Dynamic Annual Metrics for Contrast in Daylit Architecture

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Abstract

Daylight is a dynamic source of illumination in architectural space, creating diverse and ephemeral configurations of light and shadow within the built environment. It can generate contrasting levels of brightness between distinct geometries or it can highlight smooth gradients of texture and color within the visual field. Although there are a growing number of studies that seek to define the relationship between brightness, contrast, and lighting quality, the *dynamic* role of daylight within the visual field is underrepresented by existing metrics. This study proposes a new family of metrics that quantify the magnitude of contrast-based visual effects and time-based variation within daylit space through the use of time-segmented daylight renderings. This paper will introduce two new annual metrics; Annual Spatial Contrast and Annual Luminance Variability. These metrics will be applied to a series of abstract case studies to evaluate their effectiveness in comparing annual contrast-based visual effects.

1. INTRODUCTION

Perceptual qualities of daylight, such as contrast and temporal variability, are essential to our appreciation of architectural space. Natural illumination adds depth to complex geometries and infuses otherwise static interior spaces with shifting compositions of light and shadow. Architectural space is greatly altered by the ephemeral qualities of daylight, yet there is a lack of metrics that address these perceptual factors on a dynamic scale.

Over the past several decades, there have been significant improvements in our understanding of daylight as a dynamic source of interior illumination. Illuminance-based methods of daylight analysis have developed from static metrics such as Daylight Factor (Moon and Spencer 1942) to annual climate-based metrics such as Daylight Autonomy (Reinhart et al. 2006) and Useful Daylight Illuminance (Nabil & Mardaljevic 2006) to account for a more statistically accurate method of quantifying internal illuminance levels (Mardaljevic et al. 2009). While these annual illuminance-based metrics represent a significant improvement in our understanding of climate-based lighting levels across the year, they still experience many of the same limitations as daylight factor in their static representation of performance through a single surface. (Reinhart et al. 2006). As occupants perceive space from a three-dimensional vantage point, illuminance-based metrics such DA and UDI cannot express the dynamic nature of sunlight from a human perspective.

Luminance-based methods of daylight analysis are more appropriate for determining the compositional impacts of contrast as they can evaluate renderings and/or photographs taken from an occupant's point-of-view (Newsham et al. 2005). Existing luminance-based metrics can be organized into two main categories: those that predict glare-based discomfort due to high ratios of contrast within the visual field, and those that evaluate luminance ratios or ranges to infer human preferences to brightness and composition.

Those metrics that quantify luminance-based sources of glare are fragmented among no less than seven established metrics (Kleindienst and Andersen 2009). The most ubiquitous of these metrics, Daylight Glare Probability DGP (Weinhold and Christofferson 2006), establishes that high levels of contrast within our field of view negatively impact visual comfort. Although glare-based metrics are capable of quantifying contrast ratios and anticipating sources of luminance-based *discomfort* within a perspectival view, they do not provide a method for quantifying the *positive* aspects of brightness, contrast, or daylight variability.

The second category of luminance-based analysis methods relies on existing scenes and/or digital images to identify the relationship between brightness, contrast, and occupant preferences toward the luminous environment. Two dimensions that are widely accepted to impact the field of view are average luminance and luminance variation (Veitch and Newsham 2000). The former has been directly associated with perceived lightness and the latter with visual interest (Loe et al. 1994). As brightness is subjectively evaluated by the human brain, contrast is often regarded as a qualitative indicator of performance, making it difficult to quantify in universal terms. Occupant surveys of existing interior spaces were once the primary method of data collection, but digital photographs have become a useful alternative for practical purposes (Cetegen et al. 2008). One such study engages subject surveys to establish a direct correlation between the average luminance across an HDR image and its perceived 'pleasantness' or relative 'excitement' (Cetegen et al. 2008). Another example is Claude Demer's daylight classification system which categorizes images of interior architecture by plotting the mean brightness of each composition against the standard deviation of its luminance values (Demers 2007). Although this method is useful in creating an early schematic design tool for comparing contrast-driven architectural types, and survey-based methods provide us with comparative data on the luminous composition of a single space under varied lighting conditions, neither can account for the complexity of variations that occur over time. Furthermore, these methods that assess average luminance values or overall luminance range cannot distinguish between compositions that vary in the density and location of local contrast values.

This paper will propose a compositionally-dependent method of analyzing contrast through the use of matrices so that local pixel values may be quantified within their spatial framework. Using this method, we will introduce two new annual metrics; Annual Spatial Contrast and Annual Luminance Variability. These metrics will analyze a set of annual images so that dynamic conditions of contrast and luminosity may be represented across the year.

2. SPATIAL CONTRAST

In order to introduce the concept of spatial contrast, we must first consider the distinction between two images that contain a similar distribution in overall brightness, yet varied densities in the composition of dark and light values. Figure 1a shows a dense pattern of light and shadow, with each small cluster of light pixels surrounded by a tight perimeter of darker ones, whereas Figure 1b, though similar in overall brightness, shows fewer distinct boundaries between light and dark pixels. If we look at the RGB histograms, we see that each composition contains roughly the same distribution of pixels, with a peak between RGB 50-100. Figure 1a has a mean brightness of 120 with a standard deviation of 18 while Figure 1b has a mean brightness of 132 with a standard deviation of 22. Despite the obvious differences in compositional density between the two images, they are similar in contrast typology according to Claude Demers' system of classification (Demers 2007).

a.

b.

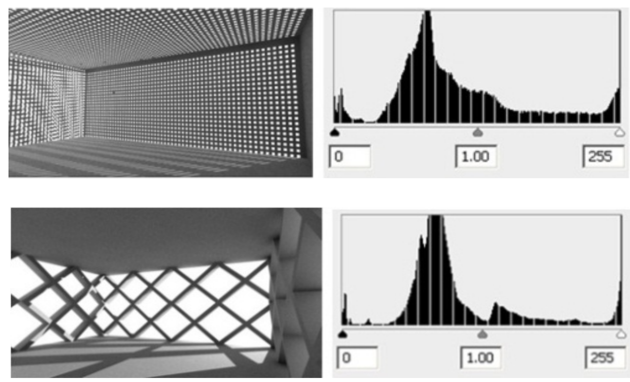
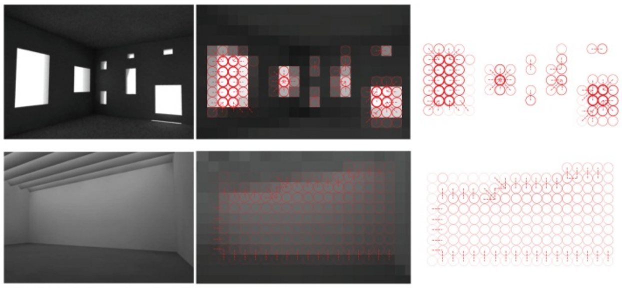


Figure 1. Mean brightness: a) 120, b) 132; Standard deviation: a) 18, b) 22.

2.1. Quantitative Approach

Rather than compute the standard deviation between luminance values, spatial contrast describes the difference between each pixel and that of its neighbor, computing the sum of all local boundaries within a given image. Figures 2a and 2b reiterate this concept through a diagrammatic representation of circles. The thickness of each circle represents the brightness of its underlying pixel, with the thickest circles representing RGB 255 (white) and the thinnest circles representing RGB 0 (black). Figure 2a shows a composition with several distinct boundaries between dark and light pixels. The abstraction of this image shows a topography of *hard peaks* between light and dark pixels. Figure 2b, on the other hand, shows a composition with few distinct tonal variations. This smooth *gradient* of tones shows pixels fading gradually in strength, whereas the density and magnitude of *peaks* represented in Figure 1b show a strong difference between light and dark pixels, increasing its spatial contrast across the image.

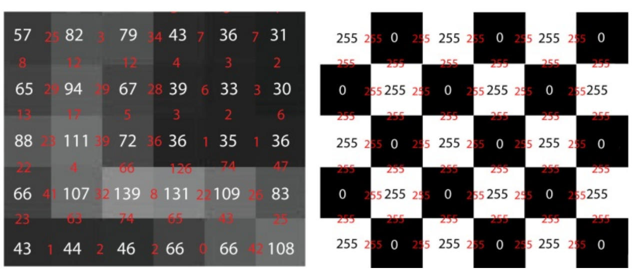


a.

b.

Figure 2. Rendering and representation of a) contrast 'peaks' (shown in red circles whose thickness corresponds to the brightness of underlying pixels), b) tonal 'gradient'

In order to compute spatial contrast across an image of higher resolution, we use matrices to find the local difference between each pixel and that of its neighbors. We then take the sum of all local differences across the resulting matrix to find the total cumulative contrast. As this number is dependent on the pixel density of the image, we must convert the cumulative sum of spatial contrast into a relative quantity or ratio. To do this, we divide the total spatial contrast by the hypothetical 'maximum contrast' that could be achieved by a corresponding image of the same dimension. Figure 3a shows a sample image (5 x 6) with local contrast values shown in red, while Figure 3b shows a corresponding checkerboard of maximum spatial contrast for an image of the same dimension. The spatial contrast is found by dividing the sum of all local values in Figure 3a by the sum of all local values in 3b.



a. b.

Figure 3. a) Sample image (5 x 6 pixels) with a cumulative spatial contrast of 1,212 (the sum of all values shown in red) b) Hypothetical maximum (5 x 6) with a cumulative spatial contrast of 12,495 (the sum of all values shown in red).

2.2. Annual Spatial Contrast

In order to understand the dynamic impacts of sunlight on our perception of spatial contrast over time, we must apply the method described in Section 2.1 to a series of images that capture the same view of space at several key moments across the year. Using a method of time segmentation that was originally developed for Lightsolve, a simulation platform for climate-based analysis and time-based visualization of daylight performance (Andersen et al. 2008, Andersen et al. 2011), we divide the year into a series of 56 symmetrical moments with 8 monthly and 7 daily intervals to generate a set of renderings for analysis. Figure 4 shows a sample set of images for a top-lit space in Boston, MA. The application of spatial contrast to this set of annual renderings allows us to calculate the cumulative *Annual Spatial Contrast* for a given view as well as plot individual instances across a temporal map to visualize daily and seasonal variations.

Spatio-Temporal Irradiation Maps (STIMAPS) were developed to represent annual data across a single graph, showing days of the year across a horizontal scale, and hours of the day across the vertical (Glaser 1999). Figure 5 shows how each of the 56 moments generated through the time segmentation method can be simultaneously represented in a temporal map. In lightsolve, these maps are used with a goal-based color scale to represent the degree to which the designer's objectives are fulfilled across the year.

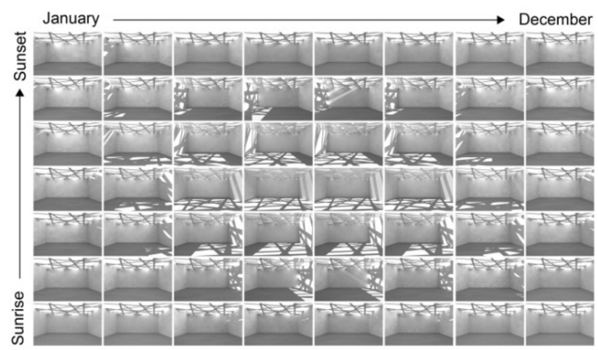


Figure 4. Sample set of 56 annual images produced using the time segmentation method developed for Lightsolve.

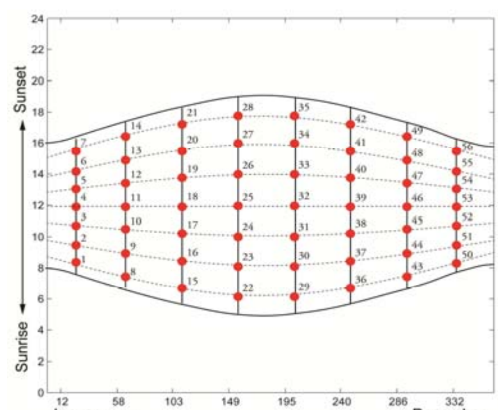
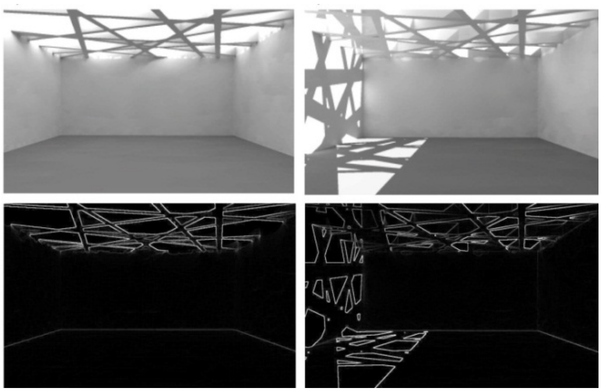


Figure 5. Temporal map showing the location of plotted values for each of the 56 renderings pictured in figure 4. Hours of the day are represented on the vertical scale, while days of the year are on the horizontal.

Annual Spatial Contrast adopts the 56 moments supported by the lightsolve method, but uses a CIE sunny sky model for all 56 renderings. This simplification allows for a consistent set of luminance maps that can be analyzed for relative changes in luminosity while creating an upper boundary for contrast and luminance variability.

2.3. Analysis and Graphical Representation

To calculate and visualize Annual Spatial Contrast, each of the 56 renderings shown in Figure 4 is processed to produce a matrix of local spatial contrast as well as a cumulative sum that represents the total spatial contrast across each image. Two sample matrices of local spatial contrast can be seen beneath their corresponding rendering in Figures 6a & 6b.



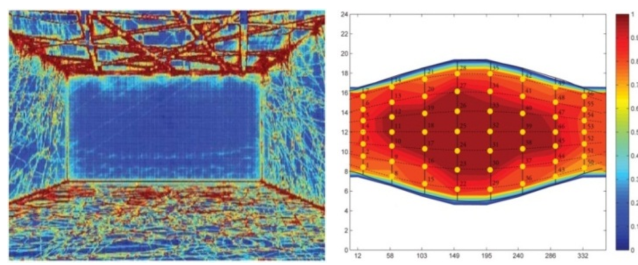
a. 1/13, 7:52 **b.** 5/30, 6:59

Figure 6. Renderings and corresponding spatial contrast maps for a selection of dates and times.

Annual Spatial Contrast takes the sum of all 56 instances to compare the magnitude and composition of spatial contrast over time. To visualize *where* this contrast occurs throughout the space, each of the 56 instances are combined to produce a cumulative matrix or image map. Figure 7a shows an example of this cumulative image map for a dramatic top-lit space in Boston, MA. The spatial contrast for each individual moment is then plotted on a temporal map to visualize *when* the space experiences the most dramatic contrast-based effects, and how abruptly it changes across the course of a day or season (shown in Figure 7b).

Annual Spatial Contrast provides the designer with a more holistic understanding of *when* and *where* sunlight impacts the composition of light and shadow within our field of view. The cumulative image map displays a dynamic range of information, highlighting both redundant and residual zones of contrast while the temporal map allows us to compare its strength and variation over time. This method of visualization challenges the static representation of contrast in daylit architecture, allowing us to represent its inherently dynamic characteristics.

The scale associated with Figure 7b has been adjusted to accommodate appropriate minimum and maximum spatial contrast values as determined by a series of case studies introduced in Section 4. As a result, Spatial contrast values between 0 and 0.33 should be considered low, values between 0.34 and 0.66 moderate, and between 0.67 and 1 are considered high. Those values exceeding 1 would represent very high spatial contrast in the context of the spaces studied. In order to create a truly universal scale for this metric, a large sample of existing architectural spaces would need to be modeled and analyzed to produce appropriate upper and lower thresholds for spatial contrast.



a. **b.**

Figure 7. a) Cumulative image map of annual spatial contrast b) Temporal map showing spatial contrast values across each of the 56 annual moments. The vertical scale represents sunrise to sunset while the horizontal scale represents January to December.

3. LUMINANCE VARIABILITY

The second metric presented by this paper describes the annual variation in luminance values across a rendered view, highlighting areas of temporal instability. Whereas Spatial Contrast identifies compositional contrast boundaries between pixel values within an image, and Annual Spatial Contrast maps the accumulation of those contrast boundaries over time, *Annual Luminance Variability* accounts for the cumulative difference in pixel values as they vary *between* images across the year. This metric is useful in describing the intensity of variation that occurs across a perspectival view of space as a product of time and dynamic natural lighting conditions. Many spaces that measure low in Annual Spatial Contrast may still measure high in Annual Luminance Variability as dramatic variations in luminosity may occur in smooth gradients or fractured patterns of contrasting light and shadow.

3.1. Quantitative Approach

The quantitative approach for this metric relies on the same 56 annual renderings introduced in Section 2.2, however it quantifies the difference between each rendering rather than treating each moment as an autonomous matrix of information. Annual Luminance Variability converts each of the 56 images into a matrix of RGB values and then computes the cumulative difference that each pixel experiences as it changes from one moment to the next. The resulting image matrix represents the cumulative sum of difference across all 56 annual moments, highlighting areas of high temporal variation.

When we use this method to quantify the variation in luminance values across a year, we must account for both daily and seasonal changes in the strength and orientation of sunlight. We must account for the difference between two renderings that occur sequentially throughout the day as well as those that occur across the seasons. In Figure 8 we see 42 data points that represent the absolute difference between neighboring moments, shown in green. This reduction of data points from 56 down to 42 occurs because we do not calculate the difference between sunrise and sunset of any given day, nor do we account for the difference between December and January of the same year.

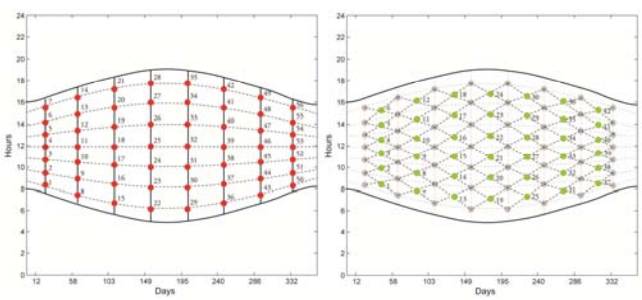


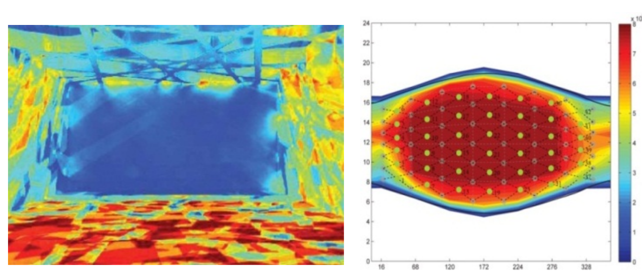
Figure 8. Reduction in data points from 56 down to 42

Annual Luminance Variability is numerically defined by the sum of all 42 annual instances and represents the total cumulative variation in luminance across a rendered view. Similar to Annual Spatial Contrast, the resulting cumulative variation cannot be compared to images that vary in pixel density until it is converted into a relative value. In order to achieve this, the total sum of luminance variation across all 42 intervals is divided by the total pixel density of the input images. The current method relies on 8-bit images to accommodate a wide range of image production techniques, yet future versions would also accommodate a more dynamic range of pixel data through the integration of HDR images.

3.2. Representing Annual Luminance Variability

The following images illustrate a full set of results for Annual Luminance Variability; Figure 9a shows a cumulative image of all 42 frames of variation which graphically represent the spatial location of luminance variability across the space and Figure 9b shows a temporal map that interpolates the 42 annual data points. The temporal map shows us *when* dynamic variations in natural light occur throughout the year and how abruptly they vary while the associated cumulative image map shows us *where* these variations occur throughout the rendered view. The maximum value for luminance variability at any one instance was found to be 8,000,000 or 8 x 10^6, established from a range of case studies in Section 4. This value represents an upper threshold in context of this study and was used to scale all subsequent data.

The temporal map shows that variations in luminance are most extreme in the summer, when the sun is moving directly overhead. The cumulative image shows the most dramatic variation occurring on the floor, as direct light moves across the roof, casting dynamic patterns of light and shadow down into the space. Some variation can also be seen on the walls, with minimal variation occurring across the roof, where uniform levels of brightness create spatial contrast, but not high levels of luminance variability. This method of visualization engages our understanding of daylit space as a dynamic composition of light and shadow, showing us where and when it transforms. Both annual spatial contrast and annual luminance variability account for distinct, yet related attributes of visual performance and help contribute to a more holistic understanding of architectural space as it is transformed by dynamic shifts in sunlight across the day and year.



a. **b.**

Figure 9. a) Cumulative image of annual luminance variability. b) Temporal map showing luminance variability values across each of the 42 data points.

4. PRODUCTION OF CASE STUDY IMAGES

In order to evaluate these new annual metrics across a series of architectural conditions, 10 case study spaces were generated to represent a gradient of natural lighting conditions, from low to high contrast and temporal variability.

4.1. Development of Case Study Spaces

The evolution of these case studies, their typological ordering, and the development of a new contrast taxonomy will be presented elsewhere. These 10 case studies represent a compact version of a larger matrix, which was composed of 74 architectural spaces across 15 categories. Figure 10 shows the compact matrix which represents the authors' hypothesized gradient of visual effects (before the application of each metric) from high spatial contrast and luminance variability on the left to low spatial contrast and luminance variability on the right. Although these abstract spaces cannot possibly cover the full spectrum of daylit architectural typologies, this linear gradient is meant to present a range of examples against which alternate spaces can be compared and contextualized.

4.2. Production of Annual Renderings

Radiance, an industry standard rendering software based on backwards ray-tracing (Ward 1994) that embeds tone mapping algorithms, was used to generate images consistent with a human's perceptual view of space, in combination with the DIVA plugin for Rhinoceros (Lagios et al. 2010) to export geometry directly to Radiance.

Each of the 10 case studies was modeled in Rhinoceros with the same floor area, ceiling height, and camera location so that results could be accurately compared. Cameras were positioned to face South, centered in the East-West direction, and offset ten feet from the back wall to ensure an even distribution of wall, floor, and ceiling surfaces within each rendering. The Diva-for-Rhino toolbar was then used to export the camera view to Radiance, where materials were set to default reflectance values for floor, wall, and ceiling surfaces (0.3, 0.7, 0.9 respectively). The resolution of each images was rendered at 'high quality' (a present in DIVA) to accommodate adequate detail with a 640 x 480 pixel aspect ratio and a rendering was generated for each of the 56 dates and times determined by the time-segmentation method (described in Section 2.2) for clear sky conditions. Boston, Massachusetts was set as the location for all case-study renderings (latitude 42 N, Longitude 72 W). When the spaces were rendered under overcast sky conditions, the contrast and temporal diversity was minimized, making it difficult to compare relative changes between each space. In order to compare the impacts of contrast over time, it is necessary to use a sky condition that allows for maximized visual effects. Once a set of renderings has been produced from this method, it is imported into Matlab and analyzed for annual spatial contrast and luminance variability.

5. CASE STUDY RESULTS

Figure 11a and 11b show a linear gradient of results across each of the two annual metrics for the 10 case studies presented in Figure 10. Annual Spatial Contrast results are shown in Figure 11a and Annual Luminance Variability results are shown in Figure 11b. Each row of images has been re-ordered from left to right to display a relative gradient of cumulative annual results, with those case studies located on the left side of each figure representing the high end of the spatial contrast or variability spectrum and those on the right representing the low end. The value beneath each image in Figure 11a represents a cumulative sum of spatial contrast for each of the 56 time-segmented instances. The value beneath each image in Figure 11b represents the sum of all 42 instances of luminance variability described in Section 3.2. These values are ordered in a linear gradient to show the relative presence of cumulative spatial contrast and luminance variability within each case study.

When compared to the hypothesized gradient in Figure 10, the results for each annual metric maintain the overall pattern of anticipated results, with most case study spaces shifting no more than one position to the left or right. Because the hypothesized gradient did not differentiate between the two metrics, the results across each individual metric produce a distinct relative order. For example, case study 1 produced a maximum relative value for annual luminance variability but placed third in annual spatial contrast. Likewise, case study 10 produced a minimum relative value for annual luminance variability, but place 6th in annual spatial contrast. These results support the need for a multitude of quantitative indicators when we discuss the relative perceptual impacts of natural light on factors of visual interest.

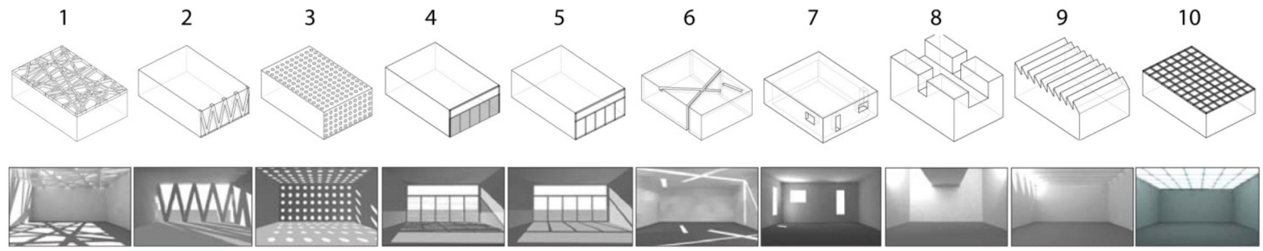


Figure 10. 10 case study models in a hypothesized linear gradient from high contrast & variability on the left

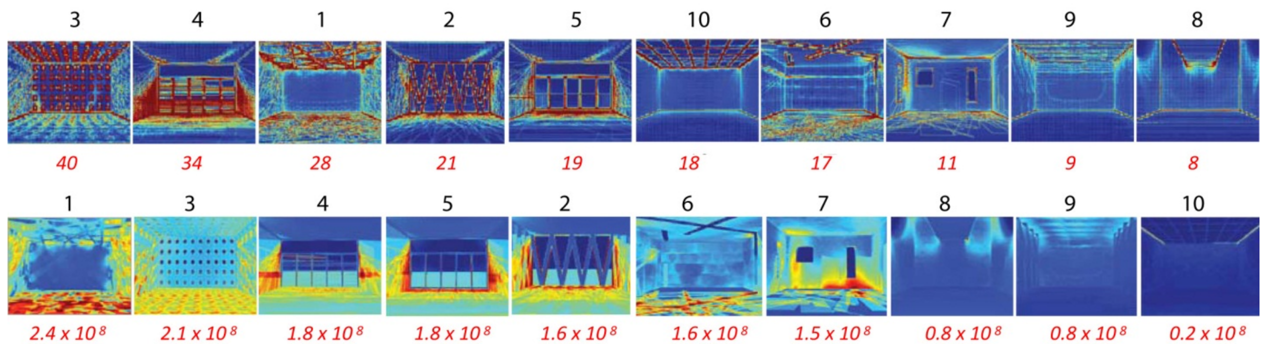


Figure 11. Analysis of all case studies re-ordered in terms of a) Annual Spatial Contrast and b) Annual Luminance Variability

A more detailed look at the temporal maps for case studies 4 and 9 (the full spectrum be presented elsewhere) show the annual variation in each metric as a product of time. The cumulative images in Figure 12 and 13 provide a spatial snapshot of results for each metric, highlighting areas of contrast or variability within each renderings, but the temporal maps represent a dynamic view of *when* those values change across the year. The temporal map for annual spatial contrast in Figure 12 shows peaks of spatial contrast in the winter months as low sun angles penetrate the louvered façade of case study 4, driving sharp shadows onto the walls and floor. This pattern can also be seen in the temporal map for annual luminance variability as dynamic patterns move across the space in the winter, while remaining relatively static in the summer months. Figure 13 shows an indirect top-lit space with low annual spatial contrast. The temporal map for luminance variability, however, shows peaks of variation in the early morning and late afternoon as low sun angles penetrate the north-facing roof monitors. This map is particularly intriguing as it illustrates an atypical condition that dramatically impacts our perception of interior space at key moments. Future avenues of research would address a climate model to compare the effects of cloud cover and weather on these patterns of contrast.

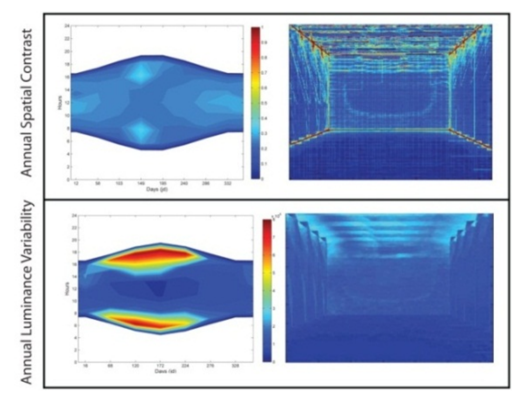


Figure 12. Cumulative image and temporal maps for case study 4: a) annual spatial contrast, b) annual luminance variability.

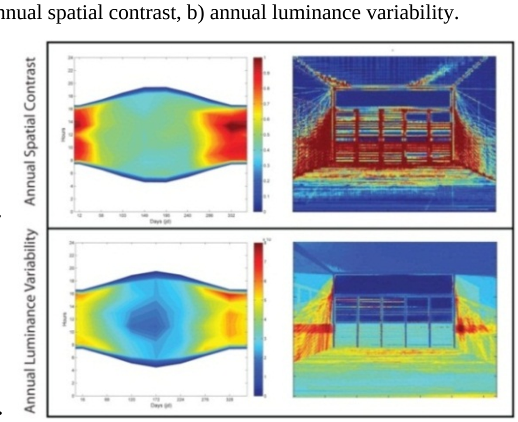


Figure 13. Cumulative image and temporal maps for case study 9: a) annual spatial contrast, b) annual luminance variability.

DISCUSSION & CONCLUSION

The metrics proposed by this paper present a new and novel approach to the dynamic analysis and visualization of contrast within architecture. Due to the spatial impacts of light and shadow on our perception of contrast and the inherent variability of daylit as a source of illumination, Annual Spatial Contrast and Luminance Variability evaluate the compositional and temporal impacts of daylight on our perception of interior space. While Annual Spatial Contrast quantifies the sum of all local contrast boundaries across a given view, Annual Luminance Variability accounts for the total change in luminance levels over time. The method of visualization for these metrics combines a cumulative image with a complimentary temporal map to identify *when* and *where* these dynamic variations occur. This approach moves beyond static representations of contrast and seeks a more specific method of quantifying compositional variations in brightness.

Each of these metrics is currently limited by the compression of annual data into a set of interpolated values. Future research will need to address a broader range of annual instances to fully validate the time-segmentation method used in this approach. Additional limitations include the time-intensive method of automated image production. A rigorous study and application of these metrics to existing architectural models will help to define a more appropriate numerical scale for resulting data. Future research must also investigate the relationship between compositional patterns of light and their impacts on our perception of contrast. An important vein of research would relate the proposed metrics to recommendations for contrast and temporal variation in programmed space.

A method of quantifying daily spatial contrast and luminance variability is currently underway using HDR time-lapse photography. This method (to be presented elsewhere) quantifies the dynamic changes in light across a much smaller interval of time. This increase in time-based resolution does raise new challenges, as moving subjects and objects within the scene provide sources of error, but it also allows designers to analyze existing buildings.

In conclusion, annual spatial contrast and luminance variability represent a shift toward dynamic luminance-based metrics that evaluate the relative impacts of contrast on our perception of architectural space over time. These metrics, although still preliminary in their development, seeks to understand the relationship between the composition and variability of daylit space. This research will help designers to contextualize positive aspects of daylit variability and compare contrast typologies on a dynamic scale.

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