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Towards a new model of light quality assessment based on occupant satisfaction and lighting glare indices

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Abstract

This study looks at the effect of daylighting on human performance. It includes a focus on glare index combined with the actual feeling of users of the classroom as a way to assess indoor lighting quality. The main objective of this research is to understand the impact of daylighting from windows on the glare sensation and also to determine which glare index is the closest to human visual sensation under local daylighting conditions in Biskra, Algeria with highly luminous climate. The study used High Dynamic Range (HDR) photography, Evaglare and Aftab Alpha software to calculate the two glare metrics Daylight Glare, Index (DGI) and the Daylight Glare Probability (DGP). A survey was also used with 90 occupants under different lighting conditions (different configurations) in a design classroom. In order to link the mathematical model and the human assessment of glare, statistical regression analysis was used. We established a statistically compelling connection between daylighting and student performance.

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Keywords: Glare metrics, HDR photography, Daylighting assessment, Machine learning, Statistical regression.

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1. Introduction

Daylighting has been used throughout history as a primary light source in buildings, so the principles of light are not new. However, the use of natural light has advantages and disadvantages; aesthetically and physically this pendulum between the extremes has been covered by architectural design throughout many decades. Glare is one of the major factors affecting visual comfort [1]. Some previous studies have proved that visual comfort is mainly achieved by avoiding glare as well as controlling the uniformity, shadows and veiling reflections so it should be avoided in general for visual tasks and especially for more visually demanding tasks such as computer screens and office work [2]. In recent years, several objective and subjective indices and indicators of glare have been developed, also significant progress has been made towards the development of computational methods that holistically evaluate the performance of occupant comfort [3]. Various tools and methods for glare assessment exist [4, 5, 6], but the most frequently used are glare indices including DGP (Daylight Glare Probability), DGI (Daylight Glare Index), UGR (Unified Glare Rating), and CGI (CIE Glare Index). DGP and DGI were specifically developed for daylight glare, which needs to be treated differently from visual discomfort issue of electrical light sources [7]. According to the equations (1, 2), a similarity can be established between the two different glare indices, since all of them are based on background mean luminance, glare source luminance, glare source position, the solid angle of glare sources, vertical illuminance, and direct vertical illuminance. The aim of this paper is to compare the two glare indices 'DGP' and 'DGI', in order to determine which of these indicators is the most adapted for the glare assessment and lighting quality measured and quality felt by users [8].

$$\mathrm{DGI} = 10 \cdot \log\left(0.478 \sum_i \frac{L_{s,i}^{1.6} \cdot \omega_{s,i}^{0.8}}{L_b + 0.07 . \omega_{s,i}^{0.5} . L_{s,i}}\right) \quad (1)$$

$$\mathrm{DGP} = 5.87 \cdot 10 - 5 \cdot E_v + 0.092 \cdot \log(1 + \sum_i \frac{L_{\mathrm{s,i}}^2 \cdot \omega_{\mathrm{s,i}}}{E_{\mathrm{v}}^2 \cdot P_{\mathrm{i}}^2 \mathrm{i}}) + 0.16 \quad (2)$$

Nomenclature

E_v	Total vertical eye illuminance (lux)
L_s	Luminance of the glare source (cd/m^2)
ω	Solid angle of the glare source (sr)
P	Weight factor based on position in a viewing hemisphere, the Position index

2. Methodology

The authors created three lighting conditions, natural light, artificial light and mixed light, in order to analyze the different users' glare perceptions in the classrooms. HDR photographies were developed in 90 different users' working positions in order to calculate the two glare indices (DGP, DGI) in each user's position using Evaglare and Aftab Alpha software. At the same time, a survey was administered to the 90 participants, 30 in each configuration. The questionnaire was repeated for the three configurations. Each of the 30 participants was exposed to the three lighting conditions of the design classroom and asked to answer questions, to evaluate their level of glare in space. The complete information was registered and used for different statistical analysis.

3. Experimental Procedure

3.1. Dynamic Range photography and glare indices

University students were exposed to three different light settings of the computer design classrooms: configuration 01 using natural light, 02 using artificial light (with black drapes), and 03 using artificial light and natural light (mixed light). There were thirty students in each configuration 12 male, 18 female. The total of (N= 90) participated voluntarily, students judged the different light settings by rating. The ninety different working positions were photographed with series of three exposures levels using a 1200D canon EOS camera using circular Fisheye lens Sigma (4.5mm f/2.8 EX DC Circular Fisheye HSM), in order to generate the spherical 180° HDR images. We have chosen the high dynamic range images because these store a much larger range of luminance information [9] in a digital image than a conventional low dynamic range (LDR) photograph, and present a similar range of luminance to that experienced with the human visual system [10]. There have been many studies using HDR for research purposes such as luminance evaluation, glare evaluation, and daylighting analysis [9, 11]. To calculate glare indices and the luminance distribution within a field of view, a Aftab Alpha software was used for evaluating glare originating from daylight and artificial light.

3.2. Photometric measurements and development of model

Experimentation and measurements were carried out on a typical Mid-season day in the Month of May 2016, under specific local sky conditions [12]. For the measurement, we have used a light meter (Luxmètre_CA_813) to measure: 1) illumination on table 2) eye level illumination, and 3) illumination on the vertical screen. The Aftab Alpha software was used to assess the following information: 1) Average luminance, 2) Maximum luminance, and 3) background luminance on the visual field. We have entered the data previously cited in statistic software.

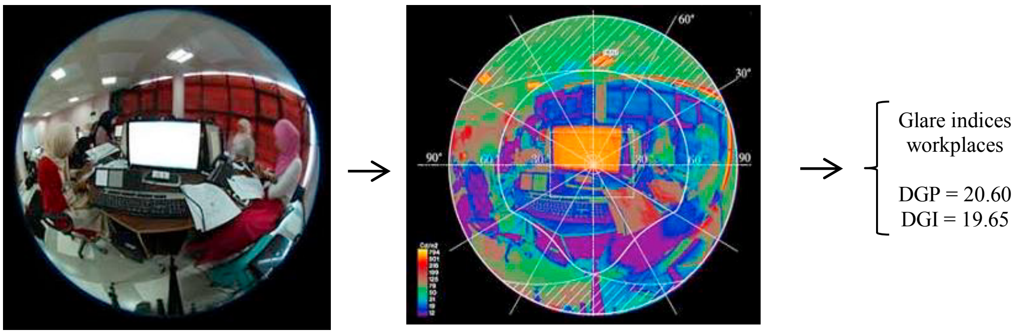

Fig. 1. Image processing / Glare indices

3.3. Data Analysis

In the literature, many different semantic glare rating scales are used that contain terms like visible, acceptable, comfortable and tolerable. However not always the same words are used, which can give different interpretations, and make the comparison between different glare indexes very difficult or even distort the reality of indicator. This is why in our study participants were asked to evaluate the different light settings by rating three qualitative factors: visual comfort, naturality, and light level, each question was answered using numbers from (2+) to (2-), where (2+) corresponded to “fully agree” and (2-) corresponded to “fully disagree”, combined with factors: ‘extent lighting noise’ in design classroom, and glare ((exist), (does not exist)). For each light setting the questions listed in table 1 were asked.

Multiple linear regression has been used to investigate the relationship between continuous variables such as lighting levels or average illuminance levels. However, we are also interested in our study to understand how glare index value and model developed value are related with glare perceived by users (actual glare). Therefore, a logistic ordinal statistic regression has been adopted, in order to visualize the performance and reliability of results. The recent years have seen an increase in the use of Receiver Operating Characteristic (ROC) graphs in the machine learning community, due in part to the realization that simple classification accuracy is often a poor metric for measuring performance [13, 14]. The graphs are useful for organizing classifiers and visualizing the performance of a different models of glare prediction [15]. That is why in our study we have plotted ROC graphs, a very useful tool for organizing classifiers and visualizing.

Table 1. A part of questionnaire submitted to the ninety students

A- "Is there a discomfort caused by the presence of light in the computer room?"							
			Yes	No			
Question 1: How do you qualify the general atmosphere created by the light in the computer room?							
(Light level)	Very Dark	-2	-1	0	+1	+2	Very Bright
(Visual comfort)	Very boring	-2	-1	0	+1	+2	Very Stimulating
(Naturality)	Very Artificial	-2	-1	0	+1	+2	Very Natural
(Visual comfort)	Very Glaring	-2	-1	0	+1	+2	Very Comfortable

4. Results and analysis

Overall, the level of significance ended up being higher for the two variables 'Visual comfort' and 'Light level' than 'Naturality' for the evaluation of visual comfort in the computer design classroom. So, the statistical analysis shows two significant correlations. The first one, between Visual comfort ($p = 0.013$) and 'Naturality' the second, between Light level and 'Naturality' equal to ($p = 0.022$). In order to check the degree of correlation and the relationship between the results obtained (significant correlation) and the glare indices 'DGP' and 'DGI', a logistic and ordinal regression has been used.

The ordinal regression was used to develop the model for glare assessment, regression analysis based on 'DGI' and 'DGP' and photometric measurements such as illumination on a table, illumination on the vertical screen, average luminance and student glare perception in the classroom. The model developed is obtained as an excel sheet outcome of ordinal regression analysis, where the quality is evaluated based on photometric measurements and glare indices inputs. In order to evaluate the accuracy of the model author's used Receiver Operating Characteristics (ROC) are a way of graphically displaying true positives versus false positives across a range of models and of selecting the optimal model. The high sensitivity corresponds to high negative predictive, high specificity corresponds to high positive predictive. The obtained results of diagnostic accuracy are shown below:

4.2. For the variables glaring and comfortable

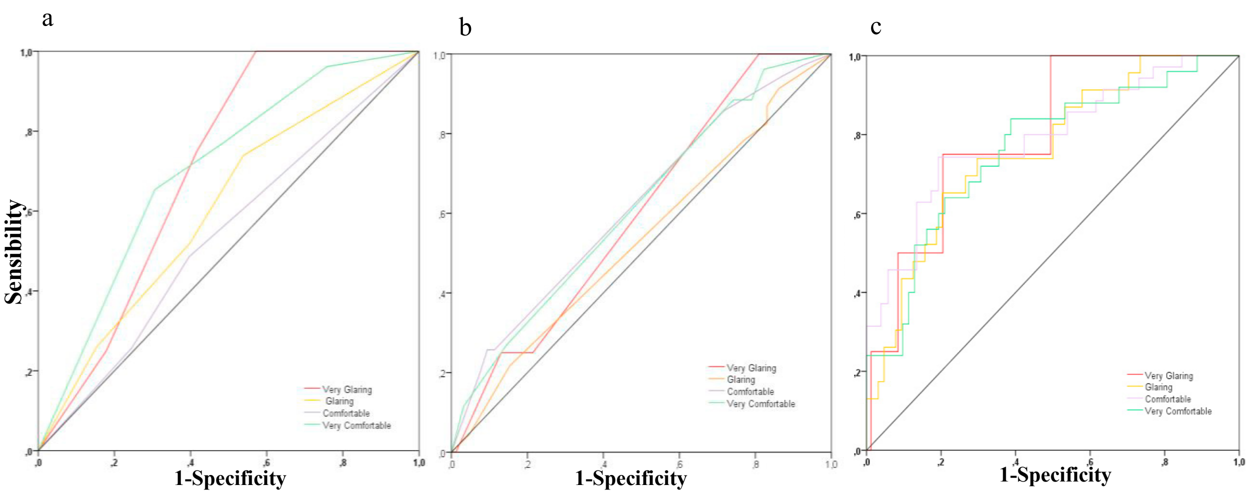

Fig. 2. (a) ROC graphs classifier DGP (Glaring vs Comfortable); (b) ROC graphs classifier DGI (Glaring vs Comfortable); (c) ROC graphs classifier Developed Model (Glaring vs Comfortable)

Comparing the different glare indexes, Fig. 2 shows that there is a big difference between the three methods of glare prediction. It can be observed that the curve Glaring / Comfortable for DGI is the closest to the reference line of the plot. This shows that the DGI has registered the maximum error pruning of the predicted discomfort with the poor performance of the decision. In addition, from Fig. 2, it can be seen that the area under a ROC of variables Glaring/ Comfortable for DGP is of higher overall accuracy than DGI. However, an area under a ROC of 'Very Glaring' is 0,705 (70%) and 'Very Comfortable 'is 0,701. It shows that the DGP can predict these two variables with a better accuracy than the others variables. However, the developed model shows probabilities much higher than the two others, since the area under a ROC of the developed model is much higher, with minimum of 0,761 (probability of 76.10 %) for variable 'Very Comfortable' and maximum of 0,801 (probability of 80.10 %) for variable 'Very Glaring'.

Tab 2. Area under a ROC of variables (Glaring, Comfortable) for DGP, DGI and model developed

	DGP		*DGI*		*Developed Model*	
		Area		Area		Area
Very Glaring	Very Glaring	0,705	Very Glaring	0,598	Very Glaring	0,801
Very Comfortable	Glaring	0,605	Glaring	0,532	Glaring	0,762
	Comfortable	0,553	Comfortable	0,618	Comfortable	0,791
	Very Comfortable	0,701	Very Comfortable	0,615	Very Comfortable	0,761

4.1. For the variables Boring and Stimulating

Fig. 3 shows that there is a big similarity between DGP and DGI of glare prediction probabilities, however, it can be observed that the curves boring/ stimulating for DGP show the lowest probabilities with poor performance values to predict light quality assessment in computer design classrooms. In addition, from Fig. 3, we can see that the area under a ROC for DGI metrics is lower than 65%. for variables 'Stimulating, Boring' which is a reasonable prediction performance, however, we have obtained a result higher than 75 % for 'Very Boring and Very Stimulating' with the developed model, and the model shows much higher probabilities than the two glare indexes mentioned above, inasmuch as area under a ROC is between minimum (probability of 71.70 %) registered for variable 'Boring' and maximum of 0.903 (probability of 90.03 %) registered for variable 'Very Boring'. In general, it can be seen that the developed model shows a better overall accuracy.

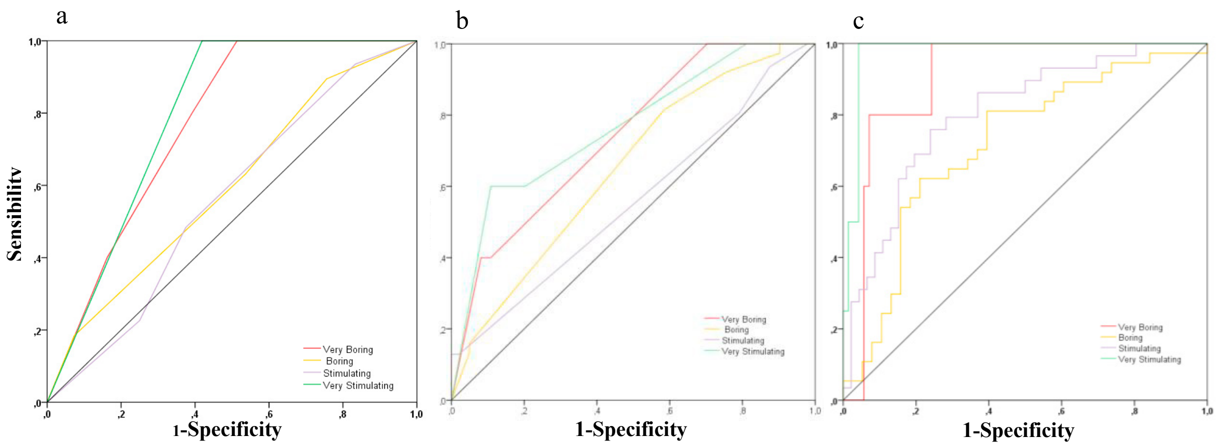

Fig. 3. (a) ROC graphs classifier DGP (Boring vs Stimulating); (b) ROC graphs classifier DGI (Boring vs Stimulating); (c) ROC graphs classifier Model Developed (Boring vs Stimulating)

Tab 3. Area under an ROC of variables (Boring, Stimulating) for DGP, DGI and model developed

	DGP		*DGI*		*Model Developed*	
		Area		Area		Area
	Very Boring	0,764	Very Boring	0,741	Very Boring	0,903
Very Boring	Boring	0,597	Boring	0,649	Boring	0,717
Very Stimulating	Stimulating	0,478	Stimulating	0,557	Stimulating	0,804
	Very Stimulating	0,791	Very Stimulating	0,765	Very Stimulating	0,975

5. Conclusion

The results from experiments by users in university computer design classrooms show that out of the three glare metrics DGP, DGI, and a developed model based on semantic rating scales, the DGI metrics is not the best for the assessment of Glaring/Comfortable but provides reasonable predictions for Boring/ Stimulating. By contrast, DGP predicts ‘Glaring’ better and Boring/ Stimulating worse. The developed model is the most robust of the three glare probabilities prediction metrics for both variables Glaring/Comfortable with probabilities prediction equal to 80.01% and 90.03% for the variables Boring/Stimulating. The authors generally recommend the use of the developed model for the assessment of light quality for indoor tasks such as computer screens and office work. We hope that this article advances the general knowledge about lighting quality felt by users, in university computer design classrooms using computer screens

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