Linking Image-based Metrics to 3D Model-based Metrics for Assessment of Visual Landscape Quality

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Abstract: Visual landscape quality represents a potential attribute of landscapes that affects people's perception and psychological well-being. With the perceived sensory dimensions as a conceptual framework, this study proposes methods to measure visual quality in both real environments and virtual models, using image-based metrics from computer vision techniques and 3D model-based metrics from parametric modelling techniques. Using the Clementi Woods Park in Singapore as a case study, we compared these two types of metrics using statistical methods and proposed an approach of using a regression model from empirical studies to estimate subjective preference for design scenarios and thus to evaluate the result of landscape design scenarios.

Keywords: Image-based metrics, 3D model-based metrics, visual landscape quality

1 Introduction

With increasing concern regarding urban dwellers' psychological well-being, studies have looked towards urban green spaces (UGS) as a potential salutogenic means of alleviating this issue. In quantifying the spatial attributes of UGS, although the quantity of greenery has been adequately studied, research on the objective and standardised quality that reflects perception, however, remains largely insufficient. In attempting to understand the subjective nature of landscape quality, visual landscape quality (VLQ) has served as a means of assessing landscapes that affect people's perceptions. However, current approaches to assessing the VLQ have some limitations. First, the conventional methods are often based on top-down measurements of the landscapes which are weak in accurately representing the scenes from the human perspective, thus leading to the inaccuracy of measurement of the human-centric experience. Secondly, as GASCON et al. (2015) pointed out, proper metrics to measure VLQ, especially those used in urban contexts and associated with perceptions, still lack exploration. The stated research gaps lead to challenges in assessing real-world environments as well as unbuilt landscape designs that link to VLQ. The objective metrics to measure VLQ based on proper conceptual and technical instruments thus needs to be further explored.

With the emerging computer vision techniques based on deep learning, an increasing number of studies have demonstrated the use of semantic segmentation and depth estimation to extract metrics such as the green view index (GVI), sky view index (SVI), and depth from real-world photographs. Photographic images can reflect spatial information that mirrors what is seen by people. Aside from photographs, 3D models also have the possibility of measuring landscapes at eye level. QI et al. (2022) utilised 3D point clouds based on terrestrial LiDAR scans for VLQ evaluation and achieved detailed measurements of various visual and spatial features, albeit costly to use. A more convenient tool to use, however, could be a 3D model based on the landscape, which allows the evaluation of designed landscapes virtually instead.

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We also realised that prevalent research focused on evaluating and measuring the VLQ of the as-is environment, but few studies have quantified the visual quality in landscape design that has yet to be built. The results of scientific research are also difficult to apply to guide design practice. LIU & NIJHUIS (2020) highlighted the importance of mapping the spatial-visual quality in improving landscape design, whereas the measurement methods were not based on evidence-based studies but solely on expert evaluation. In this paper, one of our aims is to attempt to directly apply the results from empirical studies in improving landscape design. In addition, it is targeted to utilise more common tools such as Rhinoceros and Grasshopper that can be effectively applied by designers in the practice field, not exclusively limited to academic exploration. Therefore, we consider linking the use of image-based metrics and 3D model-based metrics to measure VLQ in different contexts. Given the stated research gaps and aims, the underlying research questions are as follows:

1. To what extent do image-based and 3D model-based metrics adequately measure VLQ?
2. To what extent do image-based and 3D model-based metrics align with each other in VLQ measurement?
3. To what extent can the metrics be applied in design optimisation using results from empirical studies?

2 Methodology

Our underlying study focuses on developing and measuring metrics for assessing VLQ that mirror critical human perceptions based on conceptual frameworks and digital techniques. We consider both photographic images and 3D virtual models as useful tools to assess VLQ for the aims of assessing the real environment and measuring designed landscapes respectively. The usage of the two instruments is integrated into a holistic framework primarily by applying the conclusions from empirical studies using images and iteratively testing and improving a hypothetical design. The image-based metrics can be used to assess real environments while the metrics for 3D models can be applied to exploring different design scenarios that have the potential to promote people's subjective perceptions such as preference. The following sections show how the study is conducted to achieve the research targets.

2.1 Case Study – Clementi Woods Park in Singapore

We utilised the Clementi Woods Park in Singapore as a case study to investigate the use of image and 3D model-based metrics. Within the park, we selected ten locations that cover multiple spatial characteristics ranging from open fields to sheltered viewpoints. Onsite panoramic photos were taken at these 10 sites (Fig. 1) and their subsequent image-based metrics were measured (Section 2.2). To measure the 3D model-based metrics, however, we first had to reconstruct the park in a 3D environment inside Rhinoceros (Fig. 2). To accurately model the topography and surface elements, we used the digital terrain/surface models and airborne imagery from the Singapore Land Authority (SLA), and an orthophotograph using a drone. Trees and shrubs were modelled using adapted low-polygon-count techniques previously developed (LIN et al. 2018, GOBEAWAN et al. 2018, GOBEAWAN et al. 2021). Other elements such as paths, benches, pavilions, etc., were manually modelled based on the imagery data including maps and photos (Fig. 3).

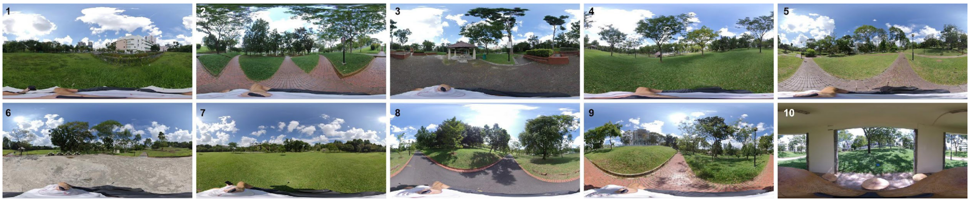

Fig. 1: Ten locations in the park were selected that covered a range of different spatial characteristics

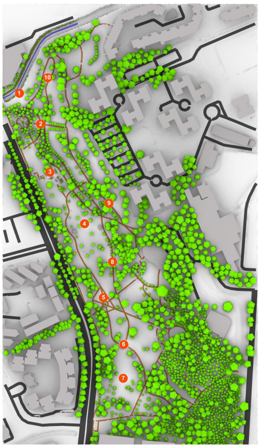

Fig. 2: A top view of the reconstructed 3D model of the park

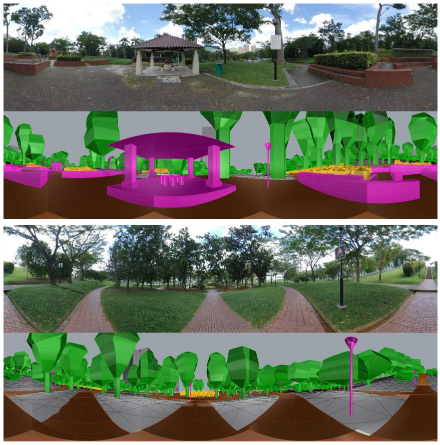

Fig. 3: The showcase of reconstructed models with their corresponding photos

2.2 Image-based Metrics and Computer Vision

Identifying the critical landscape characteristics is a prerequisite. The attention restoration theory (ART) and stress reduction theory (SRT) underscore the role of greenery in providing effortless attention to people and relieving stress levels by experiencing natural environments (KAPLAN & KAPLAN 1989, ULRICH 1983). In addition, the prospect-refuge theory (APPLETON 1975) proposed that the simultaneous presence of open enclosed space could lead to people's high preference for landscapes. The perceived sensory dimensions (PSD) proposed by GRAHN & STIGSDOTTER (2010) have been demonstrated as a useful framework that is closely associated with psychological well-being. The PSD includes eight conceptual dimensions namely nature, prospect, space, refuge, serene, culture, and social which indicate different spatial characteristics and are often measured through surveys with respondents after exposing them to a variety of landscape scenes (AKPINAR 2021).

However, few studies investigated how to use objective metrics to measure these characteristics digitally. Following the meanings of the updated version of PSD put forward by STOLTZ & GRAHN (2021), we proposed eleven metrics that follow the implications of five selected and adapted dimensions: natural, open, sheltered, cultivated, and diverse. Those metrics and their related calculations or interpretations are summarised in Table 1. These eleven metrics including tree, shrub, depth, diversity of plant groups, etc., aim at quantifying multiple landscape attributes from the visual quality perspective.

Table 1: The PSD and the corresponding metrics using images for calculation

Dimension	**Metric**	**Description of Image-based Metrics**
Natural	Tree view index	Visible tree proportion
	Shrub view index	Visible shrub proportion
	Grass view index	Visible grass proportion
	Green view index (GVI)	GVI = sum of tree, grass and shrub proportions
Open	Depth index	Average distances of pixels to the camera
	Sky view index (SVI)	Visible sky proportion
Sheltered	Overhead shelter index	Proportion of visible shelter elements above head such as tree canopy and rain canopy
Cultivated	Building view index (BVI)	Visible building proportion
	Service facility view index	Proportion of visible facilities used for living services such as benches, lampposts, etc.
	Path view index	Proportion of visible path or pavement
Diverse	Diversity of plant groups index	Shannon diversity index of proportions of visible trees, shrubs, and grass

Regarding computer vision techniques, semantic segmentation and depth estimation are used in this study. In terms of the semantic segmentation model, we chose PSPNet pre-trained based on the ADE20K dataset developed by ZHAO et al. (2017) which has been commonly acknowledged as having high performance regarding its accuracy and the number of identifiable landscape elements. As for the depth estimation, we use the R-MSFM model pre-trained based on the KITTI dataset developed by ZHOU et al. (2021). Using these tools, we can measure the above-mentioned metrics and thus evaluate VLQ from multiple dimensions.

Concerning the "natural" dimension, the visible tree, grass, and shrub can be measured. As for the open dimension, depth is a critical feature that reflects the openness of space; the visible area of the sky (SVI), also serves as an important factor for openness. Concerning the

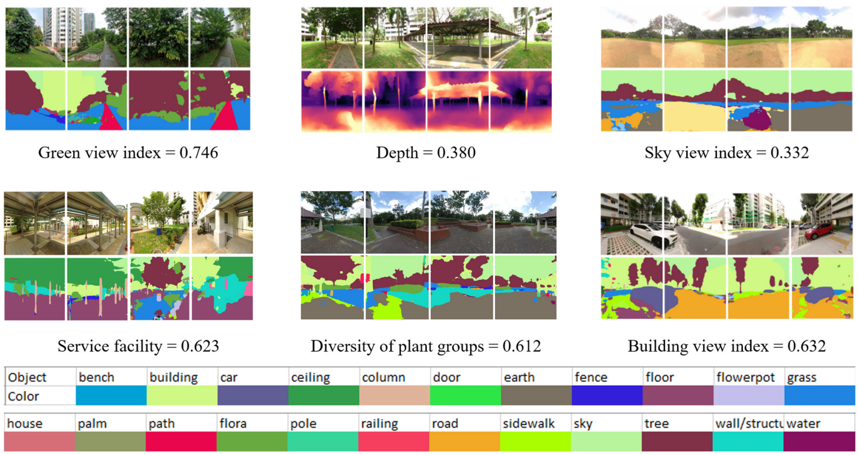

Fig. 4: Examples of scenes and their segmentation or depth images with the corresponding values of the metrics

"sheltered" dimension, we measure the tree canopy and structure that are overhead serving as refuge elements. The visible buildings, service facilities, and paths are regarded as "cultivated" components that refer to man-made and managed features of landscapes. "Diverse" in this paper particularly underlines the richness of these types of vegetation. The Shannon diversity index of the visible trees, shrubs, and grass serve as the basic method for calculating this metric. Representative examples of a few metrics to show the spatial characteristics are displayed in Figure 4.

2.3 3D Model-based Metrics and Grasshopper

The methodology of extracting image-based metrics described above is still in the process of refinement. However, one distinct limitation of this method is the inability to measure hypothetical or unbuilt landscapes such as those still in the design phase. As such, the study attempts to use the 3D model to extract the same metrics as above in anticipation that this can lead to a method to measure different design scenarios. In this study, we utilise the visual programming workflow of Grasshopper within the Rhinoceros environment to measure the model. Aligning this with the image-based methods above, we measure the proportion of various landscape elements in view, thus mimicking the image-based segmentation method.

To simulate the approximate height of a human eye, we begin by setting a viewpoint at 1.6m above the topographical mesh. From this location, a set of rays (61206 rays, each of 500m in length) are emitted spherically via a parallelised 3D IsoVist component (CASCAVAL 2019) which is typically used for viewshed analysis. These rays are then separated into two sets (Fig. 5), the first being a 120-degree (60 degrees above and below the horizon) horizontal view representative of the same viewing angle on which the image-based segmentation is based. The second is the overhead/top view (>60degree above the horizon) which is used to calculate the sheltered metric.

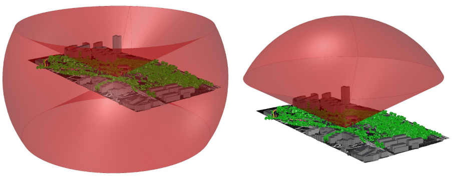

Fig. 5:
Rays were split into two sets, the first representing a 120-degree horizontal panorama (left), the second representing the overhead view (right)

The added benefit of using a 3D model is that the landscape objects are already pre-segmented as different 3D objects unlike those from a photograph which require an additional step of classification. Here, we make use of the IsoVist component to identify the different landscape elements being intersected (Fig. 6) and subsequently measure the proportion or rays hitting each of these elements. These resulting proportions eventually provide the various percentage-of-view-based metrics such as GVI, SVI, BVI, and so on. In the image-based metrics, a depth metric is calculated; similarly, here we calculate a depth metric (Fig. 6) by comparing the average distance of each intersected ray and unitise the results between 0 and 1, meaning completely enclosed and completely open respectively.

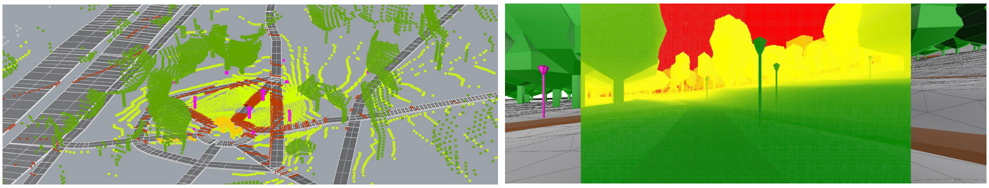

Fig. 6: A set of rays are emitted spherically from a viewpoint and the intersection points are coloured indicating the type of landscape element at the intersection (left). A visual representation of how depth is measured based on the distance between the viewpoint and the various landscape objects in the distance (right).

2.4 Data Analysis for Comparison and Application of Metrics

Upon obtaining the results of the two methods of metric measurements, we then set forth to compare them and propose a method of applying these metrics in design practice. First, to compare the quantitative characteristics of the metrics derived from images versus 3D models, we reported descriptive statistics of the calculation results, the indicators of which include mean, median, standard deviation, maximum, and minimum values. Second, to investigate the extent to which the two types of metrics align with each other, an analysis of variance and bivariate correlation between the two types of metrics was calculated for inspection. Third, as these proposed metrics are exclusively founded upon expert-based approaches and have not been verified to determine if they capture subjective perception, the regression result of an online survey from another study of ours (in writing) was applied in this paper. The online survey employed 1500 respondents to provide a range of perception-based responses to 100 interactive panoramic images of UGS in Singapore. Since "preference" is an important aspect that reflects subjective perception in general, we selected this factor for analysis. Lastly, the metrics were used to establish a regression model, the result of which would be employed to measure hypothetical design scenarios by adjusting landscape elements inside of Rhinoceros.

3 Results

3.1 Comparison Between Image-based and 3D Model-based Metrics

The result of descriptive statistics of the two types of metrics is shown in Table 2. Overall, the mean, minimum and maximum values of each metric present similar features in quantitative variation between these two types of metrics. Particularly, the values of image-based metrics regarding tree, grass, and sky were largely close to the corresponding results of 3D model-based metrics. Taking grass as an example, the results for 3D models and images were respectively 0.316 and 0.303 for the mean, 0.021 and 0.057 for the minimum, and 0.487 and 0.494 for the maximum. Furthermore, to accurately examine the extent to which the two types of metrics aligned with each other, we used analysis of variance (ANOVA) to compare them. If the p-value of Welch's ANOVA for a metric is higher than 0.05, it indicates no significant differences in this metric between images and 3D models. The result suggested that all the metrics are largely consistent, except depth. The reason was that the algorithms for depth based on the two instruments were different. Although we could measure the actual distance in 3D models, it was currently not feasible to estimate it from a single image. Thus the image-based depth was merely quantified as a relative distance. To resolve this issue for depth, we investigated the bivariate correlation based on Spearman coefficients; the coefficient of 0.903 (at the significance level of 0.05) indicated a high correlation between the two groups. To summarise, all these metrics showed consistency between the two types based on images and 3D models.

Table 2: Descriptive statistics of these two types of metrics for comparison, and the correlation between them

Metrics	**Descriptive statistics for 3D model-based metrics**			**Descriptive statistics for Image-based metrics**			**Welch's ANOVA (p-value)**	**Bivariate Correlation**
	mean	**min**	**max**	**mean**	**min**	**max**		
Tree view index	0.320	0.184	0.439	0.281	0.102	0.421	0.406	0.891***
Shrub view index	0.017	0.000	0.120	0.008	0.000	0.034	0.499	0.782**
Grass view index	0.316	0.021	0.487	0.303	0.057	0.494	0.850	0.697***
GVI	0.653	0.304	0.856	0.592	0.313	0.866	0.449	0.733**
SVI	0.121	0.049	0.216	0.137	0.018	0.354	0.712	0.903***
Depth index	0.175	0.127	0.234	0.335	0.289	0.380	0.000	0.903***
Overhead shelter view index	0.293	0	0.996	0.197	0.000	0.517	0.399	0.535*
BVI	0.023	0.003	0.135	0.051	0.006	0.134	0.138	0.600*
Service facility view index	0.076	0.002	0.356	0.022	0.001	0.071	0.270	0.527*
Path view index	0.127	0.002	0.407	0.053	0.000	0.150	0.107	0.608**
Diversity of plant groups index	0.719	0.531	0.933	0.683	0.559	0.763	0.358	0.624**

***p<0.05, **p<0.1, *p<0.2

3.2 Parametric Design with Metrics

Based on the survey data as mentioned in Section 2.4, a total of six image-based metrics were screened through a stepwise ordinary least square (OLS) regression model. The metrics include sky, tree, diversity of plant groups, service facility, depth, and shrub which are critical factors to predict subjective preference. These corresponding 3D model-based metrics would be useful for optimising the design by controlling landscape elements within the virtual model. In addition, a linear regression model is applicable in evaluating the design scenarios represented in 3D models by calculating the estimated preference (EP) as the reference to judge the design, which is:

$$EP = 2.285 * [\text{sky}] + 1.249 * [\text{tree}] + 0.656 * [\text{Diversity of plant groups}] + 0.829 * [\text{service facility}] + 2.388 * [\text{depth}] + 1.128 * [\text{shrub}] + 2.065$$

We selected viewpoints 3 and 9 as examples to display how to improve the design by adjusting the model with key metrics (Fig. 7). The main design interventions include adjusting the location of the various landscape objects such as trees and service facilities as well as the inclusion of shrubs to increase the diversity of plant groups index all while attempting to increase the sky view index simultaneously. After the adjustments, we re-calculated the metrics and the EP (Table 3). The EP value for viewpoint 9 is increased by 0.15 while viewpoint 3 only increased by 0.01.

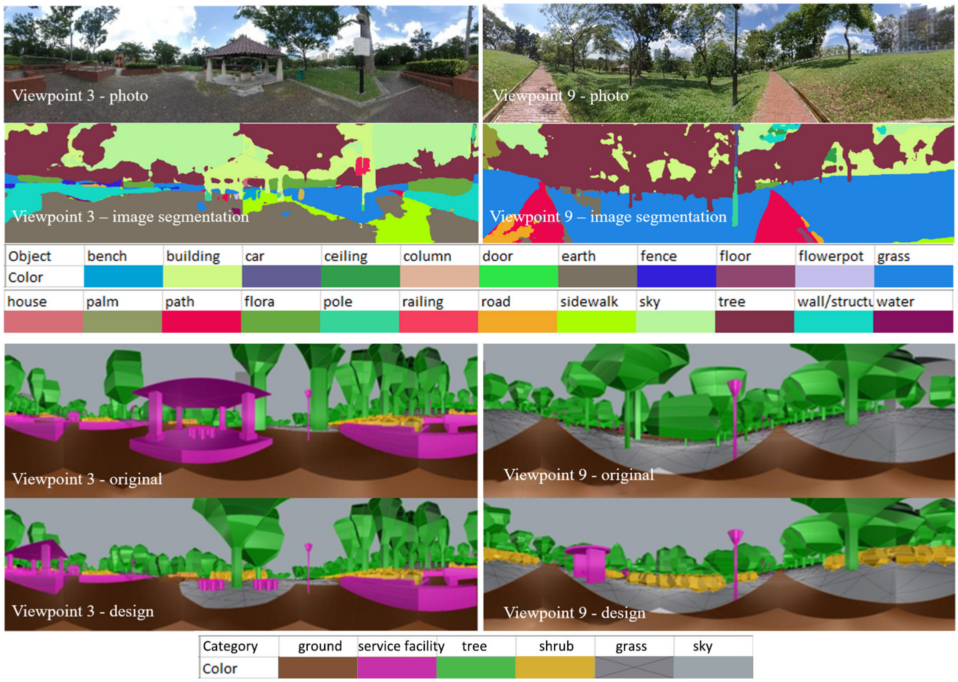

Fig. 7: The original viewpoints 3 and 9 were modified slightly to create alternative scenarios. In viewpoint 3, trees were slightly adjusted and the location of the pavilion was changed further away. In viewpoint 9, the sky openness increased by reducing the number of trees; shrubs were added to increase the diversity of plant groups.

Table 3: The results of 3D model-based metrics and estimated preference before and after design

3D model-based Metrics/ Estimated Preference	Viewpoint 3 - original	Viewpoint 3 - design	Viewpoint 9 - original	Viewpoint 9 - design
Tree view index	0.255	0.251	0.423	0.277
Shrub view index	0.029	0.035	0.000	0.112
Depth index	0.140	0.140	0.140	0.130
SVI	0.119	0.181	0.074	0.157
Service facility view index	0.340	0.187	0.008	0.032
Diversity of plant groups index	0.530	0.650	0.730	0.950
Estimated preference	2.980	2.990	2.780	2.930

4 Discussion and Limitation

This study innovatively links image-based metrics to 3D model-based metrics, demonstrating the workflow and its feasibility of employing the proposed metrics and methods to assess

VLQ of real environments and virtual design scenarios. As image-based metrics are increasingly applied in scientific studies that associate landscapes with various kinds of cultural services, our methods have successfully built a technical approach that allows the application of scientific results into a measurable design intervention. On the other hand, there are limitations to the study stemming from two sources, the first being the algorithms and accuracy of the image segmentation and the second being the oversimplification of real-world landscapes into virtual ones resulting in certain metrics (such as BVI, and service facility view index) being not completely aligned with each other, and thus with lower correlation coefficients. There are some potential reasons: First, a lack of local-based training imagery datasets may result in lower accuracy of image segmentation. Second, in 3D models, the location, size, shape, and opacity of trees and shrubs differ from those in real environments which probably decreases the visible proportions of buildings and other objects since they are occluded by the opaque vegetation, in comparison to image segmentation can recognise the objects behind vegetation with less foliage (Fig. 8).

Fig. 8: An example whereby trees in the 3D model are opaque by nature (left) compared to those photographed on site (middle) and the image segmentation result (right)

Furthermore, one of the limitations of using our proposed metrics is that the visual quality is only measured from the perspective of static viewpoints, of which the metrics can change just by adjusting the viewpoint by a few meters such that a building is no longer occluded by a tree for example. What people experience or perceive when actually visiting such landscapes is as such likely oversimplified with a handful of measurements from viewpoints. That said, there are two possible ways to alleviate this issue. The first is to use multiple viewpoints either by repeatedly photographing the site or by measuring them via the 3D model to form a map instead (Fig. 9). The map might provide us with an alternative way to visualise the different qualities of the site through a first-person view analysis. A second possible solution is to calculate 3D metrics instead as proposed by QI et al. (2022). 3D metrics based on point clouds such as green volumetric ratio (GVR) and horizontal, vertical, and distance diversity (HVDD) of various can quantify 3D spatial attributes considering the volumes rather than the visible areas of landscape elements. This method expands the scope of landscape spatial attributes that can be measured purely from a visibility analysis. In future studies, we intend to deepen the comparison between different tools including point-cloud-based 3D metrics, and integrate these metrics for comprehensive applications in multiple research contexts. Last but not least, although we used 3D models to try to reproduce the actual landscape, it was challenging to achieve identical views derived from both 3D models and images. Some inevitable errors might happen during the modelling process or in identifying the accurate locations of the viewpoints. However, statistical methods have still demonstrated the relative consistency of the two types of metrics.

These technical issues mentioned above would undoubtedly resolve as improvements are made to both image segmentation as well as virtual models. This paper illustrates the exploration of linking metrics using different tools as well as linking scientific study to design. We thus encourage any studies in the future to apply quantitative conclusions from research in design practice through a similar methodology.

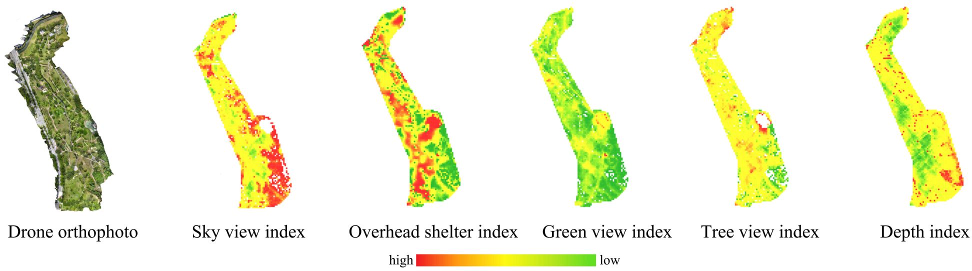

Fig. 9: An example of different metrics extracted in a grid-like manner and their respective values visualised as a map instead

5 Conclusion

We proposed image-based and 3D model-based metrics to measure VLQ of real environments and virtual models and then compared the characteristics of these two types of metrics, which allows applying findings of evidence-based scientific studies in parametric designs using Grasshopper to evaluate the design results. We also demonstrated a method of utilising regression models to estimate the potential subjective preference derived from design scenarios. Even though further studies need to optimise the digital techniques for metric calculation, the progress of linking the two types of metrics for research and design use expands the scope of the application of landscape metrics.

Acknowledgement

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