SPATIO-TEMPORAL DYNAMICS OF KOMOREBI LIGHT PATTERNS

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Abstract

Komorebi, the dappled sunlight filtering through trees, offers restorative benefits in outdoor and indoor environments. While studies have examined its presence, movement, and changes in illuminance, a comprehensive understanding of its dynamic properties remains largely unexplored. This study develops a framework to quantify the spatial and temporal characteristics of Komorebi patterns. The methodology involves collecting Komorebi scenes, extracting their temporal and spatial features, and creating a multidimensional representation to capture these features effectively. The spatial feature analysis focuses on light pattern dispersion, intensity correlations, and spectral analysis of two-dimensional patterns; the temporal analysis, on the other hand, examines movement, directional changes, and brightness fluctuations. This study introduces a novel approach for categorizing and representing different typologies of Komorebi, and establishes a basis for examining people's responses to Komorebi patterns.

Keywords: Komorebi, Dappled Sunlight, Spatial Characteristics, Temporal Dynamics

1 Introduction

Nature is widely acknowledged for its restorative qualities (Kaplan & Kaplan, 1989; Ulrich et al., 1991). Incorporating natural elements into indoor spaces thus offers the potential to enhance well-being in environments where many people spend a large majority of their time. One such element is the dappled sunlight that filters through trees, known in Japanese as Komorebi, which has shown potential for inducing restorative effects both in outdoor nature (Fujisawa et al., 2012) and indoor settings as projected light patterns (Karibe et al., 2019).

Existing studies have explored various aspects of Komorebi, including comparisons of its presence versus absence (Takayama et al., 2020), differences between static images and moving videos (Chamilothori et al., 2022) – with dynamic Komorebi seemed to enhance preference, fascination, and association with nature compared to static conditions –, light patch movement tracking (Karaman-Madan et al., 2023), and illuminance changes studied through spectral analysis (Nakamura and Kozaki, 2024). Based on these studies and others, it appears that the multidimensional spatio-temporal qualities of komorebi hold the key to its distinct well-being benefits.

Spatially, these dappled light patterns exhibit scale-invariant distributions similar to fractals, which have been associated with increased interest, preference, and relaxation (Aboushi et al., 2019). Natural patterns optimize visual processing efficiency (Taylor, 2006; Spehar et al., 2016), with most natural patterns falling close to 1/f distributions (Wilkins, 2016). The temporal dynamics of komorebi, on the other hand, arise from wind-leaf interactions that produce naturally rhythmic movements. Such natural rhythms – also present in phenomena like ocean waves and wind – often exhibit 1/f characteristics and have been associated with reduced stress and enhanced restoration (Musha, 1980) as these natural variations may induce meditative states through "soft fascination" (Kaplan, 1995). Despite these distinctive characteristics, the actual movement and directional dynamics of Komorebi remain largely unexplored. Karaman et al. (2023) did attempt to examine *komorebi*'s motion effects by isolating temporal dynamics from other natural cues, using artificially generated white circles on a black background to represent dappled sunlight. They compared three conditions: a natural-movement condition (where circles mimicked the speed and direction of real *komorebi*), a non-natural-movement condition (with randomized positions and ordered size changes), and a static control. Surprisingly, while both dynamic conditions were rated as more fascinating than static light—with no significant difference between natural and non-natural motion—neither was perceived as more strongly "associated with nature" than the other. This suggests that motion alone—without organic shapes, textures, or gradient—may be insufficient to evoke nature's restorative effects.

These findings collectively highlight the need to study Komorebi holistically, considering how its spatial organization, brightness variations, temporal rhythms, and movement patterns seem to work together in creating their unique perceptual effects.

Achieving this requires a comprehensive analytical framework capable of capturing the spatio-temporal characteristics inherent to Komorebi patterns in a systematic way, which is the goal of this study. By identifying the relevant spatial and temporal features and selecting suitable metrics, the study addresses current gaps in understanding Komorebi patterns and establishes a basis for further exploration of their restorative potential.

2 Methodology

Given the intricate spatial compositions and subtle temporal dynamics of Komorebi, an interdisciplinary approach combining findings borrowed from landscape ecology, computational vision science, and visual perception research offers a promising basis to characterize their patterns. Landscape ecology provides insights into spatial complexity and clustering patterns commonly observed in natural environments (Forman, 1986; Turner et al., 2001). Signal processing and computer vision methodologies, on the other hand, have successfully quantified subtle temporal variations in visual scenes (Simoncelli & Olshausen, 2001), particularly relevant to Komorebi's temporal variations. Additionally, visual perception research highlights significance of 1/f spectral characteristics in natural patterns, which are efficiently processed by the human visual system and linked to perceived naturalness and aesthetic preference (Field, 1987; Nishida, 2011).

To systematically characterize the unique spatial distribution of komorebi patterns, multiple methodologies were evaluated and ultimately led to the selection of the Nearest Neighbor Index (NNI) (Clark & Evans, 1954) and Moran's I (Moran, 1950). NNI was chosen over alternatives such as Ripley's K-function (Ripley, 1977) and quadrat analysis (Greig-Smith, 1952) because it quantifies clustering versus dispersion of light patches with a single normalized value, facilitating comparisons across different scenes without scale dependency. Meanwhile, Moran's I was selected among various spatial autocorrelation metrics such as Geary's C (Geary, 1954) and Getis-Ord Gi (Getis & Ord, 1992) for its ability to capture global intensity relationships while maintaining robustness across varying illumination conditions. Additionally, we applied 1/f analysis to spatial frequencies, building on evidence that natural scenes typically exhibit 1/f power spectra and that human visual systems have evolved to efficiently process such patterns.

For the temporal dynamics highlighted earlier, we implemented optical flow analysis (Horn & Schunck, 1981) after considering alternatives including feature tracking algorithms, particle image velocimetry (Adrian & Westerweel, 2011), and frame differencing (Jain & Nagel, 1979). Optical flow was selected for its ability to generate comprehensive vector fields describing both magnitude and direction of movement for each pixel region with relatively lower computational demands, capturing the subtle, complex motions characteristic of Komorebi patterns that may contribute to their "soft fascination" effects. In addition, we extended our 1/f analysis to temporal frequencies as well, examining how brightness fluctuations in Komorebi patterns exhibit fractal characteristics over time – addressing the natural rhythms discussed above. Integrating these complementary analytical techniques enables a detailed characterization of the spatial-temporal features central to Komorebi's perceptual and restorative qualities.

3 Data collection and feature extraction

This section outlines our approach for capturing Komorebi patterns under controlled conditions and details the procedures for extracting the spatial and temporal metrics defined earlier. The process started by recording videos of real Komorebi with enough spatial and temporal variations, then focused on quantifying these spatio-temporal characteristics: relative positioning and intensity of light patches (through NNI and Moran's I) and type and direction of their respective movements (optical flow and directional patterns), complemented by 1/f analyses.

3.1 Komorebi video collection

Figure 1 – Setup for Komorebi video recording

Komorebi videos were recorded in natural settings under trees, where sunlight is filtered through the leaves to create dappled light patterns (Figure 1). To eliminate distractions, a white matte surface was used as the projection plane. Recordings were conducted under clear skies using a high-resolution camera mounted on a tripod with a horizontal arm for top-down captures. The camera was set to manual mode with multi-point focus, ensuring proper focus. The luminance histogram was checked prior to recording to maintain balanced mid-tones and highlights, avoiding both overexposure and underexposure. Sufficient duration and frame rate were required to capture the temporal dynamics of the lighting patterns. For the purposes of this study, each scene was recorded for approximately 60 seconds at 24 frames per second.

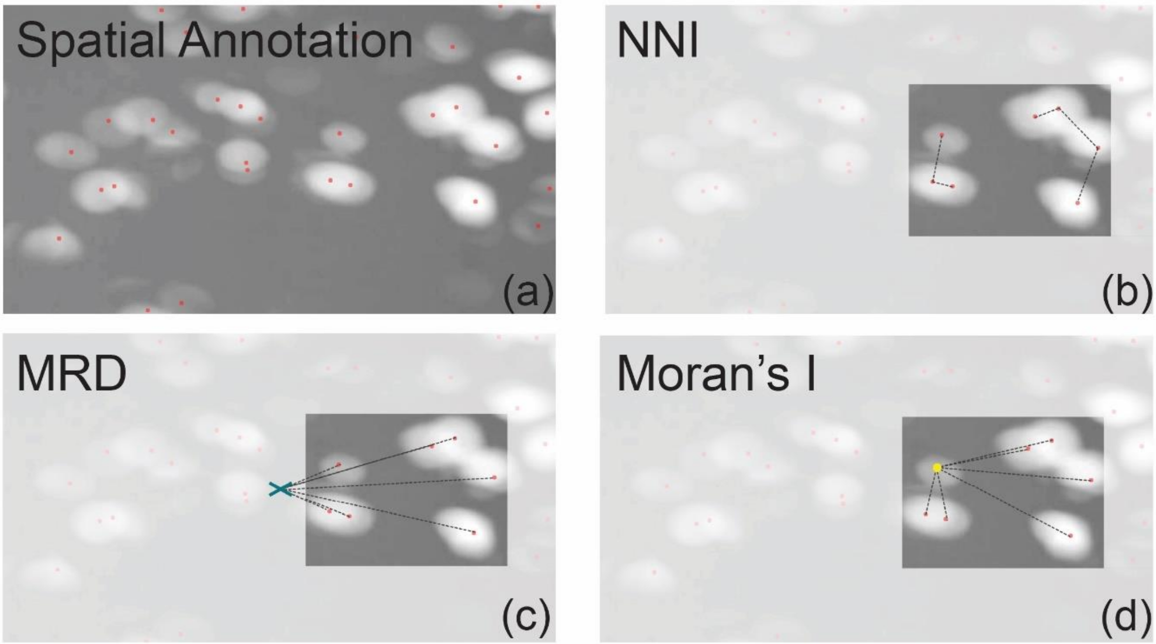

Figure 2 – Figure 2 – Spatial features analysis. (a) Spatial Annotation: Komorebi light spots marked with red points. (b) NNI: Nearest neighbor index for spatial clustering assessment. (c) MRD: Mean Ripleyan distance from reference point (blue cross). (d) Moran's I: Spatial autocorrelation with reference point (yellow) and connecting lines. Spatial features

The spatial features of the Komorebi patterns were extracted from locating the light patches' centers, as indicated in Figure 2a, at which the light intensity value was determined. Due to the blurry and overlapping nature of Komorebi, automated extraction of the light patches's centers proved unfeasible, requiring instead a manual selection process based on visual inspection. For the spatial feature analysis, light patches were selected at regular intervals throughout each video until the spatial metrics stabilized, based on the criterion of a running average change of less than 1% - a threshold commonly used in statistical convergence analysis to ensure data representativeness while minimizing sampling redundancy.

The **spatial distribution of light patches**, quantified using the Nearest Neighbor Index (NNI) (Figure 2b), compares the arrangement of points to a random distribution a low NNI (<1) indicates clustering, while a high NNI (>1) suggests dispersion. For this analysis, the centroids of each light patch was used to calculate the NNI:

$$NNI = \frac{\frac{1}{N}\sum_{i=1}^{N} d_{obs,i}}{\frac{1}{2\sqrt{\rho}}} \quad with\, \rho = \frac{N}{W \times H} \tag{1}$$

where

$d_{obs,i}$ is the nearest neighbor distance for each light patch;

ρ is the density of points, normalized by the image area;

N refers to the number of light patches;

W, H are the image width and height.

The **spatial correlation of light intensities**, analyzed using Moran's I (Figure 2d), uses a metric for spatial autocorrelation: high Moran's I values (close to 1) indicate clustering of similar intensities, while low values (close to -1) suggest randomness. The brightness at each light patch centroid was the parameter used for this analysis, where Moran's I is calculated as:

$$I = \frac{N \sum_i \sum_j w_{ij}(x_i - \overline{x})(x_j - \overline{x})}{\left(\sum_i (x_i - \overline{x})^2\right)\left(\sum_i \sum_j w_{ij}\right)} \quad with\, w_{ij} = \frac{1}{\left(\frac{d_{ij}}{\sqrt{W^2 + H^2}}\right)} \tag{2}$$

where

x_i ,x_j are the light intensity values at locations i and j;

$\overline{x}$ is the mean intensity;

d_{ij} is the Euclidean distance between points I and j;

Komorebi images were also analyzed via **spatial spectral analysis** in the frequency domain. The amplitude spectrum was derived using a Fourier Transform, with frequency components characterized by a power-law relationship where higher β values represent smoother patterns, while lower values β reflect intricate textures instead:

$$A(f) = \frac{1}{f^{\beta}} \tag{3}$$

where

β quantifies the decay of amplitude with spatial frequency.

Additionally, the **Mean Radial Distance (MRD)** (Figure 2c) was used to analyze the spatial distribution of light patches relative to the image center. A low MRD value indicates that light patches are concentrated near the center, while a high value suggests that light patches are more dispersed toward the edges. To enable cross-scene comparison, MRD was normalized using the diagonal length of the image. The complete formula is provided in **Equation (4):**

$$MRD_{norm} = \frac{1}{N\sqrt{W^2+H^2}} \sum_{i=1}^{N} \sqrt{(x_i - x_c)^2 + (y_i - y_c)^2} \quad (4)$$

where

x_i, x_j represents the coordinates of each light patch;

x_c, y_c denotes the center of the image.

3.2 Temporal features

As shown in Figure 3, the motion of Komorebi patterns was analyzed using **optical flow**, which measures movement between consecutive video frames. Average movement was quantified by calculating the magnitudes of optical flow vectors for each frame interval and averaging across the entire image. In addition to movement magnitude, the **directional variation** was assessed by computing the circular variance of the dominant direction over time. The complete formulation is shown in **Equation (5):**

$$Movement_{Avg} = \frac{\sum Optical\ Flow\ Magnitude}{W \times H},\ DirectionVar = 1 - \frac{\sqrt{\left(\sum_{i=1}^{N} cos\theta_i\right)^2 + \left(\sum_{i=1}^{N} sin\theta_i\right)^2}}{N} \quad (5)$$

where

θ is the dominant optical flow direction.

The **temporal frequency of brightness fluctuations** in the Komorebi video was analyzed using 1/f analysis on brightness time-series data. A Fourier Transform was applied to compute the power spectral density (PSD), which was then fitted to a power-law model:

$$P(f) = \frac{1}{f^{\alpha}} \quad (6)$$

where

α, determined by linear regression of log-transformed PSD data, represents the decay rate of power with frequency.

A low α value indicates rapid fluctuations, while a high α value signifies slower, smoother changes in brightness over time.

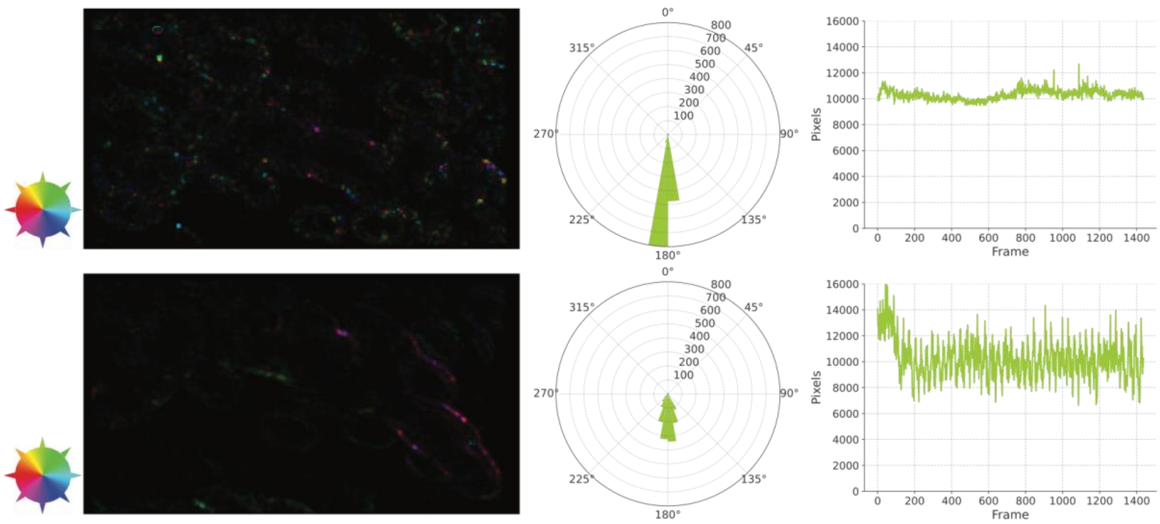

Figure 3 – Temporal feature analysis. Optical flow visualization (left) with color wheel indicating motion direction and velocity magnitude; dominant movement direction distribution (center); and movement intensity over time (right)

4 Analysis results

4.1 Spatio-temporal characteristics

The spatial analysis revealed variations in light patch dispersion and intensity correlations, along with consistent spatial spectral characteristics. The Nearest Neighbor Index (NNI) values ranging from 1.1 to 1.4 indicate that Komorebi light patches tend toward dispersion rather than clustering, with values closer to the lower end suggesting nearly random distributions and those approaching the upper end demonstrating more pronounced regular spacing between patches. Moran's I values ranged from 0.003 to 0.217, suggesting that the brightness values of Komorebi light patches are generally randomly distributed, with some scenes exhibiting moderate clustering of similar intensities at the higher Moran's I values. MRD values consistently clustered between 0.52 and 0.67, indicating that light patches maintain a relatively consistent distribution pattern around the image center across different Komorebi scenes. Spatial spectral analysis consistently yielded β values around 1, indicating a balanced representation of both smoothness and detail, which is corroborated by the literature: natural patterns seem to often exhibit $\beta \approx 1$ in amplitude spectrum analysis (Wilkins, 2016). Given the consistency observed in Komorebi's spatial spectral analysis, this feature will not be considered as one that could effectively demonstrate the variability of Komorebi, and therefore will not be shown in the feature representation of Komorebi in Figures 4 and 5.

The temporal analysis captured variability in both movement and brightness fluctuations. As shown in Figure 3, the natural wind-driven Komorebi (top row) shows movement concentrated within a narrow directional range and with stable intensity over time. In contrast, the hand-induced movement (bottom row) displays both greater directional diversity and higher temporal fluctuations in intensity. Temporal frequency analysis revealed α values from 1 to 2.7, with values near 1 indicating faster, more dramatic changes, and higher values indicating slower, smoother fluctuations. Previous studies, using a rough grid of illuminance measurements, reported α values between 1 and 2 (Nakamura and Kozaki, 2024). Our analysis – which evaluated brightness variations across the entire frame with a broader selection of Komorebi scenes – captured a wider range, with α values extending to 2.7.

Overall, our analysis represents the first quantitative methodology to fully characterize Komorebi features across both spatial and temporal dimensions. While previous studies simply categorized Komorebi as dynamic or static, or assessed movement broadly as random versus natural, our approach provides specific quantitative references for measurable properties defining the Komorebi phenomenon. This comprehensive quantification creates a basis for precise characterization of Komorebi.

4.2 Representation and scaling

Given the multidimensional nature and interrelated characteristics of Komorebi patterns, radar plots were chosen to visualize the spatial and temporal features simultaneously, capturing their relative magnitudes and interactions within a single, intuitive layout while effectively highlighting differences and similarities among the Komorebi patterns' characteristics of interest. To ensure meaningful comparisons among features with different scales, data were normalized using z-scores. A snapshot of the corresponding video is shown next to each radar plot in Figure 4 to allow a quick reference when it comes to spatial features. These snapshots are grouped by similar spatial distributions (NNI and MRD values), though their corresponding radar plots often show distinct temporal characteristics due to varying dynamic conditions - such as differences in wind strength (from gentle breezes to strong gusts) or manual interactions (including both regular oscillations and random shaking motions).

This representation reveals in particular that artificially manipulated Komorebi (indicated by bold outline) show pronounced increases in temporal variability compared to natural wind-driven Komorebi. Among the spatial features, Moran's I shows the highest variability - even within the same Komorebi scene group (comparable NNI/MRD). This likely occurs because Moran's I, while a spatial metric, captures temporal fluctuations in light intensity patterns that get averaged into its final value across video frames. By merging multiple dimensions into a single coherent representation, subtle yet meaningful distinctions in how Komorebi differs become readily perceptible, enabling researchers to understand, identify, compare, and group light patterns based on their comprehensive spatio-temporal characteristics.

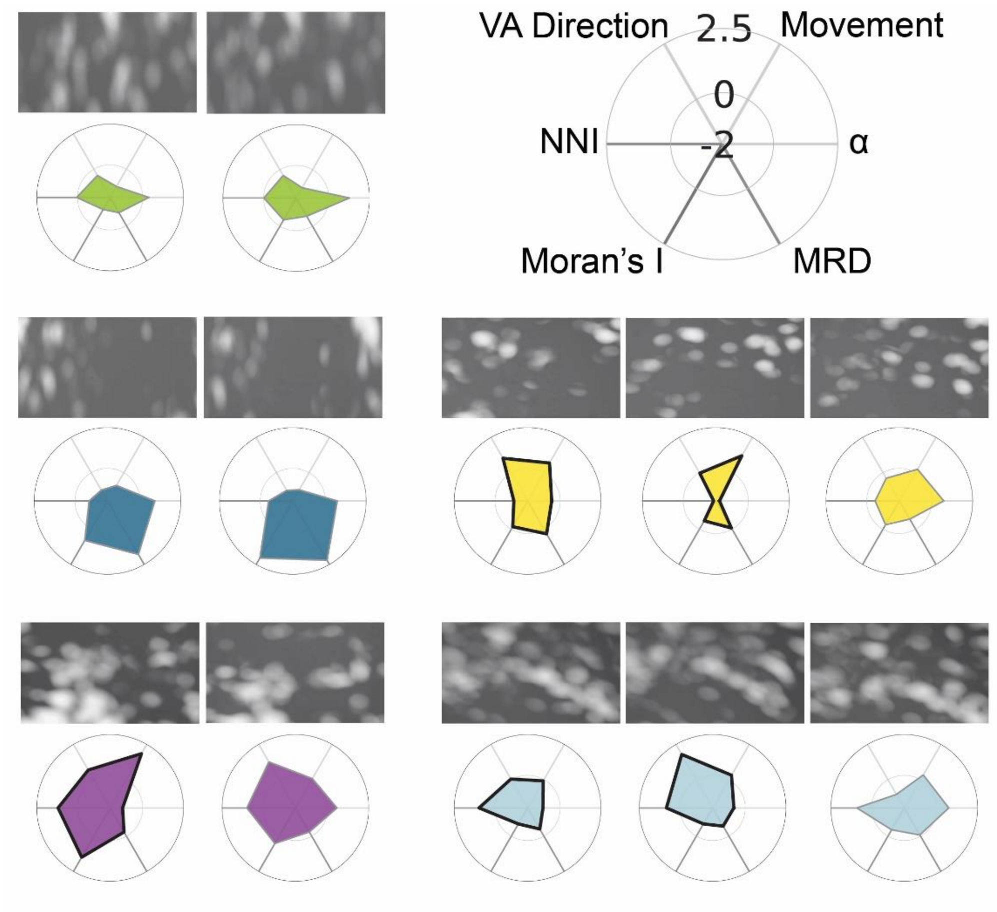

Figure 4 – Radar plots of spatio-temporal Komorebi features. Top right: Reference guide showing six dimensions (light gray: temporal features; dark gray: spatial features). Remaining plots: Feature profiles for different Komorebi scenes, with bold outlines indicating artificially manipulated Komorebi.

4.3 Clustering typologies

Further analysis through clustering of Komorebi videos revealed distinct groupings based on a combination of spatial and temporal features, illustrated by Figure 5. Using the elbow method, we determined the optimum number of clusters as the smallest number beyond which further increasing *k* yields minimal improvement. These statistically meaningful clusters capture natural divisions in the data that correspond to distinct Komorebi pattern types with shared characteristics.

The cluster analysis of spatio-temporal Komorebi features reveals a clear two-class structure across all six measured dimensions, with scenes captured at the same location exhibiting strong clustering behavior in spatial characteristics. Manually activated Komorebi (bold outlines) demonstrate distinctive grouping patterns in temporal dynamics, particularly clustering movement and α features. This separation is most pronounced in the α dimension, where all manually activated instances consistently group in the low-α region compared to natural Komorebi, suggesting that artificial manipulation produces more spectrally predictable brightness changes that distinctly differentiate from the dynamic spectral characteristics of naturally occurring Komorebi. In contrast, while the variation in direction feature maintains the overall two-class structure, the separation between manually activated and natural instances is less pronounced, with both types distributed across the boundary, indicating this feature is less capable of distinguishing between natural and artificial Komorebi variations.

The clusters reveal that Komorebi patterns actually resolve into distinct typologies with specific spatio-temporal features. This classification goes beyond the traditional binary labels and offers a more refined understanding of both distinctions and commonalities among various Komorebi patterns. In practical terms, what was once simply deemed a "dynamic" or "natural" Komorebi pattern can now be recognized as one of several dynamic sub-types with particular spatio-temporal signatures.

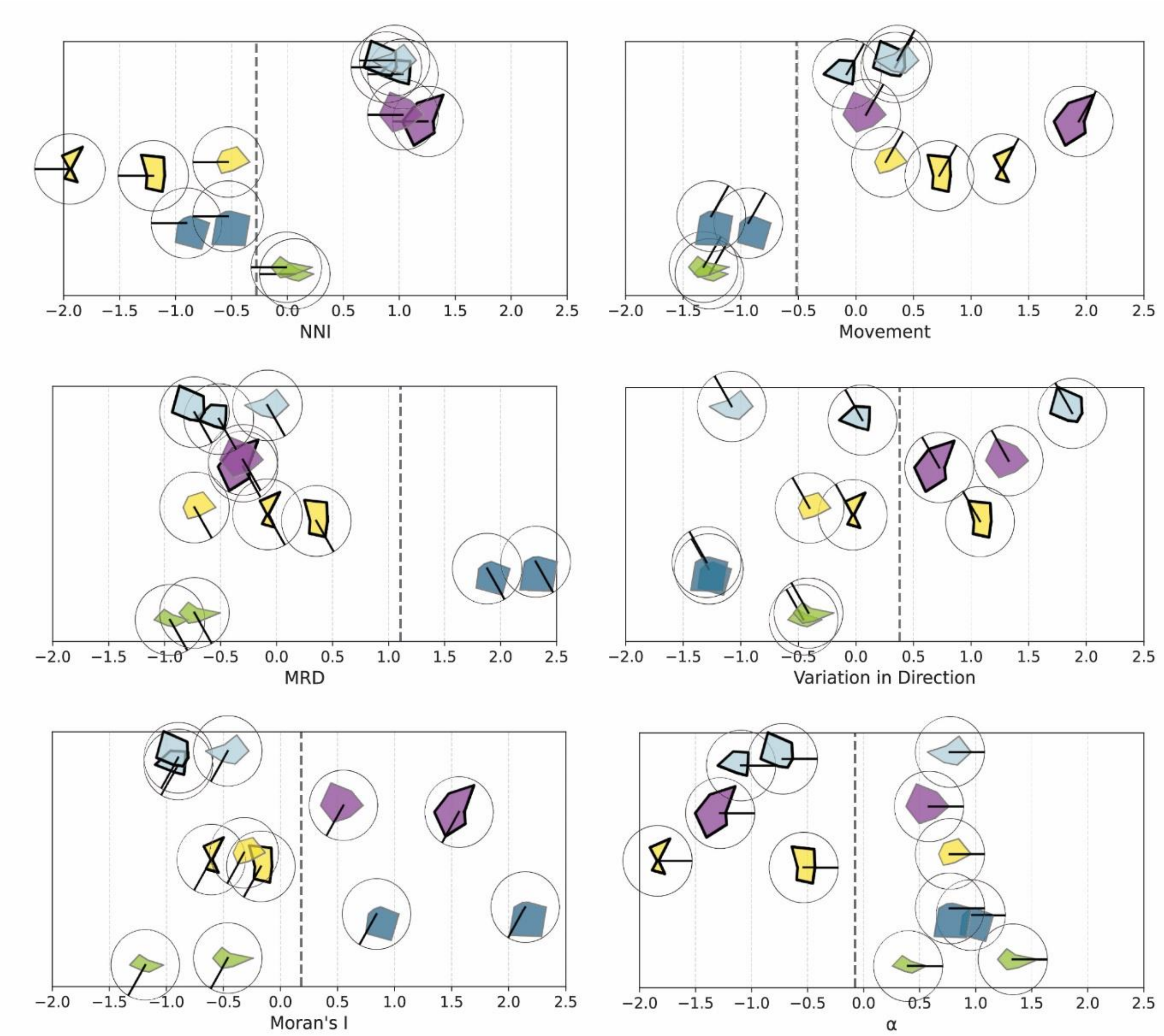

Figure 5 – Clustering of Komorebi videos with radar plots

4.4 Limitations of framework

While this study provides a useful framework for analyzing and representing the spatio-temporal dynamics of Komorebi, certain limitations remain. The features analyzed are simplified representations of a complex natural phenomenon. Although the proposed measures capture key dynamics of Komorebi, considering additional aspects—such as the orientation and size of light patches—could provide useful complementary perspectives.

Regarding the actual extraction of parameters or their analysis, the manual way of noting the light patterns may introduce variability in annotation consistency; employing multiple annotators to independently document patterns could potentially mitigate this bias. Furthermore, the current approach represents light patches as point locations with single intensity values, which may oversimplify their complex, gradient-based characteristics. Future work could explore alternative representations such as contour mapping or intensity-weighted regions to better capture the variations within light patches. The framework also does not account for human perceptual thresholds—some measured variations might be imperceptible to human observers and thus less relevant for restorative effects research. This relationship between measurable features and perceptual significance will need to be evaluated through further perception studies.

5 Conclusions

The application of texture and video feature analyses specifically to Komorebi patterns represents an important advancement by providing a comprehensive quantitative characterization previously unavailable in the literature. Our findings extend beyond broad categorizations of Komorebi, uncovering distinct typologies within them based on detailed spatial and temporal properties.

This study provides several important new discoveries. The spatial analyses reveal distinct patterns of dispersion and intensity correlation, demonstrating that Komorebi light patches consistently tend toward dispersion rather than clustering, with distributions ranging from nearly random to moderately regular spacing. Our temporal analyses provide a refined understanding of Komorebi's movement dynamics, revealing clear distinctions between artificially manipulated and naturally occurring Komorebi, with artificial instances particularly clustering in low-α regions indicating more spectrally predictable brightness changes compared to the dynamic spectral variations of natural occurrences. Additionally, the multidimensional representation and clustering of Komorebi features introduced in this study offer an intuitive way of identifying and comparing pattern variants.

By effectively capturing these spatial and temporal dynamics, our framework enables the design of targeted experimental stimuli for future research exploring relationships between specific Komorebi features and human responses. In the long term, the quantitative spatial and temporal features proposed in this paper could serve as a methodological foundation for designing shading systems or indoor lighting that replicates the dynamic qualities of Komorebi, thereby enhancing indoor experiences.

References

ABOUSHI, B., NEUMANN, T., WORTHINGTON, M., DIBERARDINO, A., MALKAWI, A. 2019. Fractals in architectural facade design: A case study of light levels in indoor space. *Building Simulation*, 12(4), 679-689. https://doi.org/10.1007/s12273-019-0532-6

ADRIAN, R.J., WESTERWEEL, J. 2011. *Particle image velocimetry*. Cambridge: Cambridge University Press.

CHAMILOTHORI, K., LEMMENS, R.M.M., KARAMAN-MADAN, Ö., DE KORT, Y.A.W. 2022. Effects of dappled light patterns on preference, fascination, and restoration in an online study. In: *Proceedings of Lux Europa 2022*.

CLARK, P.J., EVANS, F.C. 1954. Distance to nearest neighbor as a measure of spatial relationships in populations. *Ecology*, 35(4), 445-453. https://doi.org/10.2307/1931034

FIELD, D.J. 1987. Relations between the statistics of natural images and the response properties of cortical cells. *Journal of the Optical Society of America A*, 4(12), 2379-2394. https://doi.org/10.1364/JOSAA.4.002379

FORMAN, R.T.T., GODRON, M. 1986. *Landscape ecology.* New York: John Wiley & Sons.

FUJISAWA, M., TAKAYAMA, N., MORIKAWA, T., KAGAWA, T. 2012. Study on physiological response and subjective appraisal brought visually by a light environment of a forest. *Environmental Information Science*, ceis26, 103-106.

GEARY, R.C. 1954. The contiguity ratio and statistical mapping. *The Incorporated Statistician*, 5(3), 115-127. https://doi.org/10.2307/2986645

GETIS, A., ORD, J.K. 1992. The analysis of spatial association by use of distance statistics. *Geographical Analysis*, 24(3), 189–206.

GREIG-SMITH, P. 1952. The use of random and contiguous quadrats in the study of the structure of plant communities. *Annals of Botany,* 16(2), 293-316. https://doi.org/10.1093/oxfordjournals.aob.a083317

HORN, B.K., SCHUNCK, B.G. 1981. Determining optical flow. *Artificial Intelligence*, 17(1-3), 185-203. https://doi.org/10.1016/0004-3702(81)90024-2

JAIN, R., NAGEL, H.H. 1979. On the analysis of accumulative difference pictures from image sequences of real world scenes. *IEEE Transactions on Pattern Analysis and Machine Intelligence,* 1(2), 206-214. https://doi.org/10.1109/TPAMI.1979.4766906

KAPLAN, R., KAPLAN, S. 1989. *The experience of nature: A psychological perspective*. Cambridge: Cambridge University Press.

KAPLAN, S. 1995. The restorative benefits of nature: Toward an integrative framework. *Journal of Environmental Psychology,* 15(3), 169-182. https://doi.org/10.1016/0272-4944(95)90001-2

KARAMAN-MADAN, Ö., LINDERS, I.K., CHAMILOTHORI, K., DE KORT, Y.A.W. 2023. Effects of dynamic light patterns with natural and non-natural temporal composition on reported stress recovery, fascination, and association with nature. In: *The 30th Quadrennial Session of the CIE (CIE 2023)*, Ljubljana, Slovenia.

KARIBE, Y., URUSHITANI, A., IKEDA, T., HOSONO, T. 2019. Effects of indoor greening on physiological and psychological function with simulated "Komorebi" (sunlight through the leaves). *Journal of Japanese Society of People-Plant Relationships*, 18(2), 37-46.

MORAN, P.A.P. 1950. Notes on continuous stochastic phenomena. *Biometrika*, 37(1-2), 17-23. https://doi.org/10.1093/biomet/37.1-2.17

MUSHA, T. 1980. *Yuragi no sekai: The mystery of 1/f fluctuations in nature.* Tokyo: Kodansha.

NAKAMURA, Y., KOZAKI, M. 2024. The geometrical design of light-environment of "Komorebi" with the application of two-dimensional grid measurements of illuminance. In: K. Takenouchi (Ed.), *ICGG 2024 - Proceedings of the 21st International Conference on Geometry and Graphics*.

NISHIDA, S. 2011. Advancement of motion psychophysics: Review 2001-2010. *Journal of Vision*, 11(5), 11. https://doi.org/10.1167/11.5.11

RIPLEY, B.D. 1977. Modelling spatial patterns. *Journal of the Royal Statistical Society: Series B (Methodological)*, 39(2), 172-192. https://doi.org/10.1111/j.2517-6161.1977.tb01615.x

SIMONCELLI, E.P., OLSHAUSEN, B.A. 2001. Natural image statistics and neural representation. *Annual Review of Neuroscience*, 24(1), 1193-1216. https://doi.org/10.1146/annurev.neuro.24.1.1193

SPEHAR, B., WALKER, N., TAYLOR, R.P. 2016. Taxonomy of individual variations in aesthetic responses to fractal patterns. *Frontiers in Human Neuroscience*, 10, 350. https://doi.org/10.3389/fnhum.2016.00350

TAKAYAMA, N., MORIKAWA, T., YAMAUCHI, K., ITO, S. 2020. Differences in mind and body restorativeness and job satisfaction with the Komorebi irradiation system during the rest time for the nursing home staff. *Landscape Research Japan Online*, 13, 87-93.

TAYLOR, R.P. 2006. Reduction of physiological stress using fractal art and architecture. *Leonardo*, 39(3), 245-251. https://doi.org/10.1162/leon.2006.39.3.245

TURNER, M.G., GARDNER, R.H., O'NEILL, R.V. 2001. *Landscape ecology in theory and practice: Pattern and process*. New York: Springer.

ULRICH, R.S., SIMONS, R.F., LOSITO, B.D., FIORITO, E., MILES, M.A., ZELSON, M. 1991. Stress recovery during exposure to natural and urban environments. *Journal of Environmental Psychology*, 11(3), 201-230. https://doi.org/10.1016/S0272-4944(05)80184-7

WILKINS, A.J. 2016. A physiological basis for visual discomfort: Application in lighting design. *Lighting Research & Technology*, 48(1), 44-54. https://doi.org/10.1177/1477153515612526