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Establishing optimal illuminance for pedestrian reassurance using segmented regression

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Abstract

The optimal illuminance from road lighting for pedestrian reassurance after dark is that beyond which further increase in illuminance has no significant effect on reassurance. Previous studies have not revealed a precise estimate of optimal illuminance. The current study investigates the use of segmented regression for defining optimal illuminance, applied to 25,662 reassurance evaluations by 380 test participants who recorded their reassurance assessments in 253 locations in three cities in Israel. Segmented regression led to models which better fit the empirical data than their unsegmented counterparts and offered precise estimates of optimal illuminance, these ranging from 8.9 lx to 26 lx, depending on location.

1 Introduction

The reduction in adaptation luminance after dark leads to deterioration in visual performance.[1] One reason for installing road lighting is to offset this impairment and support the visual needs of all road-users, and, in subsidiary roads, lighting aims to meet primarily the needs of pedestrians.[2] According to application experience[3] and mobile eye tracking in natural settings,[4,5] two critical visual tasks of pedestrians are the detection of obstacles and hazards to safe movement and the evaluation of other people (their identity and/or intent).[6] Lighting also makes a location feel safer, or, more reassured.[7-11]

'Reassurance' describes the confidence a pedestrian might gain from road lighting (and other factors) to walk along a footpath or road, in particular if walking alone after dark.[6] Promoting reassurance is of societal benefit because greater reassurance leads to more time spent walking,[12-14] and supports policies to encourage walking rather than driving for local journeys. As Foster *et al.*[12] found, for every increase of one level on a 5-point Likert scale measure of perceived safety, the amount of time spent walking within the neighbourhood increased by 18 minutes per week on average for each person.

While the installation of road lighting has many benefits,[15] there are also unwanted consequences, including the consumption of energy, sky glow and detrimental impact on the natural environment.[16-18] It is therefore imperative that design guidance reaches a compromise between the benefits and consequences of road lighting; current design guidance, however, may not be sufficient.[19,20] This article describes research carried out to identify the optimal illuminance for pedestrian reassurance.

2 Background

2.1 Interpretation of optimal illuminance

The degree of reassurance offered by road lighting is evaluated in surveys, typically conducted after dark using category rating, and typically comparing locations with different lighting to reveal the effect of changes in illuminance on evaluations of reassurance rating, e.g.[21-23] In this approach, with road lighting evaluated after dark, the better lighting is that which yields the higher rating of reassurance. An extension to this is the 'day-dark' method,[24,25] that retains the use of category rating to evaluate a location, but each location is evaluated in daytime as well as after dark and the dependent variable is the difference between the daytime and after dark ratings: better lighting is that which minimises the difference between the daytime and after dark evaluations.

Whether the after-dark-only approach or the day-dark approach is used, a similar method of analysis has so far been used, with the dependent variable plotted against illuminance or some other characteristic of the road lighting. Figure 1 shows the results of an after-dark study carried out in the city of Tel Aviv-Yafo by Svechkina *et al.*,[23] while Figures 2 and 3 show the results of evaluations of reassurance in car parks in the USA from Boyce *et al.*[24] and in residential roads in a UK city centre from Fotios *et al.*,[25] with both latter studies using the day-dark approach. In each case, these were redrawn from graphs shown in the original publications.

The data points in Figures 1 to 3, these being average ratings for each location, are widely scattered which makes it more difficult to establish a well-fitting regression line. It is expected that the relationship between reassurance and illuminance is monotonic: with increasing illuminance, reassurance might also increase or remain unchanged, but is unlikely to decrease (unless a light source of increased brightness leads to significant discomfort or disability from glare). While a linear function is monotonic, by its nature it is unable to reveal an optimal illuminance, logarithmic functions are monotonic and concave, so can also reveal a decreasing effect of illuminance on reassurance. In their analysis, Fotios *et al.*[25] used a logarithmic function in Figure 3 (Figure 6 in the original publication) because the fit was better (R^2=0.56, p=0.013, n=10) than for a linear function (R^2=0.42, p=0.044, n=10).

The regression lines in Figures 1 to 3 all suggest the same trend: at low illuminances, a small change in illuminance leads to a larger change in reassurance evaluations than does a similar change at higher illuminance. This trend means that there are diminishing returns of illuminance in terms of reassurance, which implies that there is a certain illuminance, or, at least, a small range of illuminances, which are optimal for reassurance because lower illuminances offer significantly less reassurance while higher illuminances bring only a negligible increase in reassurance. However, in none of these graphs does the curve define a precise location for an optimal illuminance. In Figure 3, the regression line intersects the abscissa at the day-dark difference of zero, and this point implies an optimal illuminance. In this case, however, the regression line intersects the abscissa because for one location, an underpass, reassurance was higher at night than in daytime. For most situations it is not expected that reassurance at night will reach the same level as in daylight (as seen in Figure 2), leading to a day-dark difference of greater than zero, and thus such intersection is unlikely to be revealed in surveys conducted on typical roads.

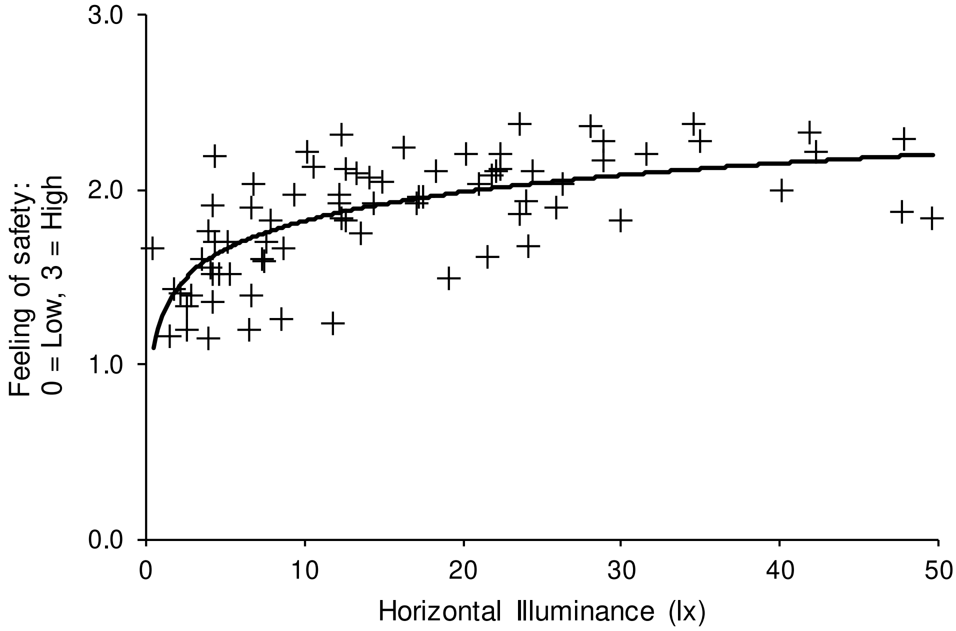


Figure 1 Ratings of the Feeling of Safety estimated for the City of Tel-Aviv-Yafo in Israel and plotted against illuminance (after Svechkina *et al.*[23])

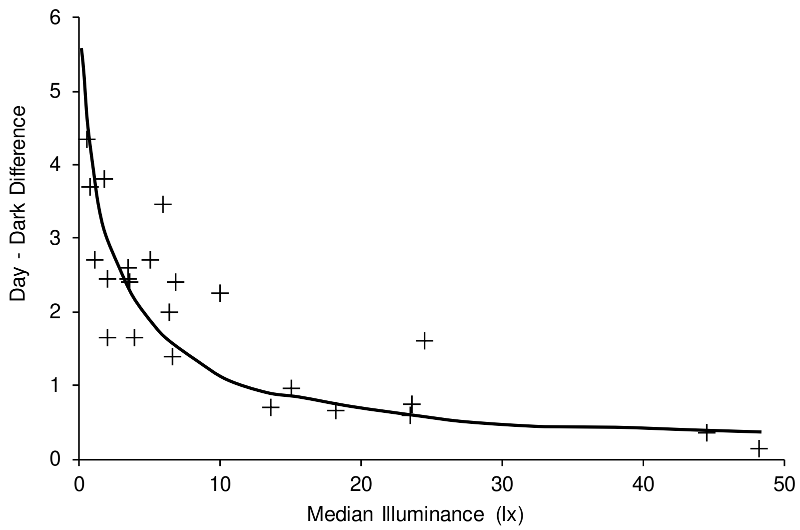


Figure 2 Difference between daytime and night-time ratings of perceived safety of car parks plotted against median illuminance, after Boyce *et al.*[24] Note: best fit line drawn here is approximated from original work.

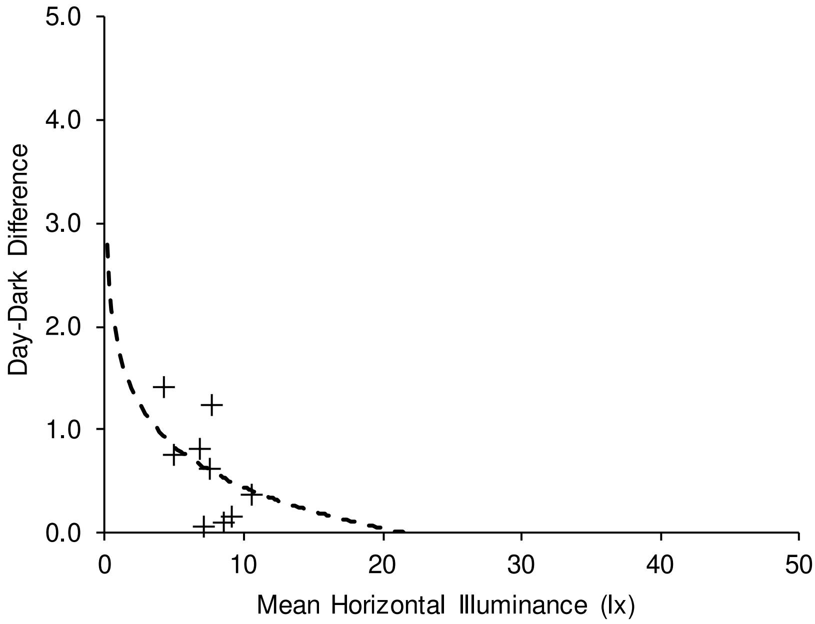


Figure 3 Difference between daytime and night-time ratings of reassurance in ten pedestrian routes roads plotted against mean illuminance, after Fotios *et al.*[25]

In some cases, interpretation is related to the change in reassurance ratings. Boyce *et al.*[24] used a hyperbolic fit line to model their results and reported that "*above 10 lx the difference is less than one scale unit and above 30 lx the difference is less than half a scale unit*" with the day-dark differences established using a 7-point rating scale. Fotios *et al.*[25] also interpreted their results by establishing the illuminance needed for a certain day-dark difference. This suggested mean illuminances of about 8 lx and about 4 lx for day-dark differences of 0.5 and 1.0 units respectively on their 6-point rating scale. In both studies the interpretation of suitable illuminance is made assuming that day-dark differences of 1.0 or 0.5 units are reasonable, but that remains to be validated. Svechkina *et al.*[23] concluded from their after-dark surveys that reasonably high levels of reassurance would occur for illuminances in the range 5 to10 lx, with further increase in illuminance giving only a minor rise in reassurance, but that, again, remains the authors' interpretation of the graph. It would thus be informative to establish a more objective interpretation of optimal illuminance from data such as these.

2.2 Segmented Regression

In empirical studies modelling the relationship between two or more variables, it is common to use straight lines or smooth curves (e.g., logarithmic curves, parabolas or hyperbolas), e.g.[23,24,26,27] Although this approach helps to identify trends, it does not make it possible to determine whether the trend changes, e.g., whether at some point the slope of the line becomes zero or changes sign.[28]

Linear models presume a constant trend over the entire data range. In the case of curved models, the trend is assumed to evolve smoothly, thus not having any specific points where the relationship between the dependent and independent variables changes.[28] To identify such points, known as *breakpoints*, the relationship between variables may be estimated by segmented regression models, where a number of straight, inter-linked, segments, are fitted to the data.[29]

Segmented regression has been used for the identification of breakpoints in research data about health, mortality and morbidity,[29-34] as well as for economic research.[35] Often, the method is applied to time series data, to identify distinctive trends during different periods, e.g., before and after an intervention. In such cases, segmented regression can be used to distinguish the effect of the intervention from that which would have happened even in the absence of the intervention.[32]

The lines fitted to reassurance data in Figures 1, 2 and 3 were determined using standard regression. An alternative approach therefore is to use segmented regression, in which the independent variable (here, illuminance) is partitioned into two or more intervals, separated by a breakpoint or breakpoints, and regression lines are fitted to the data within each interval.

In the current analysis we explore the use of segmented regression for analysis of reassurance evaluations where the dependent variable is *illuminance*. Segmented regression would be of benefit to the analysis of optimal illuminance for pedestrian reassurance if it would reveal two conditions in the data: first, that it is possible to define a break point which distinguishes two (or more) separate regions, each displaying a different relationship between reassurance and illuminance; and, second, that the final region (second, in the case of a single break point) is characterised by a gradient, which is not statistically different from zero, that is, a horizontal line, indicating no benefit of further increase in illuminance.

2.3 Aim

This article reports an investigation using segmented regression to determine whether this method of analysis will yield a precise estimate of the optimal illuminance for reassurance. The data for this investigation were gained for the same locations as in Svechkina *et al.*[23] but with a larger sample of respondents. The ability of segmented regression to do this, and, specifically, to result in a more powerful model than standard regression, was determined by testing three hypotheses:

H1: Breakpoints exist in the relationship between illuminance and pedestrian reassurance, i.e. the trend changes with different levels of illuminance. This hypothesis will be confirmed if the performance of segmented models (bold dotted and solid lines in Figure 4) exceeds that of continuous models (thin dotted line in Figure 4).

H2: For a given data set there is more than one breakpoint. This will be confirmed if the performance of segmented models with two or more inflection points (b(2), …b(n)) in Figure 4) exceeds that for the model with only one inflection point (b(1)).

H3: There is a plateau (horizontal line) after the final breakpoint. This will be supported if the slope of that line is not statistically different from *zero*.

Support for H1 and H3 results also in the estimation of optimal illuminance, i.e., the illuminance of the final breakpoint (E_O). Support for H2 means that the final break point, E_O, was correctly recognised. These three hypotheses were examined for the whole dataset of the three cities in which reassurance surveys were carried out, as well as for each city, individually.

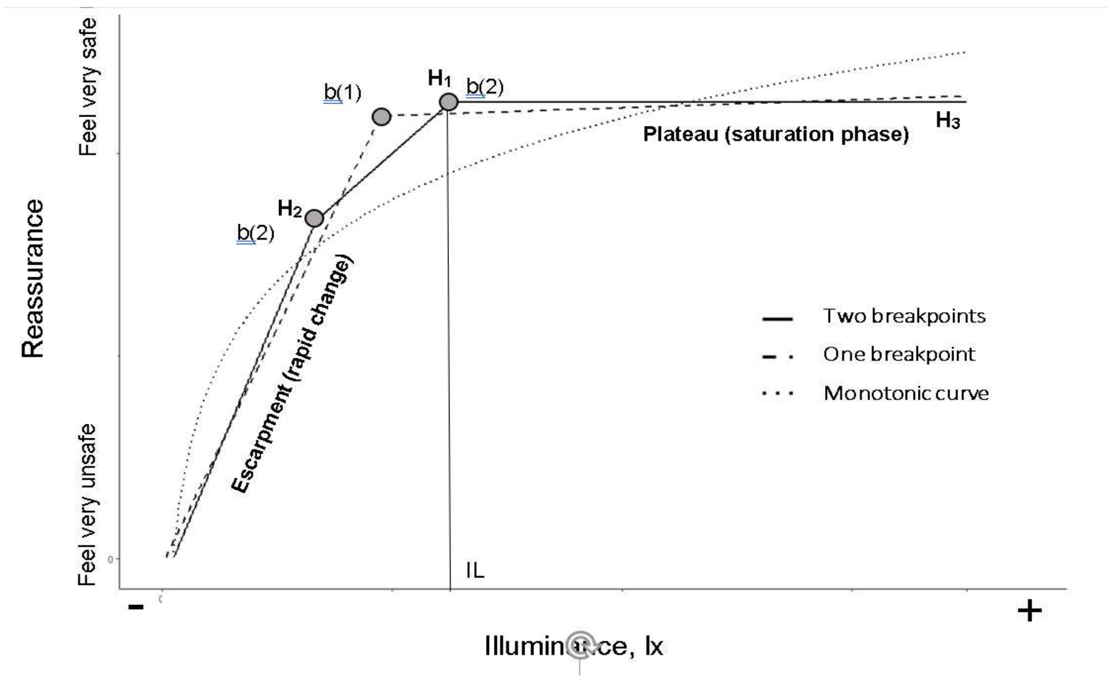


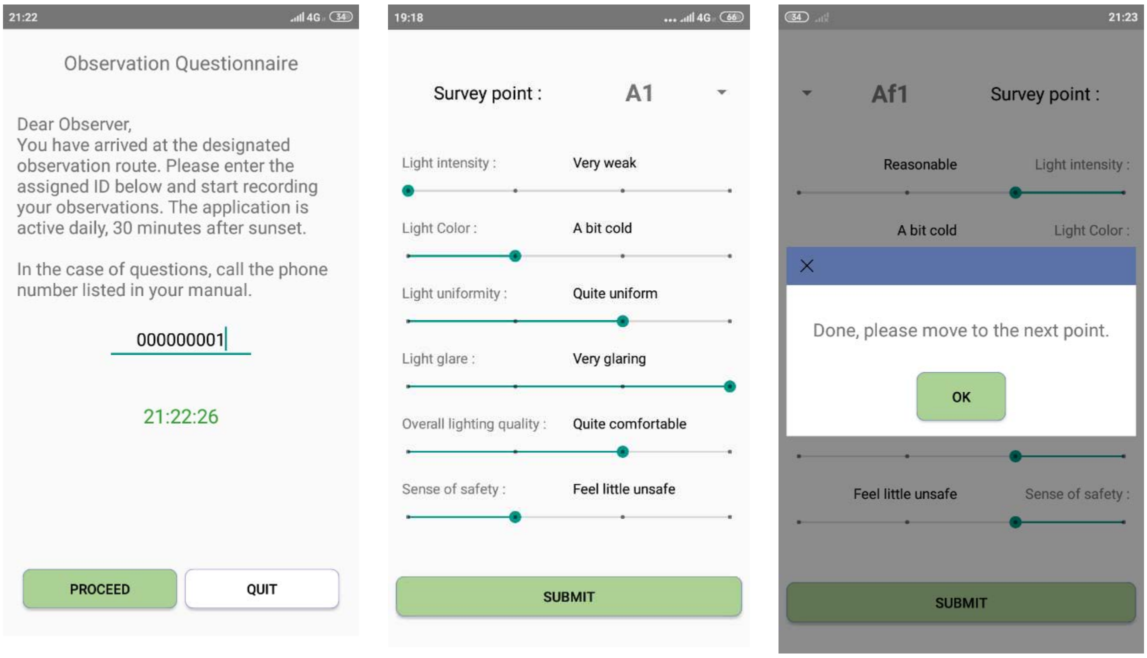
Figure 4 The expected relationship between illumination and pedestrian reassurance (see text for explanations)

3. Method

3.1 Data collection method

The data for this analysis were reassurance evaluations for the same locations as in Svechkina *et al.*,[23] but for a larger sample, incorporating about 20,000 additional assessments recorded since publication of that work. As in the former study,[23] the data were collected using a bespoke mobile phone application, CityLights^{TM}, which allows data to be collected in real-time at the evaluation location. The time and location of the observation are recorded automatically using the mobile phone's GPS. Each respondent receives a unique ID number to activate the app (see Figure 5).

Participants were guided to the assessment points by information provided in advance, and were asked to use the mobile phone app to report their level of reassurance at each location using a 4-point Likert scale (Figure 5B). The response categories (feel very unsafe, feel little unsafe, feel reasonably safe, feel very safe) were subsequently numbered 0 (feel very unsafe) to 3 (feel very safe) for quantitative analysis. The participants also evaluated other aspects of the environment (including light intensity, light uniformity and glare) but these are not included in the current work.



A B C

Figure 5 Sample screens from the CityLights™ mobile phone application [After Svechkina *et al.*,[23]]. A – the opening screen (shown once, when application is activated); B – survey questions screen; C – survey point redirection screen

3.2 Study locations

The study was conducted in three cities in Israel: Tel Aviv-Yafo, Haifa and Beersheba. These cities differ in their geographic location and climate (Tel Aviv-Yafo and Haifa are coastal cities with Mediterranean climate, Beersheba is an inland city, where the climate is hot semi-arid with Mediterranean influences) but are similar in population density and have relatively low crime levels.[23] Ten typical densely populated neighbourhoods were selected within these cities, four in Tel Aviv-Yafo (the largest city under study) and three each in Haifa and

Beersheba. All ten neighbourhoods were built in the 1980s-1990s and are characterised by similar multi-storey buildings.

In each neighbourhood, reassurance was evaluated at 25-30 locations, giving in total 257 evaluation locations across the three cities. Within a given neighbourhood the survey locations were located on a continuous walking route, spaced at intervals of approximately 20 to 30 m. The survey points were located near local landmarks, such as fire hydrants, bus stops or public benches, to enable simple descriptions for identification by survey participants. Of the total evaluations, 41.9% were recorded in Tel Aviv, 28.5% in Haifa and 29.6% in Beersheba. On average, each participant submitted assessments at 72 assessment locations in three separate neighbourhoods.

Horizontal illuminance was measured at the same evaluation locations, with these being spot measurements at each location using a PRC RadioLux 111 illuminance meter. The meter was elevated by up to 300 mm to a horizontal position, as ensured by a spirit level. The measurements were performed by an independent measurement laboratory (IBN labs) certified by the Israel Laboratory Accreditation Authority. To promote comparability across locations, all measurements were conducted in clear weather on weekdays, starting at least 30 minutes after sunset and ending before midnight. Illuminance data were missing for four locations and hence these were omitted from the analysis, leaving 253 locations. Table 1 summarises the range of illuminance measurements in the ten neighbourhoods.

3.3 Test participants

Reassurance evaluations were gained from 380 test participants, recruited through a specialist organization. The participants represented the local population in terms of gender and age with a margin of ±5%. Each participant was allowed to perform assessments at any location, but most (~97%) performed assessments for the three or four neighbourhoods in one city only. The observers were also permitted to make assessments twice, once in the early evening, between 20:00-22.00, and later on, between 22.00 and 24:00, but were not permitted to do so for the same location on the same day. They were also allowed to make assessments twice during a year, during winter and fall (October through February) and during spring and summer (March – August).

3.4 Segmentation Analysis

The data were first fitted using linear regression with illuminance modelled as both linear and logarithmic scales. Segmented regression was then applied with assumptions of one, two and three breakpoints. This process was repeated for the data as a whole, and subsequently fitted individually to the data from all neighbourhoods in each city.

Segmented regression analysis was performed using “R” software,[36] using the ‘segmented’ function. In particular, the following generic form for *L*-breakpoints was used for the analysis:

$$R_i = a + b_0.Eh_i + b_1.(Eh_i - BP_1)\,D_1 + \ldots + b_L.(Eh_i - BP_L)D_L \qquad (1)$$

where: R_i is the level of reassurance in location *i*, estimated from the average reassurance rating at each location *i* (i= 1, …, 253); Eh_i is horizontal illuminance (lx) measured at location *i*; *BP* is the breakpoint identified, and *D* is a dummy variable, which returns the value 1 if illumination value is larger than that observed in a specific BP or returns 0 otherwise; *L* is the number of break~~ing~~ points found to be significant in the developed model; and $a, b_0, \ldots, b_L$ are regression coefficients.

The segmented regression analysis was performed in several steps. The analysis starts with an *a priori* definition of the initial breakpoint, which is placed at the beginning of a data series. Linear segments are then fitted into data before and after the breakpoint, using ordinary least square (OLS) regression. Next, the models were estimated again by repositioning the breakpoint. At each iteration, individual linear regressions were fitted to the data on the left and right of each breakpoint. After that the calculation moved to the next potential breakpoint. The iterations continued until segmented models for each interval fitted as closely as possible into the data. If there is no break point, the slope of the fitted first segment does not differ from the next fitted segment, implying that the difference between the two slopes is not statistically different from *zero*.[29]

4. Results

Figure 6 shows participants’ evaluations plotted against illuminance for the pooled sample and for the three cities separately. Each data point represents the mean reassurance evaluation of a location averaged across all responses.

Table 2 shows regression estimates for the pooled sample and for each city separately, estimated using continuous regressions (linear and logarithmic fit). The regression lines shown in Figure 6 assume logarithmic transformation of horizontal illuminance. As shown in Table 2, linear regressions yield R^2 values ranging from 0.096 in Haifa to 0.394 for Tel Aviv-Yafo, with R^2=0.251 for the pooled dataset which includes all three cities. With logarithmic regressions R^2 increases in all four cases, now ranging from 0.280 in Haifa to 0.619 in Tel-Aviv-Yafo, and 0.426 for the pooled dataset.

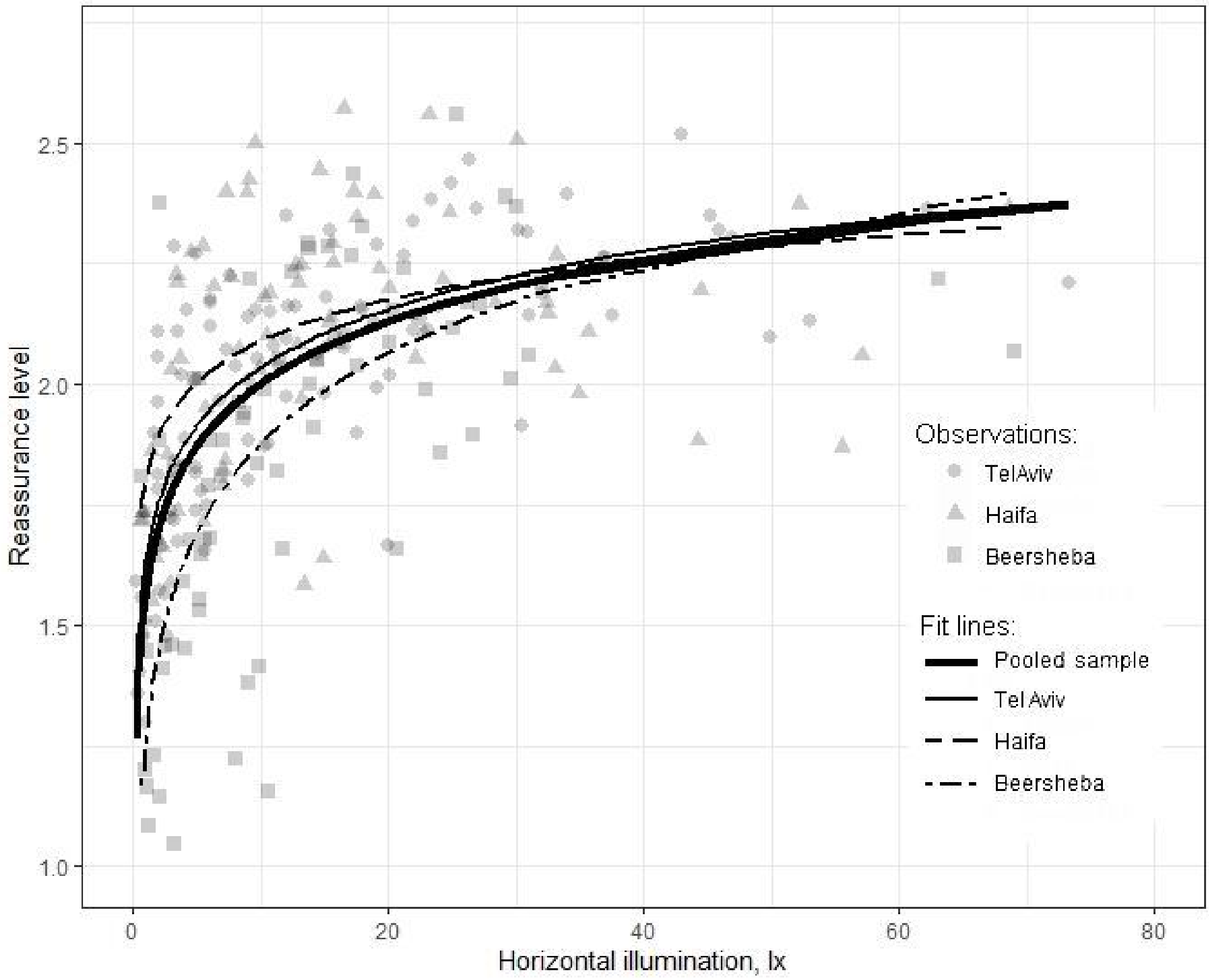


Figure 6 Mean reassurance rating at each location plotted against illuminance. Best fit lines for logarithmic regression are shown for each city separately and for all three cities combined. Note: The fit lines were drawn before segmentation.

Table 3 shows regression estimates for the pooled sample and for each city separately, estimated using segmented regression. Segmented regression leads to R^2 values of 0.357 for Haifa (with one breakpoint), 0.518 for Beersheba (one breakpoint) and 0.634 for Tel Aviv-Yafo (two breakpoints); the pooled sample yields R^2=0.452 (two breakpoints). Adding further breakpoints to the models did not significantly improve the fit. These models developed using segmented regression are statistically significant increases ($p<0.05$) compared with continuous regression (Table 4: note, for brevity only the χ^2 stats only for the pooled dataset are shown).

For each data set in Table 3, and for the last identified breakpoint in each data set, the slope of the final segment is not statistically different from zero ($p>0.05$), i.e. it is a horizontal line, which indicates the change in reassurance has reached a plateau. For those data sets with more than one breakpoint, it is this final breakpoint before the horizontal line that identifies the optimal illuminance.

Figure 7 shows regression lines drawn following the segmented regression. The final breakpoints suggest optimal illuminances of 17 lx in the pooled sample, 26 lx in Tel Aviv, 8.9 lx in Haifa and 15.4 lx in Beersheba.

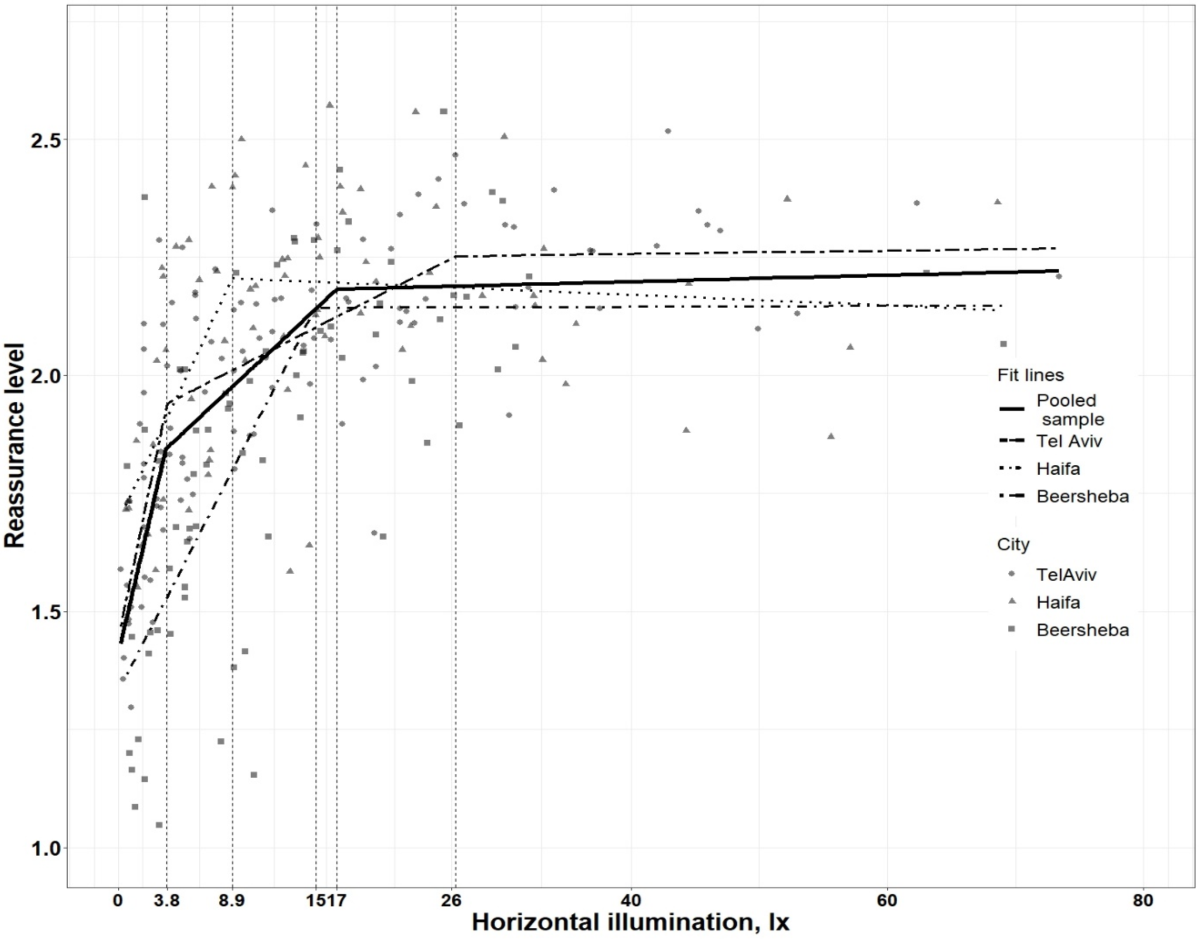


Figure 7 Mean reassurance rating at each location plotted against illuminance. Best fit lines, fitted using segmented regression, are shown for each city separately and for all three cities combined

5. Discussion

In previous studies, the relationship between illumination and pedestrian reassurance was commonly analysed by assuming a monotonic relationship between reassurance and illuminance.[23-25] However, while this approach reveals regions where the relationship between illuminance and reassurance exhibits rapid change (the escarpment) and negligible change (the plateau), the transition between these regions is blurred and does not indicate a discrete optimal level.

This study used an alternative modelling tool, segmented regression, which targets one or more discrete breakpoints between regions of differencing relationship between illuminance and reassurance. The success of this approach at revealing an optimal illuminance can be demonstrated by confirmation of the three hypotheses stated in section 2.3. These hypotheses were tested for the pooled dataset, incorporating data from all three cities under study, and for each city separately.

Hypotheses H1 was that there are breakpoints in the relationship between illuminance and pedestrian reassurance. This was confirmed by comparison of models for continuous and segmented regression: it was found that the models based on segmented regression provided better fit than those based on continuous regression. This confirms that the relationship between pedestrian reassurance and illuminance changes for different levels of illuminance.

Hypothesis H2 stated that a given data set has more than one breakpoint, as revealed by comparison of segmented regression models with one, two or three breakpoints. For reassurance evaluations in Haifa and Beersheba, H2 was rejected; model performance did not increase with the use of more than one breakpoint. However, for the pooled data set, and for Tel Aviv-Yafo, H2 was retained; model performance was better with two breakpoints than with one. What this means is that the numbers of breakpoints in the relationships were correctly identified.

Hypothesis H3 stated that the line beyond the final breakpoint was statistically indifferent from horizontal. This was confirmed, for the pooled sample and for the individual cities, because the slope of the regression line beyond the final breakpoint was not suggested by the *t*-test to be significantly different from zero. This means is that the final breakpoint before the horizontal line is the optimal illuminance for that data set and that no significant increase in reassurance occurs after reaching that illuminance level. These final breakpoints occur at 17 lx in the pooled sample, 26 lx in Tel Aviv, 8.9 lx in Haifa and 15.4 lx in Beersheba.

There are several limitations of the present study. The data originally collected were ordinal, that is, they were represented by ordered categorical values, reflecting the feeling of safety by individuals at given locations, from feeling *very unsafe* to feeling *very safe*. However, in the present study these data were converted into averages over assessment points. The averaging approach simplifies the analysis and helps to graphically represent the results. However, the main drawback of this approach is loss of information due to aggregation.[37] Data averaging also requires to assume explicitly that observers' assessments are reported with uncorrelated errors. In future studies, alternative statistical tools, which control for individual attributes of observers (e.g., ordinal logistic regression) might be used to relax these assumptions and improve estimates. Using such statistical multi-variate statistical tools in future studies would help to address another potential limitation of the study, namely repeated assessments of the same locations by the same observers.

It should also be noted that test participants were allowed to perform evaluations during different time periods (that is, early or late in the evening), to investigate the effect of the temporal factor on the perceived level of reassurance, albeit such repeated assessments were not allowed on the same day. Nevertheless, such repeated assessments, at least in theory, might be a source of bias, unless properly controlled for individual attributes of the observers and assessment time.

Evaluations in the three cities led to different estimates of optimal illuminance, 8.9 lx, 15.4 lx and 26 lx in Haifa, Beersheba and Tel Aviv-Yafo respectively. If illuminance were all that mattered for reassurance then it would be expected that the same optima were revealed at each location. That they do not agree suggest there are other influences, including those associated with environmental differences between the locations and those associated with response biases. Therefore, it is not known the extent to which the breakpoints estimated in the current study are relevant for other locations. Further work is required to extend the methods of data capture and analysis used in this study to a broader range of locations.

Horizontal illuminances at each evaluation location were characterised by spot measurements. Road lighting, however, is designed with consideration to the average and minimum of an array of spot measurements extending across the length and width of the lit area. Further work is need to determine how these spot measurements translate to the conventional system.

6. Conclusion

In previous studies of illuminance and pedestrian reassurance the findings do not enable an optimal illuminance to be precisely estimated. One reason for this is that the relationship between reassurance evaluations and illuminance was modelled assuming the relationship between illuminance and reassurance to be continuous, leading to a gradual change rather than abrupt change.

Segmented regression instead helps to break the dataset into two or more intervals of illuminance, separated by breakpoints, and with each interval characterised by a different regression model. Where the slope of the line after the final breakpoint is horizontal, the final breakpoint offers a precise estimate of optimal illuminance.

Segmented regression was used to analyse using 25,662 reassurance evaluations from 380 test participants at 253 locations in three cities in Israel. The analyses were successful in that breakpoints were found before final intervals of slope statistically not different from *zero*, suggesting optimal illuminances ranging from 8.9 lx to 26 lx, depending on location. Furthermore, models developed from analyses by segmented regression led to significantly better data fit than did analyses assuming continuous reassurance-illuminance association in the data sets.

This work therefore successfully met the aim of demonstrating the benefit of segmented regression at revealing a *precise estimate of optimal illuminance*. The next task is to establish optimal illuminances that are generalizable to other locations, which requires further work applying this approach, which demonstrated its utility in the present study, to more countries and locations.

Conflict of interest

The authors declare no potential conflicts of interest with respect to the research, authorship and/or publication of this paper."

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Figure captions

Figure 1 Ratings of the Feeling of Safety estimated for the City of Tel-Aviv-Yafo in Israel and plotted against illuminance (after Svechkina *et al.*[23])

Figure 2 Difference between daytime and night-time ratings of perceived safety of car parks plotted against median illuminance, after Boyce *et al.*[24] Note: best fit line drawn here is approximated from original work.

Figure 3 Difference between daytime and night-time ratings of reassurance in ten pedestrian routes roads plotted against mean illuminance, after Fotios *et al.*[25]

Figure 4 The expected relationship between illumination and pedestrian reassurance (see text for explanations)

Figure 5 Sample screens from the CityLights^{TM} mobile phone application [After Svechkina *et al.*,[23]]. A – the opening screen (shown once, when application is activated); B – survey questions screen; C – survey point redirection screen

Figure 6 Mean reassurance rating at each location plotted against illuminance. Best fit lines for logarithmic regression are shown for each city separately and for all three cities combined. Note: The fit lines were drawn before segmentation.

Figure 7 Mean reassurance rating at each location plotted against illuminance. Best fit lines, fitted using segmented regression, are shown for each city separately and for all three cities combined

Table 1 Summary of illuminances recorded in each neighbourhood.

City	**Neighbourhood**	**Horizontal illuminance (lx)**				
		Mean	**SD**	**Min**	**Max**	**No. of locations**
Tel Aviv-Yafo	1	15.4	14.8	0.9	53/0	26
	2	24.3	18.7	1.7	73.4	25
	3	11.0	12.3	0.19	49.9	31
	4	9.62	9.47	1/0	34.0	24
Haifa	1	17.6	11	1.5	44.5	24
	2	12.3	15	0.6	57.1	25
	3	20.0	17.5	0.7	68.6	23
Beersheba	1	15.5	8.5	2.1	32.1	23
	2	14.9	17.7	0.7	69.1	27
	3	9.42	7.08	0.9	26.2	25

Table 2 Performance of different models using **continuous** regression

Data set	**Number of assessment points**	**Regression type**	**R^2**	**a**	***t*-stat**	**b_0**	***t*-stat**
Pooled dataset	253	Linear regression	0.251	1.807	69.961**	0.012	9.165**
		Logarithmic regression [a]	0.426	1.572	46.870**	0.186	13.650**
Tel Aviv	106	Linear regression	0.394	1.828	61.976**	0.011	8.221**
		Logarithmic regression	0.619	1.636	50.310**	0.173	13.010**
Haifa	72	Linear regression	0.096	2.004	45.684**	0.005	2.728**
		Logarithmic regression	0.280	1.805	29.591**	0.123	5.217**
Beersheba	75	Linear regression	0.299	1.603	28.188**	0.017	5.578**
		Logarithmic regression	0.483	1.261	16.338**	0.268	8.258**

[a] Linear regression with log transformation of the horizontal illumination; ** significant at a 1% significance level.

Table 3 Performance of different models using **segmented** regression

Data set	L	R^2	a	*t*-stat	b_{L-1}	*t*-stat	u_L	*t*-stat	$b_L = b_{L-1} + u_L$	*t*-stat
Pooled dataset	1	0.427	1.576	40.879**	0.046	7.497**	-0.044	-6.949**	1.7e-3	1.291
	2	0.452[a]	1.410	19.614**	0.026	3.684**	-0.025	-3.805**	7.0e-4	0.46
	3	0.453	-	-	-	-	-	-	-	-
Tel Aviv	1	0.606	1.521	28.506**	0.087	5.701**	-0.082	-5.319**	5.0e-3	4.075**
	2	0.634[a]	1.443	20.780**	0.014	-3.742**	-0.014	-2.827**	5.0e-4	0.195
	3	0.639	-	-	-	-	-	-	-	-
Haifa	1	0.357	1.690	21.457**	0.058	3.621**	-0.059	-3.655**	-1.3e-3	-0.603
	2	0.371	-	-	-	-	-	-	-	-
Beersheba	1	0.518	1.330	18.179**	0.053	5.832**	-0.053	-5.210**	1.0e-04	0.027
	2	n/a	-	-	-	-	-	-	-	-

[a] Significant change in compare to the previous model, as estimated by the X^2 Likelihood test; L is the number of break points; b_L, u_L relate to the last segment estimated for each model (in this table b_L is the cumulative coefficient); ** indicates significance at a 1% significance level; "n/a" indicates that as data do not allow an additional breakpoint, the value cannot be calculated.

Table 4 X^2 Likelihood test of the comparative performance of different models for the pooled dataset

	Linear regression	**Linear regression with log transformation**	**Segmented regression with one break point**	**Segmented regression with two break points**
Linear regression with log transformation	67.391^{**}	-	-	-
Segmented regression with one break point	67.704^{**}	0.3132^{ns}	-	-
Segmented regression with two break points	79.103^{**}	11.711^{*}	11.398^{**}	-
Segmented regression with three break points	79.393^{**}	12.002^{ns}	11.688^{*}	0.290^{ns}

Note: ** = significant at a 1% significance level; * = significant at a 5% significance level; ns = not significant