architectural space than the average of multiple samples with a similar hue angle. Accordingly, two light sources with equal Local Chroma Shift values could render a specific object color differently—although the degree of difference is likely much less than if only average color fidelity is considered. Like any hue-specific measures, they cannot be used alone to specify color rendition, as anything is possible in the other hues. Still, based on recent experiments on human perceptions, they convey critical information about color rendition.

3.3 Alternative to IES $R_{\mathrm{cs,h}j}$

Another method for calculating a similar value to Local Chroma Shift would be simply calculating ΔC_j, or the difference in chroma for the average test and reference condition in a given hue-angle bin (**Equation 3**), using CIECAM02. This method has the benefit of relying on a more straightforward and established calculation, although it is slightly removed from the CVG. As with IES $R_{\mathrm{cs,h}j}$, the values are appropriately represented as a percentage.

$$\Delta C_j = \frac{C_{test,j} - C_{\mathrm{ref},j}}{C_{\mathrm{ref},j}} \qquad \textbf{Equation 3}$$

Figure 13 compares ΔC_j and IES $R_{\mathrm{cs,h}j}$ for four representative hue-angle bins (1, 3, 9, and 13). As can be seen, the relationship between the two measures is strong, but not perfectly linear. The relationship varies somewhat based on hue-angle bin, since hue shifts are more likely in some bins than others. IES $R_{\mathrm{cs,h}j}$ tends to moderate very large positive chroma shift values compared to ΔC_j. The measures are approximately linearly related in the smaller region of interest for commercial light sources, so they can be expected to perform similarly for characterizing human perceptions.

As the body of knowledge surrounding IES TM-30-15 grows, it will be appropriate to revisit the included measures and evaluate whether revision or substitution is warranted. IES TM-30-15 provides a core calculation methodology, from which numerous values can be calculated. During development, the values deemed most likely to be useful were formalized and given names, but that does not mean that other calculations cannot be made, evaluated, and proposed for future inclusions in revised versions of IES TM-30.

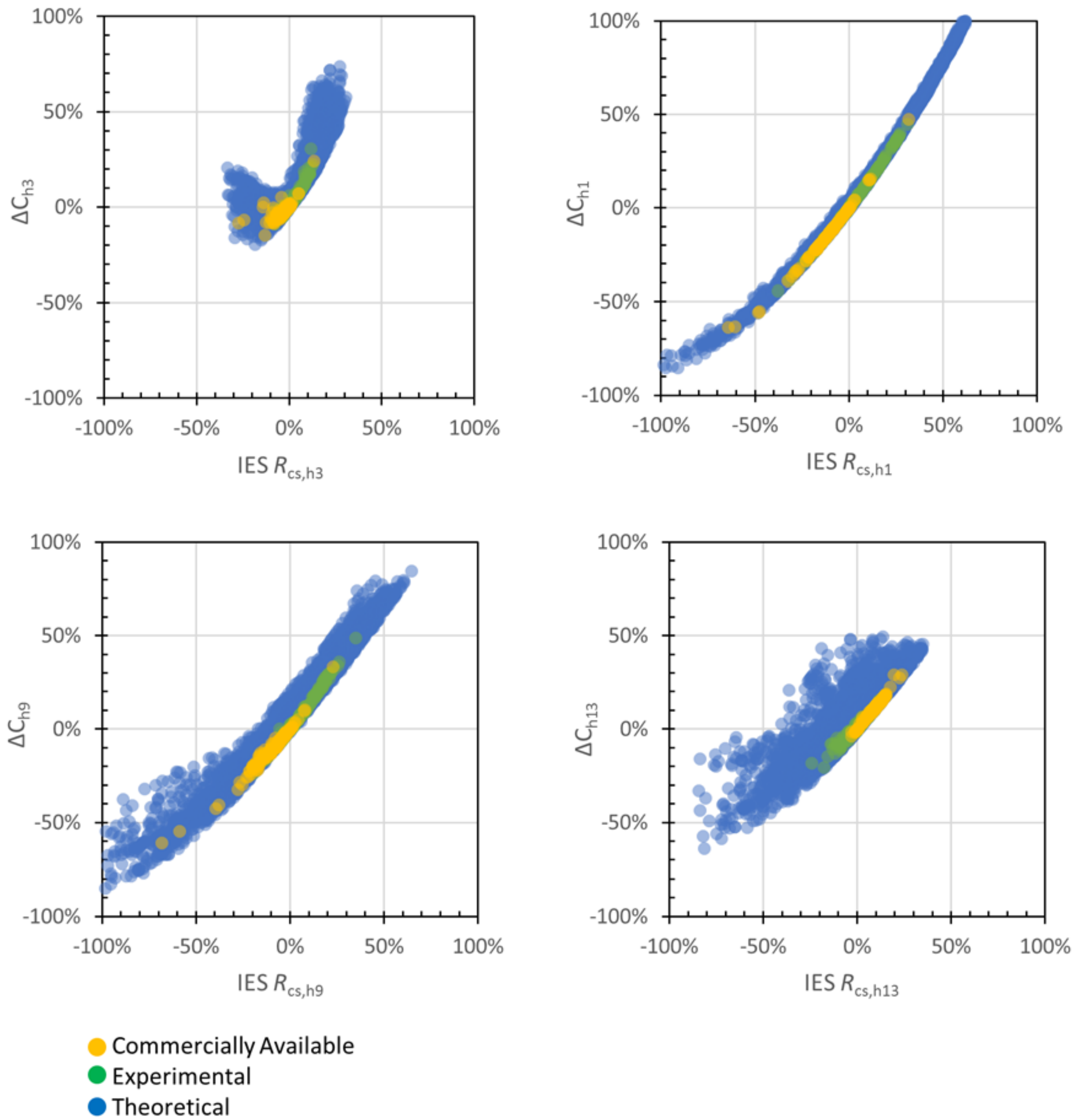


Figure 13. Approximate range of potential values for each Local Chroma Shift value. The bottom graph is limited to only SPDs with IES $R_f \geq 70$, which also limits the range of potential values.

4 Conclusions

This article discusses two concepts in color rendition, gamut shape and chroma shift, that have been recently formalized as part of IES TM-30-15. The Color Vector Graphic (CVG) and Local Chroma Shift (IES $R_{cs,hj}$) facilitate the prediction and understanding of how object colors rendered by a light source will be perceived by moving beyond average values. Neither average color fidelity, gamut area, nor a combination of the two can effectively identify how a light source will be perceived, because their computation requires averaging across all hues; this limitation will carry forward with any future improvements or alternative measures that discard hue-specific information through the averaging process. The Color Vector Graphic and Local Chroma Shift values are more granular measures that supplement blunt averages, although they also discard information about individual sample shifts.

Both the Color Vector Graphic and Local Chroma Shift values are enabled by the greater number of samples in IES TM-30-15, which allows the sample set to be divided into 16 hue-angle bins. The Color Vector Graphic allows rapid visual understanding of color rendition characteristics for different hues and enables gross comparisons of light sources, but is not useful for establishing numerical specification or identifying small differences between light sources. Local Chroma Shift values address this limitation via bi-directional measures of chroma change that can be more informative than hue-specific fidelity values, since the same fidelity value may result from an increase, decrease, or no change in chroma.

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