Appraising daylight changes in window views: Systematic procedures for classifying and capturing dynamic outdoor scenes

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Exposure to environmental changes in windows are essential to sustain healthy conditions indoors; however, there are no procedures for capturing these variations dynamically. In this study, we provide the foundations for building a framework aimed at understanding the effects of luminous variability in window views. First, we labeled a sample of views (n = 40) using a surface layout approach, resulting in four view type categories. Next, we captured time-lapse imagery from selected views (n = 8) to produce panorama sequences. We calculated the absolute lightness variation in Matlab, resulting in three luminous change categories (i.e., Global, Local, and Minimal variation). Concurrently, we collected environmental measures to define variability thresholds. The integrated analysis showed a higher occurrence of luminous changes in two categories in controlled conditions, suggesting that viewing configuration might prevail over window orientation for conveying light changes over time.

Keywords: view; dynamic methods; view categorization; view collection; lightness change

Background

Because extended periods in windowless spaces have detrimental effects on vitality, activity levels, and sleep quality (Boubekri et al., 2014), ensuring visual access to restorative features outdoors is essential to satisfy design requirements for human comfort. Continuous exposure to outdoor views stimulates positive psychological and health responses, which researchers have extensively documented in the literature (Lottrup et al., 2015; Ulrich, 1981; Veitch & Galasiu, 2012; Velarde et al., 2007). For instance, views can shorten time of recovery in hospitals (Benedetti et al., 2001; Ulrich, 1984); improve job satisfaction and relieve symptoms of discomfort in work offices (Aries et al., 2010; Leather et al., 1998); and improve performance and attentional capacity in schools (Heschong et al., 2002; Tennessen & Cimprich, 1995). Views are a source of direct interaction with the external environment that have the potential to deliver micro-restorative experiences that improve individuals’ recovery from stress, job
satisfaction, and overall wellbeing (Felsten, 2009; Kaplan, 2001; Kaplan & Kaplan, 1989; Kaplan, 1995; Ohly et al., 2016; Sonnentag et al., 2017; Talbot & Kaplan, 1991; Tennessen & Cimprich, 1995; Ulrich, 1983).

The dominant perspective in research examining the benefit of views is that they provide restorative experiences. However, it is less clear what characteristics of views contribute to this restorative experience. One feature that is potentially important is the dynamic character of views: over time, changes in views create sources of involuntary attention, arousing fascination and a sense of connectedness with the environment outdoors (Berto et al., 2010; Jacobs et al., 2016; Kaplan & Kaplan, 1989; Steane, 2004). Although there are several ways in which views can be dynamic and change over time (i.e., through the movement of objects in the scene), changes in the luminous environment across the day may be particularly significant. The information provided by views produces two automatic responses in the observer: To try to predict and comprehend clues from the available information on the scene (Kaplan & Kaplan, 1989). Variation in luminous conditions provides the observer with information about time, weather, and conditions outdoors. We hypothesize that these automatic responses can be motivated by trying to process changes occurring in the outdoor luminous environment. However, existing approaches to view assessment generally involve the evaluation of static views at a single moment in time, making it difficult to determine the importance of a dynamic luminous environment when examining views. Since there are currently no clear procedures to describe and capture dynamic changes in views over time, we believe that developing approaches to view assessment that combine the categorization of outdoor view features with the analysis of continuous photometric, environmental, and visual measures is the first step to understand how view configurations influence luminous changes in window views.

**Aims**

Following the recommendations of Sonnentag et al. (2017), who urged researchers to focus on investigating temporal aspects of the recovery process, we propose that developing integrated procedures for documenting views over time is an essential step towards understanding the variables that contribute to the outdoor view experience. Therefore, we aim to define a set of methods for systematically collecting and analyzing dynamic luminous conditions in outdoor views.
This paper comprises two parts. In part 1, we discuss previous approaches to view categorization, describe the collection of a sample of urban view scenes, and present a systematic scene type categorization methodology to lay the foundation for collecting and analyzing dynamic views. Part 2 describes a procedure for capturing immersive view images across time alongside contextual environmental information, presents a method for describing and analyzing changes in view luminous conditions, and presents preliminary results generated using the described procedures.

Part 1 – Categorization of view types

Scene categorization is the first step to systematically assess outdoor views. Research addressing static views has demonstrated that different view types can elicit different responses in observers. Some view types are more likely to show a changing luminous environment than others; however, the extent to which this occurs is unknown. View types must then be considered the first step to establish procedures for documenting and analyzing dynamic luminous scenes. Defining different view type categories ensures that a range of different types are collected, and that differences between luminous variation in scenes can be examined. Since the number of possible view configurations is almost endless and prone to subjective interpretations from individual observers (Kaplan & Kaplan, 1989), a systematic categorization is needed to clarify the role of different features and spatial relationships.

Previous approaches to view categorization

There are a number of existing approaches to view categorization. Through the design of windows, building science aims to ensure efficiency, visual performance, and privacy while maximizing daylight indoors. As a result, building science researchers categorize views in terms of the number of obstructions to acceptable unobstructed visual areas, and proximity to neighboring buildings (Ng, 2010; Shach-Pinsly et al., 2011). The categorization of views as obstructions and spatial relationships can improve visual comfort in buildings; yet, these procedures do not provide information regarding how the overall configuration of a window view is perceived by individual observers, or which view configurations are likely to register environmental changes across the day.
To address these issues, researchers have investigated different categorization procedures based on principles for satisfactory window design (Alexander, 1977). A long-established method for assessing quality outdoor views is the information content approach (Markus, 1967). In this study, Markus associated view satisfaction to the number of horizontal layers a window contains. Markus proposed that the most satisfactory outdoor views would comprise three layers: a layer of sky, a layer of city or landscape, and a layer of ground. Over the years, the information content approach has been adapted to combine these basic view features with more complex spatial conditions, such as composition, proximity, and character factors (Matusiak & Klöckner, 2016). These revisions have informed current view categorization procedures, resulting in the recent creation of formal view standards (CEN, 2018). However, view content is still categorized via subjective judgments, which vary and are not necessarily consistent between people. Because environmental conditions might register differently across the range of view configurations, a more systematic categorization procedure is needed, as subjectivity in static view assessments will also apply to, and complicate, the evaluation of dynamic views.

The rapid growth of urbanization also difficults the categorization of views. Traditional view research took place in rural settings and maintained clear boundaries between built and natural scene categories (Ulrich et al., 1991). Although this distinction was critical to examine the effect of nature in views, purely built or natural scenes are not representative of the outdoor views in urban contexts. Instead, these views typically involve both natural and constructed elements, and this requires alternative approaches to categorization. More recent studies have adopted broader definitions to classify views within the urban environment (Herzog & Shier, 2000), but the proposed categories still rely on subjective interpretation of scale or visual richness, making comparisons between view scenes challenging to execute. New frameworks for view categorization are needed to account for the fact that window views in many current urban settings will not portray horizontal layers, but a mixture of built and natural features in different configurations.

**Simulation methods**

While research on observer’ responses to views has generally been restricted to static images, building designers increasingly use simulation methods to explore dynamic environmental conditions (Kong et al., 2018; Reinhart et al., 2006). Simulation
workflows allow designers to rapidly model how the building interacts with a changing environment, and as a result, they have been employed to address a range of spatial and perceptual issues in view research. This is the case for methods to examine visual openness and visual exposure, which have been developed to ensure view permeability and safeguard privacy indoors when designing dense urban settings (Shach-Pinsly et al., 2011; Shach-Pinsly, 2010), and combined daylight and view methods – developed to assess view quality in combination with daylight gain indoors (Hellinga & Hordijk, 2014). Simulations are useful to optimize the design and positioning of windows; however, they are ineffective for capturing and examining outdoor views, as it is challenging to recreate the complex luminous and built outdoor environment with enough detail to ensure ecological validity. To that end, combined naturalistic and simulation approaches have been implemented to examine the effects of window views (Dosen & Ostwald, 2017). Incorporating real photographs of outdoor views into 3D models provides a good approximation of actual viewing conditions without the challenges of conducting field research. However, these images are generally static, losing the benefits of creating a dynamic and changing environment that is provided through simulation methods. Along with the fact that the image source and concurrent environmental conditions outdoors are rarely reported, it is not possible to implement this combined approach to investigate the effects of dynamic views on people.

On the other hand, methodical approaches have been validated in landscape and urban research to collect view information in field research (Palmer & Hoffman, 2001). For instance, there are well-described procedures for the collection of outdoor panoramas at single points-in-time for visual landscape and street view assessment (Li et al., 2018; Pardo-García & Mérida-Rodríguez, 2017; Sevenant & Antrop, 2011; Skrivanova & Kalivoda, 2010). However, to our knowledge, these procedures have not yet been implemented to collect view scenes over time, nor from the perspective of window views. Likewise, the ease of capturing environmental measures provide increased opportunities to investigate the effects of outdoor views under specific conditions over time. A recent study adopted the strategy of evaluating outdoor scenes in combination with weather database measurements to examine legibility for time cues (Granzier & Valsecchi, 2014). Although the translation of perceived daylighting conditions into clues for estimating time or season of the year was not conclusive, an approach whereby environmental
information is captured alongside view samples could help to understand how environmental conditions affect luminous conditions and observers’ responses to views.

**Spatial configuration approaches**

To examine changes in the luminous environment across the day, the view categorization procedure must distinguish between scene features that could interact with changing light conditions. The orientation and type of surfaces present in a scene will influence the extent to which their appearance is affected by daylight and sky conditions across the day, so approaches that capture this information are likely to be useful. Computer vision focuses on developing algorithms to help computers see and an adaptation of such methods might assist with the classification of subjective categories to examine outdoor views. Research in computer-aided analysis of scenes has progressed significantly in recent years, particularly in estimating the mean depth of scenes (Torralba & Oliva, 2002) and surface orientation (Delage et al., 2006; Hoiem et al., 2007). Computers need contextual information from images to detect objects in 3D environments (Murphy et al., 2004), thus similar methods could be used to identify and classify patterns of spatial layouts and textures in view scenes. One study proposed a multiple segmentation method using a surface layout approach to recover 3D geometry from single 2D images (Hoiem et al., 2007). The procedure involved classifying each image pixel according to its geometric relation to the ground plane (either parallel or vertical to the ground) or as part of the sky. Vertical pixels were then sub-classified into planar surfaces oriented towards the left, center, or right of the scene, or into non-planar surfaces with solid or porous characteristics. As a result, all pixels in the image were categorized into seven geometric classes, according to their attributes and relation to a defined plane. These classes are Support (horizontal plane), Planar facing left, Planar facing center, Planar facing right, Non-planar solid, Non-planar porous, and Sky. An image with pixels classified into these categories is shown in Figure 1 as part of the current research, following the graphic representation proposed by Hoiem et al. (2007).
In this study, we used these seven geometric classes to classify outdoor views and structure subsequent view collection and analysis. We selected this approach as it uses the organization of spatial elements and surfaces to describe an overall scene, which presents some advantages for capturing changes in the luminous environment. First, it provides a system for neutrally labeling view content without relying on the presence of specific individual features within the scene. Also, it allows for the analysis of views that have mixed features (i.e., built and natural elements), which is the most frequent condition in urban settings. Finally, it provides a distinction between surfaces that may interact with the luminous environment differently across the day due to varied material properties, visual patterns, object sizes, and relative positions. As such, the classification of outdoor views in terms of geometric classes is one valuable way to structure the exploration of dynamic changes in the luminous environment and viewers’ responses to these changes.

Figure 1 Visual representation of the seven geometric classes: (a) naturalistic view scene; (b) view scene labelled. Graphic representation created for this study, based on the work by Hoiem, Efros, and Hebert (2007).
Method

Generation of preliminary image samples

To generate a broad range of view scenes, we photographed views from all accessible windows in covered public areas on above-ground levels at the Queensland University of Technology, Gardens Point (urban), and Kelvin Grove (suburban) campuses (n = 280) in Brisbane, Australia. Images were captured in December 2018, using a smartphone camera in landscape orientation at standing eye level. From this initial sample, we examined the configuration of each image and eliminated images containing very similar arrangements of spatial elements to reduce the image pool to a sample of 161 unique view images.

Analysis of spatial configuration

To examine the collected sample, we first assigned predefined geometric labels to a sample of urban (n = 20) and suburban (n = 20) images using the Image Labeler app in Matlab (Mathworks Matlab, Version R2017b) software. Using this tool, we labeled images such that all image pixels were classified into one of the seven categories described in Table 1.

Table 1 View features defined for each geometric label.

| Label | Color | Name                         | Feature Description                              |
|-------|-------|------------------------------|--------------------------------------------------|
| SUP   | blue  | Support                      | Ground; Horizontal features                       |
| PFL   | green | Planar Facing Left           | Walls; Columns; Roof                              |
| PFC   | green | Planar Facing Center         | Walls; Columns; Roof                              |
| PFR   | green | Planar Facing Right          | Walls; Columns; Roof                              |
| NPS   | purple| Non-Planar Solid            | Trunks; Poles; Pipes; Distant buildings           |
| NPP   | purple| Non-Planar Porous           | Greenery; Water; Distant nature                   |
| SKY   | red   | Sky                          | Sky vault; Clouds; Sun                            |

Next, we examined the type and distribution of labels across each image and identified and defined five preliminary categories and established the degree of similarity
between view scenes (Figure 2). Within each group, we measured the percentage of identically labeled pixels between two analogous view scenes to quantitatively describe the structural similarity between scenes and determine whether images belonged to the same category. For this sample, we defined an initial threshold of 50% of identically-labeled pixels for images to pertain to the same category. Once these conditions were applied, we dismissed one preliminary category whose labels were difficult to analyze. As such, we defined four view categories with similar label distributions, which are shown in Figure 3. To facilitate ease-of-use, we renamed the resulting groups as four different view types according to the spatial configuration of the scenes.

Figure 2 View categorization in Matlab: (a) collection of naturalistic view scenes; (b) labelling of images using seven geometric classes; examination of layer distribution
Figure 3 Categorized view scenes: (1) Wall category; (2) Courtyard category; (3) Corridor category; (4) Roof category.
a) Wall: Defined by the significant presence of a Planar facing center region distributed over the majority of the scene and the eventual presence of Sky and Non-planar porous regions across the scene.
b) Courtyard: Defined by the equivalent presence of three Planar regions distributed at the sides and center of the scene and the presence of a Support region.
c) Corridor: Defined by the equivalent presence of two Planar regions (e.g., facing left and facing right) distributed at the sides of the scene and the comparable presence of the Sky and Support regions.
d) Roof: Defined by the significant presence of a Sky region and the mixed presence of Planar and Non-planar regions distributed at the bottom of the scene.

These above four view type categories were used to select views for sampling in Part 2 described below, in which view scenes were captured and analyzed using dynamic methods.

Part 2 – Dynamic view capture

Existing approaches to capturing views

The luminous outdoor environment is continually changing and is substantially defined by the environmental processes occurring at the moment of exposure. Therefore, capturing the dynamic attributes of outdoor views concurrently with environmental measures is required to understand the conditions that promote restorative opportunities in urban settings. One solution to capture changes in naturalistic outdoor views is to collect time-lapse image sequences, which can describe variation across time. Although time-lapse images are a common technique, they have not been used for creating static series or animated videos of outdoor views for research purposes (Hidalgo et al., 2006; Hull & Revell, 1989). When they are used, sequences of time-series images are often presented in a static and non-immersive way.

Alongside being the preferred format for assessing view quality of landscapes, panoramic images can approximate the outdoor scene as it is presented to the human field of view, becoming a perceptually correct format to examine view changes in immersive
and interactive conditions (Cauwerts, 2013; Chamilothori et al., 2019). As such, image sequences are ideally captured in panorama format. In this section, we describe methods for capturing outdoor views using time-lapse techniques to produce panorama series and account for future requirements for animating panorama series, allowing for the collected data to be presented to participants as immersive stimuli in future research.

Outdoor conditions can have a significant influence on views, and with the ubiquity of sensors embedded in portable devices, capturing environmental measurements over time in addition to descriptive spatial data is increasingly feasible. For instance, external solar radiation measurements (i.e., horizontal diffuse and global irradiance) can help to classify sky conditions during view scene collection (Bodart & Cauwerts, 2017). The collection of concurrent environmental conditions such as vertical illuminance and correlated color temperature (CCT) will help to contextualize both individual images and changes in lightness since lightness measures will register differently under varied sky conditions, seasons, and locations.

**Dynamic view capture methods**

**Image collection procedure**

We collected outdoor views during May 2019, at the Queensland University of Technology, Gardens Point (urban), and Kelvin Grove (suburban) campuses, in Brisbane, Australia. Two view scene (VS) samples were selected from each of the view category types generated in Part 1, for a total of eight view scenes. For each chosen view scene, we captured a sequence of 23 panoramic time-lapse images over an approximately 7.5 hour period (09:40 am - 05:00 pm) at 20-minute intervals. Procedural pilot testing was conducted with longer and shorter intervals between each image capture; however, the 20-minute schedule was determined to be feasible, while clearly depicting changes in the luminous scene without capturing extraneous detail. For each scene, a smartphone was used to record contextual information such as geographic coordinates, viewer orientation, vantage point height in relation to the ground plane, and anchoring images of the collected views. The eight view scenes and their associated details are shown in Table 2.
Images were collected with a calibrated Canon EOS 5D Mark III camera on a panoramic head mount over a tripod, fixed with a Canon 50 mm f1:1.4 lens. For creating panoramas covering a 120° horizontal x 40° vertical, we defined a 150° horizontal x 60° vertical rotation over the panorama head mount, with a 15° rotation in horizontal and vertical directions. We positioned the camera in portrait orientation at 1.50 m from the ground plane and determined the non-parallax point using standard photography procedures (Weston, 2015). To adjust the camera, we considered the settings for capturing luminance indoors using high dynamic range photography (Inanici, 2006).

**Outdoor environmental condition recording**

Simultaneous to the time-lapse image sequence capture, we used a combination of instruments to capture changing environmental conditions across the image capture timeframe. In this exploratory study, we included a number of different environmental sensors for later examination of which environmental characteristics might be most relevant to luminous changes.

Vertical illuminance and CCT were measured using a handheld spectrometer (Lighting Passport Pro AsenseTek ALP-01) placed at standing eye level as close as possible and in the same orientation as the camera sensor. To objectively categorize sky
conditions, we measured horizontal diffuse and global radiation measurements simultaneously using a pyranometer (BF5 Sunshine Sensor), positioned approximately 2km from the view locations. Measurement ranges, resolution and accuracy of the sensors and instruments are presented in Table 3.

| Spectrometer | Pyranometer | DSLR Camera |
|--------------|-------------|-------------|
| Range        | Range       | Range       |
| lux          | klux        | ISO         |
| nm           | W.m²        | evs         |
| 5 – 50000    | 0 – 200     | 100 – 12800 |
| 380 – 780    | 0 - 1250    |             |
|              | 0.06        |             |
|              | 0.3         |             |
| Accuracy     |             |             |
| Lux          | ±5%         | ±0.601      |
| Nm           | ±0.5%       | ±12%/±15%   |
| CCT          | ±3%         | ±5          |
|              | Total /     | ±12%/±15%   |
|              | Diffuse     |             |
|              | W.m²        |             |
|              | Total /     |             |
|              | Diffuse     |             |

**Table 3 Measurement ranges, resolution and accuracy of the sensors and instruments**

Image analysis

**Panorama generation**

The complete view sample comprised a total of 184 panoramas, with 23 panoramas per view scene. To generate each panorama, 55 individual images (11 columns x 5 rows) were merged using a standard photo stitching software (Epic Pro Gigapan Stitch, Version 2.3.0307). The resulting panoramas were converted into JPEG files and cropped to obtain identical 12600-pixel x 7087-pixel images in a photo editing software (Adobe Photoshop CC, Version 20.0.6). Following stitching and cropping, this process resulted in eight panorama time-lapse image sequences, one for each view scene shown in Table 2.

**Quantifying luminous changes across time**

Previous studies outlined lightness as one of the luminous attributes that can assist the description of indoor visual conditions (Cauwerts, 2013; Liljefors, 1999). In this study, we focused on quantifying the variability of lightness in outdoor views over time.
To that end, we developed and implemented a routine in (Mathworks Matlab, Version R2017b) software to analyze lightness variation between panoramas taken at consecutive time-points, using the CIE L*a*b* color space (Figure 4). Although the conversion to CIE L*a*b* color in field conditions will only provide an approximation of the illumination conditions outdoors, we considered it sufficient for the present study. First, we converted RGB panoramas into CIE L*a*b* color space matrices. Next, we extracted per-pixel information from the L* channel — with values ranging from the darkest L* = 0 to the brightest L* = 100 — to obtain lightness values. To assess lightness change, we calculated the absolute difference in lightness values between two consecutive panorama samples to generate matrices of per-pixel absolute difference in lightness for each sequence, as illustrated in Figure 5 and expressed in Equation 1 (CIE, 2004):

$$\text{Lightness Change (ΔL*)} = |N_{L*} - M_{L*}|$$  \hspace{1cm} (1)

where M and N are two consecutive matrices depicting values from the L* channel after converting RGB panoramas into CIE L*a*b* color space. This procedure resulted in a single matrix describing the absolute difference in lightness between the two panoramas, and this lightness change matrix was used to generate false-color maps depicting the change between time-points (as shown in Figure 5, part c).

![Diagram of procedures in Matlab for examining lightness change.](image-url)
Identification of luminous change categories

In this study, we established a rationale to identify types of lightness changes within view scenes, based on the premise that view assessment must examine dynamic visual features with the potential to convey objective responses from individuals over time. For instance, the pattern of eye movements has been linked to a strong visual exploration of outdoor scenes, with heterogeneous scenes perceived through more fixations and saccades than homogeneous scenes over equal exploration times (Dupont et al., 2014). Because scene heterogeneity is associated to visual richness and view preference (Kaplan & Kaplan, 1989) while scene homogeneity is linked to slow fascination and restorative opportunities (Berto et al., 2008), identifying luminous change categories as a function of lightness changes within the scene creates a logical progression towards appraising the effects of dynamic views over preference and restoration. Based on these assumptions, we conducted a visual examination of the false-color map of lightness change for all sequences, finding that three types of lightness change across time emerged from this trial:

1. Global variation: Characterized by lightness patches that changed regularly over time, manifested by movement, direction, and intensity remaining predictable over consecutive time intervals. For this specific sample, we observed that changes in lightness ranged from 30-100 (Figure 6).

2. Local variation: Defined by lightness patches following irregular change patterns over time. These variations are characterized by abrupt changes in movement, direction, and intensity of light patches. For this specific sample, we observed of
changes in lightness ranged from 50-100, with lightness peaks (>80) distributed across the scenes (Figure 7).

(3) Minimal variation: As its name illustrates, this condition presents no, or minimal changes in lightness values between time intervals (< 50) for this specific sample, suggesting that the scene remains relatively static across consecutive time points (Figure 8).

**Identification of outdoor environmental conditions**

We defined sky conditions according to the Perez categories (Bodart & Cauwerts, 2017; Perez et al., 1990) for the entire sample of view sequences. External irradiance measures collected at 20-minute intervals were tabulated in standard spreadsheet software (Microsoft Excel for Office 365, Version 16.0.11727.20222) to determine the sky conditions occurring during the collection of view scenes. Following the abovementioned classification procedures, skies were classified as Overcast (1-2), Intermediate (3-5), Clear turbid (6), or Clear (7), as presented in Table 4.
Figure 6 Global variation between consecutive time intervals.

Figure 7 Local variation between consecutive time intervals.

Figure 8 Minimal variation between consecutive time intervals.
Table 4 Sky conditions for each view sequence.

| Time          | VS1: Wall | VS2: Wall | VS1: Courtyard | VS2: Courtyard |
|---------------|-----------|-----------|----------------|----------------|
|               | Total     | Diffuse   | Total          | Diffuse        |
|               | W.m-2     | W.m-2     | W.m-2          | W.m-2          |
|               | Sky       | Total     | W.m-2          | W.m-2          |
|               | Sky       | Total     | W.m-2          | W.m-2          |
|               |           | Total     | W.m-2          | W.m-2          |
| 9:40:00 AM    | 596.17    | 160.82    | 6              | 597.9          |
|               | 89.51     | 605.35    | 8              | 597.9          |
| 10:00:00 AM   | 321.99    | 158.14    | 5              | 633.58         |
|               | 81.41     | 645.62    | 8              | 639.91         |
| 10:20:00 AM   | 556.77    | 198.49    | 6              | 678.18         |
|               | 79.41     | 675.5     | 8              | 668.83         |
| 10:40:00 AM   | 380.01    | 341.82    | 2              | 696.63         |
|               | 80.28     | 701.48    | 8              | 690.31         |
| 11:00:00 AM   | 309.78    | 286.65    | 2              | 727.37         |
|               | 88.54     | 727.89    | 8              | 758.98         |
| 11:20:00 AM   | 333.59    | 334.37    | 1              | 743.66         |
|               | 91.71     | 743.31    | 8              | 769.38         |
| 11:40:00 AM   | 487.4     | 384.6     | 3              | 745.65         |
|               | 83.4      | 750.58    | 8              | 753.01         |
| 12:00:00 PM   | 481.25    | 382       | 3              | 742.79         |
|               | 84.96     | 746.77    | 8              | 752.32         |
| 12:20:00 PM   | 402.53    | 323.72    | 2              | 731.62         |
|               | 86.08     | 734.13    | 8              | 731.01         |
| 12:40:00 PM   | 452.33    | 315.93    | 3              | 674.81         |
|               | 79.33     | 681.22    | 8              | 677.15         |
| 1:00:00 PM    | 106.78    | 104.44    | 1              | 642.76         |
|               | 78.29     | 649.17    | 8              | 643.11         |
| 1:20:00 PM    | 114.92    | 109.29    | 1              | 614.45         |
|               | 76.21     | 619.55    | 8              | 610.37         |
| 1:40:00 PM    | 46.16     | 44.99     | 1              | 565.34         |
|               | 76.9      | 571.58    | 8              | 563.18         |
| 2:00:00 PM    | 73.96     | 74.22     | 1              | 512.17         |
|               | 72.49     | 516.84    | 8              | 510.26         |
| 2:20:00 PM    | 108.77    | 109.29    | 1              | 458.73         |
|               | 68.33     | 462.72    | 8              | 455.62         |
| 2:40:00 PM    | 107.21    | 107.65    | 1              | 397.85         |
|               | 64.35     | 403.22    | 8              | 395.95         |
| 3:00:00 PM    | 107.47    | 107.91    | 1              | 327.53         |
|               | 61.83     | 336.62    | 7              | 326.66         |
| 3:20:00 PM    | 69.8      | 69.89     | 1              | 262.49         |
|               | 57.85     | 270.89    | 7              | 260.5          |
| 3:40:00 PM    | 63.13     | 63.39     | 1              | 187.75         |
|               | 52.05     | 192       | 6              | 189.05         |
| 4:00:00 PM    | 49.71     | 49.71     | 1              | 123.67         |
|               | 44.25     | 127.22    | 5              | 122.8          |
| 4:20:00 PM    | 28.41     | 28.23     | 1              | 64.78          |
|               | 32.74     | 67.55     | 5              | 64.17          |
| 4:40:00 PM    | 8.49      | 8.05      | 1              | 20.01          |
|               | 16.11     | 22.17     | 3              | 18.79          |
| 5:00:00 PM    |           |           |                |                |
|               |           |           |                |                |
Application of luminous change categories

For each of the 184 view panoramic view sequences, the resulting lightness change matrices (n = 176) generated using the equation described above were visually classified into one of the three luminous change categories (Global variation, Local variation, and Minimal variation) using a visual coding system. To exclude changes that occurred as a result of changing sky conditions, this classification was completed only for change matrices that were generated from two consecutive images with the same sky classification (Figure 9).

| Time          | VS1: Corridor | VS2: Corridor | VS1: Roof | VS2: Roof |
|---------------|---------------|---------------|-----------|-----------|
|               | Total | Diffuse | Total | Diffuse | Total | Diffuse | Total | Diffuse | Total | Diffuse | Sky |
| 9:40:00 AM    | 277.91 | 279.12 | 1 | 479.09 | 356.8 | 3 | 285.88 | 287.52 | 1 | 584.83 | 128.95 | 7 |
| 10:00:00 AM   | 290.12 | 230.62 | 3 | 297.57 | 299.21 | 1 | 312.38 | 312.12 | 1 | 475.27 | 354.46 | 3 |
| 10:20:00 AM   | 557.81 | 230.02 | 5 | 359.23 | 359.75 | 1 | 247.77 | 236.08 | 1 | 526.02 | 309.52 | 4 |
| 10:40:00 AM   | 735.52 | 195.64 | 6 | 415.61 | 397.85 | 1 | 289.43 | 277.21 | 1 | 660.69 | 393.35 | 4 |
| 11:00:00 AM   | 254.61 | 162.55 | 4 | 420.8 | 421.41 | 1 | 277.39 | 278.25 | 1 | 437 | 368.58 | 2 |
| 11:20:00 AM   | 226.99 | 217.89 | 1 | 379.84 | 381.48 | 1 | 618.95 | 383.22 | 4 | 538.41 | 318.87 | 4 |
| 11:40:00 AM   | 533.99 | 165.84 | 6 | 450.77 | 424.09 | 1 | 379.49 | 381.66 | 1 | 710.05 | 176.32 | 6 |
| 12:00:00 PM   | 729.02 | 122.2 | 7 | 249.68 | 245.26 | 1 | 390.84 | 393.18 | 1 | 756.21 | 190.79 | 6 |
| 12:20:00 PM   | 756.47 | 179.35 | 6 | 304.75 | 302.24 | 1 | 458.39 | 460.73 | 1 | 703.99 | 126.18 | 7 |
| 12:40:00 PM   | 743.57 | 214.95 | 6 | 518.75 | 451.98 | 2 | 472.59 | 454.58 | 1 | 669.87 | 128.34 | 7 |
| 1:00:00 PM    | 570.62 | 171.73 | 6 | 150.17 | 151.03 | 1 | 330.3 | 332.29 | 1 | 683.9 | 162.29 | 6 |
| 1:20:00 PM    | 624.23 | 173.72 | 6 | 183.25 | 184.46 | 1 | 425.56 | 424.53 | 1 | 749.72 | 316.27 | 5 |
| 1:40:00 PM    | 635.58 | 168.27 | 6 | 194.77 | 196.07 | 1 | 78.55 | 78.64 | 1 | 534.34 | 246.12 | 5 |
| 2:00:00 PM    | 533.64 | 140.38 | 6 | 174.76 | 175.89 | 1 | 152.94 | 153.81 | 1 | 627 | 221.01 | 6 |
| 2:20:00 PM    | 506.97 | 191.48 | 5 | 140.21 | 140.9 | 1 | 121.59 | 122.11 | 1 | 596.95 | 222.05 | 5 |
| 2:40:00 PM    | 131.46 | 129.56 | 1 | 167.58 | 167.23 | 1 | 105.14 | 104.44 | 1 | 239.37 | 191.91 | 3 |
| 3:00:00 PM    | 132.42 | 89.55 | 3 | 80.45 | 80.11 | 1 | 40.1 | 38.71 | 1 | 315.41 | 126.01 | 5 |
| 3:20:00 PM    | 90.59 | 90.67 | 1 | 68.59 | 67.46 | 1 | 59.06 | 59.24 | 1 | 313.33 | 89.81 | 6 |
| 3:40:00 PM    | 258.68 | 102.54 | 5 | 115.27 | 112.41 | 1 | 84.18 | 84.44 | 1 | 235.82 | 69.2 | 6 |
| 4:00:00 PM    | 48.24 | 48.15 | 1 | 90.67 | 88.77 | 1 | 70.15 | 70.32 | 1 | 168.1 | 61.31 | 5 |
| 4:20:00 PM    | 62.44 | 60.88 | 1 | 39.58 | 39.49 | 1 | 40.01 | 39.58 | 1 | 116.48 | 60.97 | 4 |
| 4:40:00 PM    | 25.63 | 24.42 | 1 | 22.34 | 22.17 | 1 | 22.52 | 22.34 | 1 | 62.09 | 45.12 | 3 |
| 5:00:00 PM    | 8.23 | 7.79 | 1 | 5.46 | 5.11 | 2 | 4.5 | 4.16 | 2 | 11.34 | 10.65 | 2 |
Next, to examine the influence of environmental measurements in luminous change categories, we developed a second visual coding system that integrated points-in-time measures of vertical illuminance and CCT with their correspondent type of lightness change and naturalistic view scene. As described above, we evaluated luminous change only under similar sky conditions (Figure 10).

![Visual coding system to quantify luminous change categories over time.](image)

**Figure 9** Visual coding system to quantify luminous change categories over time.

Next, to examine the influence of environmental measurements in luminous change categories, we developed a second visual coding system that integrated points-in-time measures of vertical illuminance and CCT with their correspondent type of lightness change and naturalistic view scene. As described above, we evaluated luminous change only under similar sky conditions (Figure 10).

![Visual coding system to analyze the influence of environmental measurements in luminous change categories.](image)

**Figure 10** Visual coding system to analyze the influence of environmental measurements in luminous change categories.

**Results**

The previously described methods present one possible approach for classifying views and collecting and quantifying luminous changes in view. Here, we use these methods to present a preliminary descriptive summary of luminous changes as a function of different view types, view orientations, and heights. From the original sample of 176 lightness change matrices, 119 occurred across two images with similar sky classifications (See Table 4) and were included in the below results.
Changes across view types

In controlled sky conditions (Table 5), we observed that the Courtyard category presented the highest occurrence of Local variation (31%) and combined Global and Local variation (88%). These results could be linked to the characteristics of the view type, which may depict different planes rendering predictable and unpredictable variability patterns over time. Likewise, we observed that the Roof category presented the highest occurrence of Global variation (68%) and the second-highest occurrence in combined Global and Local variation (84%). Although Local variation in this view type is relatively little in comparison with the one registered in the Courtyard category, the high Global variation suggests the potential to inform about predictable light changes over time.

Changes across view orientations

To examine luminous change from the perspective of orientation, we selected six panorama sequences with similar orientations towards North, South, and East, and registered luminous variation under controlled sky conditions (Table 6). Although image sequences oriented towards the West had slightly more Local variation (31%) and less Global variation (25%) than did sequences oriented to the North and South, there were no apparent differences between them.

Changes across view height

To examine the role of the viewing position on registering luminous changes, we grouped all image sequences in relation to the height of the vantage point (i.e., 4 m, 6 m, 9 m, and 12 m) and examined variation under similar sky conditions (Table 7). The percentage of transitions classified as Minimal variation decreased as height increased, suggesting that higher views may have increased luminous variability.
Table 5 Luminous change for each view type (i.e. Wall, Courtyard, Corridor, and Roof).

|                | [P02 L*-P01 L*] | [P03 L*-P02 L*] | [P04 L*-P03 L*] | [P05 L*-P04 L*] | [P06 L*-P05 L*] | [P07 L*-P06 L*] | [P08 L*-P07 L*] | [P09 L*-P08 L*] | [P10 L*-P09 L*] | [P11 L*-P10 L*] | [P12 L*-P11 L*] | [P13 L*-P12 L*] | [P14 L*-P13 L*] | [P15 L*-P14 L*] | [P16 L*-P15 L*] | [P17 L*-P16 L*] | [P18 L*-P17 L*] | [P19 L*-P18 L*] | [P20 L*-P19 L*] | [P21 L*-P20 L*] | [P22 L*-P21 L*] | [P23 L*-P22 L*] |                      | Total classified | % Global Variation | % Local Variation | % Min Variation |
|----------------|------------------|------------------|------------------|------------------|------------------|------------------|------------------|------------------|------------------|------------------|------------------|------------------|------------------|------------------|------------------|------------------|------------------|------------------|------------------|------------------|------------------|------------------|------------------|------------------|
| Wall           | VS 1             | G                | N                | G                | L                | N                | N                | N                | N                | N                | N                | N                | N                | N                | N                | N                | N                | N                | N                | N                | N                | N                | N                | N                | 2                | 32               | 6                | 34               |
|                | VS 2             | G                | G                | G                | G                | G                | G                | G                | G                | G                | G                | G                | G                | G                | G                | G                | G                | G                | G                | G                | G                | G                | G                | G                | 16               | 32               | 2                | 34               |
| Courtyard      | VS 1             | G                | G                | G                | L                | L                | L                | L                | L                | N                | N                | N                | N                | N                | N                | N                | N                | N                | N                | N                | N                | N                | N                | 6                | 35               | 8                | 31               |
|                | VS 2             | G                | G                | G                | G                | G                | G                | G                | G                | G                | G                | L                | N                | L                | G                | G                | G                | G                | G                | G                | G                | G                | G                | 14               | 35               | 3                | 31               |
| Corridor       | VS 1             | G                | G                | N                | N                | N                | N                | N                | N                | N                | G                | N                | N                | N                | N                | G                | L                | N                | N                | N                | N                | N                | N                | 2                | 26               | 12               | 16               |
|                | VS 2             | N                | N                | N                | L                | N                | N                | N                | N                | G                | N                | N                | G                | N                | N                | N                | G                | L                | N                | N                | N                | N                | N                | 3                | 26               | 12               | 69               |
| Roof           | VS 1             | G                | G                | G                | L                | G                | G                | G                | G                | G                | G                | G                | N                | N                | N                | N                | N                | N                | N                | N                | N                | N                | N                | 13               | 25               | 68               | 16               |
|                | VS 2             | G                | G                | G                | G                | G                | L                | N                | N                | N                | N                | N                | N                | N                | N                | N                | N                | N                | N                | N                | N                | N                | N                | 4                | 25               | 68               | 16               |


Table 6 Luminous change for three orientations (i.e. North, South, West).

| North  | NE10 9 | G | N | G | L | N | N | N | N | N | N | N | 2 | 1 | 11 |
|--------|--------|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
|        | N351   | G | G | N | G | G | G | L | G | G | G | G | G | G | N | N | N |
|        |        | 13 | 2 | 4 | 33 | 46 | 9 | 46 |
| South  | S167   | G | G | G | G | G | G | G | G | G | L | N | L | G | G | G | G |
|        | SW28   | N | N | N | L | N | N | N | N | G | N | N | G | N | N | G | L | N |
|        |        | 3 | 2 | 13 | 36 | 47 | 14 | 39 |
| West   | W289   | G | G | G | G | G | G | L | L | L | L | N | N | N | N | N | N |
|        | W290   | G | G | L | G | G | G | L | L | L | L | N | N | N | 6 | 9 | 3 | 36 | 25 | 31 | 44 |
Table 7 Luminous change for different heights (i.e. 4, 6, 9, and 12 m).

| Height (m) | Global Variation | Local Variation | Min Variation | Total classified | % Global Variation | % Local Variation | % Min Variation |
|------------|------------------|----------------|--------------|----------------|-------------------|------------------|----------------|
| 4 m        |                  |                |              | 4.30 m         |                    |                  |                |
|            | G                | G              | N            | 6.90 m         | 9                 | 3                | 32             |
| 6 m        |                  |                |              | 6.20 m         |                    |                  |                |
|            | G                | G              | G            | 6.40 m         | 3                 | 1                | 36             |
| 9 m        |                  |                |              | 9.10 m         |                    |                  |                |
|            | G                | G              | N            | 9.50 m         | 1                 | 0                | 26             |
| 12 m       |                  |                |              | 12.20 m        |                    |                  |                |
|            | G                | G              | G            | 12.80 m        | 4                 | 0                | 25             |

Note: The table values are hypothetical and for demonstration purposes only.
Examining environmental measures in variability conditions

To examine how objectively measured changes in the overall outdoor luminous environment may be relevant, we defined a sample of Global variation (n=60), Local variation (n=22), and No luminous variation (n=37) sequences recorded in similar sky conditions and examined simultaneously measured vertical illuminance and CCT. We only analyzed clear and overcast sky conditions, since both Global and Local variation over time were observed in these sky conditions. For this preliminary exploration data, only vertical illuminance measures are discussed below, as CCT values were not conclusive without reflectance values from neighboring surfaces.

Global variation

Since the predictable lightness change patterns depicted in Global variation are seemingly related to the relative position of the sun, we expected to observe vertical illuminance peaks when the light source faced the viewer position. As such, in clear sky conditions, we observed vertical illuminance peaks in the Wall category when direct sunlight reached a reflective surface (Figure 11). In overcast sky conditions, peak vertical illuminance was registered in the Roof category (Figure 12), which is consistent with the significant presence of Sky regions and the height of the viewing position.

Figure 11 Photometric measures informing Global variation in clear sky conditions.
Local variation

Since Local variation is seemingly linked to unpredictable lightness peaks, we expected to observe them mostly under clear sky conditions, as direct sunlight reaching surfaces with different positions and material properties would produce a broader range of luminous responses. These vertical illuminance peaks under clear sky conditions were observed in a Courtyard category (Figure 13), presumably linked to the configuration of Planar and Non-planar regions. In overcast sky conditions, vertical illuminance peaks were observed in all Roof categories (Figure 14). Since the Sky region in the Roof category is predominant, it is possible that changes in brightness of the sky produced by heterogeneous clouds influence how Local variations are registered for this particular view category. More data is needed to understand the mechanisms through which luminous changes become apparent in the different view categories.

Figure 12 Photometric measures informing Global variation in overcast conditions.
Figure 6 Photometric measures informing Local variation in overcast sky conditions.

Figure 14 Photometric measures informing Local variation in clear sky conditions.
Discussion

This paper is the first to propose a comprehensive methodology to examine changes in outdoor views dynamically, which comprises stages of categorization of view scenes, collection of view scenes and environmental measures, and integrated analysis of the procedures. The efforts of building this framework represent a fundamental first step that will permit us to examine the role of environmental changes in views as suggested by scholars in the environmental psychology field (Sonnentag et al., 2017). There is minimal research on how views change across the day, and this paper contributes to a methodical way of understanding the effects of luminous variability in window views.

View categorization

To categorize views, we used a systematic labeling method generated using computer vision methods (Hoiem et al., 2007) to test its validity for assessing luminous variability in mixed urban views. Contrasting with the horizontal stratification approach defined by Markus (1967), this procedure provided an opportunity to systematize a range of urban view configurations to assess luminous conditions over time. Limitations of the procedure used to generate view types should be kept in mind when considering their generalizability. Although we defined view types from a combined sample of urban (n = 20) and suburban views (n = 20), our scenes were collected over a limited geographical area (radius = ~2 km), with a limited set of built environment types, and therefore the sample depicts a limited range of possible view configurations. The four generated categories were appropriate for the location where this study was conducted, but it is possible that different spatial configurations would be relevant in different types of urban settings (e.g., residential neighborhoods). Future research will explore urban areas with different building morphologies to examine whether the distribution of labeled regions can be effectively classified into the categories described in the current study, or whether additional types of spatial and surface classes may be appropriate.

Dynamic view collection

Next, we collected view scenes across time to quantify changes in the luminous aspects of view. In the second section of this study, we defined settings for time-lapse collection and described an image-processing routine to categorize lightness changes over
time. As a result, three luminous change categories emerged (i.e., Global variation, Local variation, and Minimal variation), which we used to conduct preliminary explorations into the luminous variation in view sequences. Limitations of the sample to estimate the lightness thresholds should be considered when appraising their generalizability. Although we proposed luminous change categories from a substantial sample size ($n = 184$), panoramas were collected over a limited time frame and with a limited range of sky classifications, thus the sample shows a limited range of possible luminous conditions in view scenes.

As for the capturing procedures, despite we acknowledge that not all daily lighting changes will be captured using a predefined photo interval of 20 minutes, more frequent capturing intervals will pose other challenges, such as larger image datasets to record and process, which would require more resources and automated solutions. As such, we consider that 20-minutes intervals have an appropriate sensitivity to describe and quantify luminous changes in views, but we will consider complementing the capturing and processing of time-lapse image sequences with a continuous video recording of views to appraise luminous changes within this intervals.

This study aimed to capture view scenes in a way that approximated the human field of view (i.e., panorama images), and could, therefore, be presented to participants in futures studies in an immersive way. These images were collected in a high-quality format using a DSLR camera. However, this procedure made the capture of images very time-consuming, as these were manually captured every 20 minutes, reducing the feasibility of this method for large-scale data collection. We are currently exploring whether the images produced from lower-quality cameras that require less manual intervention are sufficient for conducting the image processing routines we describe in this paper, as this may increase the feasibility of the described methods.

Although environmental measures are critical for contextualizing outdoor viewing conditions (Granzier & Valsecchi, 2014) and describing the overall luminous environment, current procedures to examine views do not stress the importance of reporting this data. By capturing concurrent environmental photometric measures (i.e., external solar radiation, vertical illuminance, CCT), we were able to conduct a preliminary examination of the sky conditions in which luminous variation occurs (i.e., by combining external radiation measures to classify skies (Perez et al., 1990). Even
though this information is appropriate for portraying and comparing luminous changes in different view scenes, more work must be done regarding the analysis of image details (e.g., color contrasts, object sizes, and visual patterns), to understand the mechanisms by which visual elements and surfaces contribute to intensifying dynamic luminous changes in view scenes. For instance, because neighboring surfaces and heterogeneous natural features (e.g., clouds) proved to influence changes in brightness levels, future research will incorporate imaging techniques (Inanici, 2006) to estimate the extent by which luminous change categories are conditioned by differences in reflectance values, visual patterns and apparent positions within the scene.

As a final step in this study, we integrated the systematic categorization and dynamic capturing procedures, aiming to quantify luminous change from three approaches (i.e., view types, orientation, and height) and to examine the influence of environmental measures (i.e., vertical illuminance, CCT) in two luminous change categories (i.e., Global and Local variation). In the final section of this study, we defined two coding systems that helped us comparing photometric measures and view scenes, and permitted us to select the research sample in controlled conditions. As preliminary results, we observed that two view types (i.e., Courtyard and Roof) showed the highest potential to convey luminous variations and noted that the assessment of view types provides a better depiction of luminous changes outdoors in comparison to more established spatial measures, as orientation or height of the vantage point. Additionally, by examining photometric measures concurrently with image sequences, we found that vertical illuminance is a good predictor for luminous changes over time. Results presented in this study are exploratory only and were presented to demonstrate the described methods. Further work with a larger sample size and inferential statistical analysis will be needed to formally examine relationships and differences in view characteristics, aimed at providing recommendations to improve the design process and the evaluation of view quality in urban settings.

**Future steps**

In this paper, we presented an exploration to test luminous change categories within view types and demonstrated that such variations could be structured within ranges of predictability (i.e., Global variation) and unpredictability (i.e., Local variation) across a range of environmental conditions. As such, we hypothesize that trying to predict clues
from the dynamic luminous environment may result in sources of involuntary attention; and that trying to appraise temporal cues via *comprehending* the luminous environment outdoors can have a mediating effect on individuals’ preference for views. Future studies will test this hypothesis using the procedures in this paper in immersive view interventions to propose a systematic design and evaluation guidelines that take into consideration the specific spatial and dynamic characteristics of a view outdoors.

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