Let Me Count the Light. Accounting for Intensity, Duration and Timing of Light When Predicting Sleep and Subjective Alertness in Field Studies

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ABSTRACT
Throughout the day, we are exposed to light that varies drastically over time. Correct quantification of the light is important when predicting sleep and subjective alertness in the field, yet doing so, is a complex challenge. In the current manuscript, we explore the feasibility of a novel, practical method to quantify light exposure, based on the data collected in two field studies (in late spring and winter). Data include indicators of sleep, subjective alertness, and personal luminous exposure. We explored Time above Threshold (TaT) and Mean Light Timing above Threshold (MLT) metrics, as well as their interaction, to quantify intensity, timing, and duration of light in testing not only circadian but also acute alerting effects of light in the field during office hours. For both measures, sensitivity analyses were performed across a large range of illuminance thresholds. The aim was to explore if these analyses would render indications for (a range of) effective thresholds, and to test if this alternative method of quantifying light would outperform simple averaging over specific time intervals. Despite the relatively small data set, the current approach seems promising particularly for predicting sleep: models performed slightly better than traditional models using average light exposure as predictor. More importantly, this method takes into account intensity, duration and timing, providing more detailed insights in the relation between luminous exposure and different outcome measures. We encourage this method to be explored further with larger data sets, discuss shortcomings of the current analyses and suggest potential directions for improvement.

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1. Introduction
Throughout the waking episode we are continuously exposed to light, with light settings varying drastically over time (Espiritu et al. 1994; Peeters et al. 2021; Scheuermaier et al. 2010; Smolders et al. 2013). These naturalistic exposure patterns contrast substantially with typical light exposure patterns in laboratory-based research, in which participants are exposed to light of a constant intensity throughout the experiment (Daurat et al. 1993; Phipps-Nelson et al. 2003; Smolders and de Kort 2014) or to several distinct light blocks (Iskra-Golec and Smith 2008; Yang et al. 2019, 2018). Importantly, whereas such block exposures of light are relatively easy to time, quantify and compare across conditions and studies, it still remains an open question what the most appropriate method is to quantify luminous exposure in field research. Yet correct quantification and timing of the independent variable (in this case light) are of course crucial for modeling or making predictions of any dependent variable (e.g., daytime functioning or sleep-related marker) in research. Hence, how we quantify light dosage in field research, i.e., of irregular and highly dynamic light patterns, is an important consideration if we want to advance knowledge on the effects of light beyond vision from studies in ecologically valid conditions.

Earlier research has shown that, both for circadian and acute effects, the response to a light stimulus is dependent on its intensity, as reflected in so-called dose–response curves (Cajochen et al. 2000). In addition, research has shown that the magnitude of the effect of light on phase shifting, melatonin suppression, and self-reported sleepiness is dependent on the duration of the light exposure (Chang et al. 2012). Third, a major role is played by the timing of the luminous exposure, which not only impacts the size, but even the direction of an effect, as illustrated in phase–response curves (Crowley and Eastman 2017; Khalsa et al. 2003; Minors et al. 1991; Rüger...
et al. 2013; St Hilaire et al. 2012; van Cauter et al. 1994) that describe the phase delay or phase advance as a function of (intimal) timing of the light stimulus. In general, there also seems to be a time-of-day dependency for the acute effects of light, though the magnitude and direction are not always as clear (An et al. 2009; Huiberts et al. 2017; Rüger et al. 2006). It has been suggested that higher luminous exposures are more effective in the morning in terms of the acute alerting effects (Smolders et al. 2012, 2013), although according to recent reviews, the literature is quite equivocal on this (Lok et al. 2018a; Souman et al. 2018).

Besides higher luminous exposures and its timing, the spectral composition of the light plays a role as well in both circadian and acute effects. Studies have shown that higher CCT levels – most likely containing more power in the melanopic sensitivity range – during the day can lead to enhanced alertness, performance, and improved subjective sleep quality (Keis et al. 2014; Mills et al. 2007; Rahman et al. 2014; Viola et al. 2008), though not always (Ru et al. 2019; Smolders and de Kort 2017; Souman et al. 2018). Nighttime exposure to higher CCT levels or monochromatic light of shorter wavelengths leads to stronger suppression of melatonin and improves subjective alertness (Brainard et al. 2001; Cajochen et al. 2005; Chellappa et al. 2011). However, due to the lack of spectral information, the current manuscript will only focus on intensity, timing, and dosage.

The problem we address in the current manuscript is that block-like exposures employed in laboratory studies do not align with the light exposure patterns we are exposed to in naturalistic conditions. In everyday life, the light we are exposed to is actually (extremely) variable over time (Cole et al. 1995; Hébert et al. 1998; Heil and Mathis 2002; Okudaira et al. 1983; Peeters et al. 2020; Savides et al. 1986), which not only makes the measurement, but also the correct quantification of light exposure – in terms of intensity, timing and duration – quite a challenging issue. In the current manuscript, we will propose the use of an alternative method to quantify light and demonstrate its feasibility and potential by employing it on a modest data sample collected in the field.

1.1. Quantification of light in the field

The majority of field studies that investigated correlations between naturalistic light exposure and sleep, alertness, and related variables have used the sum or average intensity of the (often log-transformed) light exposure over a certain time period to quantify light dosage (Boubreki et al. 2014; Figueiro and Rea 2016; Figueiro et al. 2017; Hubalek et al. 2010; Jean-Louis et al. 2000; Smolders et al. 2013; Tsuzuki et al. 2015). However, given the fact that we would expect a quite pronounced sigmoidal, that is, non-linear dose-dependent response (as established for nocturnal circadian and acute effects, see Cajochen et al. (2000) and Zeitzer et al. (2000)), a linear average of past exposure may not be the most sensible measure to predict effects. Important to note also is that laboratory studies that focused on different durations of light exposure, have indicated that light is also not integrated linearly over time by our circadian system (Gronfier et al. 2004; Najjar and Zeitzer 2016; Rimmer et al. 2000). These studies demonstrated that brief, intermittent light pulses were almost as effective as continuous light exposure, even though the total duration of exposure to light was substantially shorter. Additionally, several studies have indicated that the prior light exposure (or light history) moderates the effectiveness of a light intervention in terms of both acute and circadian effects (Chang et al. 2013; Chang et al. 2011).

Alternatively, several field studies have quantified light exposure as the time above a given threshold (TaT) – often 1000 lx (either at the eye or measured from the wrist) (Espiritu et al. 1994; Hubalek et al. 2010; Smolders et al. 2013; Tsuzuki et al. 2015). Elegantly, this measure actually integrates duration and intensity. Yet here the problem lies in that the critical daytime threshold level has not yet been established (though not for a lack of trying, e.g., see (Smolders et al. 2018) or (Lok et al. 2018b), so any specific choice of a threshold is basically arbitrary.

From this perspective, an interesting approach was taken by Reid et al. (2014). Instead of linearly averaging measurements over time or selecting an arbitrary threshold, they performed a sensitivity analysis, exploring multiple thresholds between 10 and 3000 lx (determined at the wrist). For each of these thresholds, they calculated the total time light
levels raised above those values, and used these to subsequently determine the best fitting threshold for predicting their outcome variables: body mass index (BMI) and sleep timing. Reid and colleagues (2014) introduced a related approach to also quantify the timing of light in the day for field studies. To this end, they conceptualized the so-called mean light timing above threshold (MLiT), which is the average timing of the periods that the participants were exposed to light above a given threshold. MLiT, thus describes the average timing of the light exposure over the day for a given threshold. Again, by employing sensitivity analyses, using a wide range of thresholds, one could explore which threshold is sensitive to temporal dependency of light-induced modulations in the specific outcome measures. Since its introduction, it appears that only a handful of studies have been published that employed this type of sensitivity analysis (Joo et al. 2017; Pattinson et al. 2016; Slyepchenko et al. 2019). The MLiT metric was used to predict the relationship with subjective sleep quality (Joo et al. 2017), BMI (while controlling for sleep duration and timing) and mood disorders (Slyepchenko et al. 2019). Others have used a very coarse approach for timing, employing 5 hours of lowest light exposure and 10 hours of highest light exposure (Dawson et al. 2020), or the average light exposure over a certain period such as the morning or afternoon (Figueiro et al. 2017; Peeters et al. 2021; Smolders et al. 2013). Studies that have employed the “threshold sensitivity analysis” method for MLiT (or TaT) found that optimum thresholds for the prediction of circadian effects as well as other outcome measures emerged around 200 lx (Joo et al. 2017; Pattinson et al. 2016), 500 lx (Reid et al. 2014; Slyepchenko et al. 2019) or 1000 lx (Slyepchenko et al. 2019) for MLiT, and 10 lx (Pattinson et al. 2016), 100 lx (Reid et al. 2014) and 2500 lx (Pattinson et al. 2016) for TaT. All light measurements were performed at the wrist. To our knowledge, no one has attempted to predict acute effects with this strategy yet.

The elegance of the above-mentioned time and timing above threshold metrics is in their simplicity and hence applicability. More advanced approaches have also been proposed, for instance, by Amundadottir et al. (2017), Bonarius et al. (2020) and Woelders et al. (2017). They suggest using advanced mathematical modeling, for example incorporating the models of Forger et al. (1999) and Kronauer et al. (2000), to account for variable intensity, timing, and duration of luminous exposure in the prediction of circadian effects. These models incorporate the concept of a time-dependent phase response, as well as a duration-dependent light drive (Process L), caused by the activation and subsequent saturation and regeneration of photopigments in the human retina. Such perceptive adaptation processes explain why, with prolonged duration, light exposure will become less effective.

The use of these advanced models comes with a number of downsides, however. First, they are quite complex, involving Van der Poll-type oscillator modeling with multiple differential equations and require not only accurate, but also complete, 24/7 exposure data over prolonged time (days to weeks ideally) which are quite hard to collect in realistic day-to-day situations. Second, the Kronauer and subsequent models only pertain to circadian entrainment and sleep timing, not to the effects of light on sleep quality or acute, alerting effects of light. Third, the models – and all the parameter estimates in them – are mainly based on a small number of studies of nocturnal block-type light exposures (Boivin et al. 1996; Zeitzer et al. 1997), and have not been thoroughly validated with real-world data. In fact, there are very few studies investigating entrainment in natural conditions (Stothard et al. 2017; Wright et al. 2013). Whether the various parameters fitted in these advanced models also bear relevance in naturalistic conditions remains an open question. Although the aforementioned sensitivity analyses based on TaT and MLiT metrics cannot account for all the complexities discussed above (e.g., they do not yet compensate for adaptation after prolonged exposure), they do offer a potential interesting methodology to predict effects of intensity, duration, and timing of light measured in the field.

### 1.2. Current study

The goal of this study was to explore, as a proof of concept, whether the method of employing TaT and MLiT metrics is a promising direction for quantifying light exposure in future and perhaps
also past field studies. In the current study, a relatively small data set was used in order to see if we could learn more about the relationship between sleep (and daytime alertness) and intensity, timing and duration of light.

Another goal was to see whether clear optimal ranges of threshold levels would emerge in sensitivity analyses when employing multiple light threshold levels while modeling light-induced effects on sleep timing, duration and quality, and on momentary alertness. The emergence of pronounced optimal ranges would support the existence of a sigmoidal, or at least step-based, dose–response relationship between field-based luminous exposure data and sleep-related and alertness-related markers. Additionally, we wanted to explore the relative and combined contribution of dosage and timing in our modeling efforts.

In the current study, we employed the TaT and MLiT metrics to quantify intensity, timing, and duration of light in testing not only circadian but also acute-alerting effects of light in the field during the workday (08.30–17.00). In doing so, we modeled the data on luminous exposure (measured during the workday), acute alertness and sleep, that were collected in the context of two three-week field studies, one in spring and one in winter (the same data as reported in Peeters et al. (2021)). Instead of employing the average light exposure over a certain time period, we performed sensitivity analyses using TaT and MLiT metrics across a large range of threshold levels. Additionally, the interplay between time above threshold and timing of time above threshold was explored. Such analyses could not only illustrate the importance of the specific time and timing above threshold for real-world alerting and sleep-related effects, but might also suggest the most likely range in which the threshold for diurnal nonvisual light effects lies. In that sense, one could consider this a revisit of the search for a diurnal dose–response curve (Lok et al., 2018b; Smolders et al. 2018), but this time based on naturalistic data obtained in the field. Moreover, in view of recent indications of potentially strong interindividual differences in responsiveness to the acute effects of light as assessed with melatonin suppression (Phillips et al. 2019), we included in our analyses an exploration of interindividual differences in sensitivity to the acute alerting effects of light.

2. Method

2.1. Design

For this manuscript, the same datasets were used as collected in Peeters et al. (2021). Over a continuous period over three weeks (once in spring and once in winter), objective light exposure data was measured using light loggers worn on the chest. Sleep data was collected using both actigraphy and a sleep diary. Subjective alertness ratings were collected through an experience sampling method (ESM).

2.2. Participants and setting

Data from the same participants (office workers, N = 7 (1 female, M_age = 42, SD_age = 11.44, range = 25–53) and N = 10 (1 female, M_age = 44, SD_age = 11.01, range = 25–55) in spring and winter respectively) in the same office setting as in Peeters et al. (2021) were included in the analyses.

2.3. Measurements and procedure

Below we present the most relevant information on the data collection, for more details we refer to Peeters et al. (2021).

2.3.1. Sleep

Sleep measurements were collected on a daily basis during both field study periods. Objective sleep measures were collected using an accelerometer (Philips Respironics Actiwatch Pro with MEMS type accelerator), with a sampling rate of 30 seconds. Participants were asked to wear them continuously during the sampling week. Additionally, a sleep diary, based on the Karolinska Sleep Diary (Åkerstedt et al. 1994), was completed on a phone using the MetricWire application, on a daily basis in the morning after awakening. For both objective and subjective sleep measures the following variables were computed and used: Sleep Duration (in hours), Midsleep, and Sleep Onset. Additionally, Subjective Sleep Quality obtained in the sleep diary was used.

2.3.2. Subjective alertness

Subjective alertness was measured using the Karolinska Sleepiness Scale (Åkerstedt & Gillberg,
When participants received an ESM notification, they completed several questions, including the 9-point KSS scale probing alertness (1 = “Very alert”) to sleepiness (9 = “Very sleepy”). The KSS was formulated as follows: “How alert/sleepy do you feel at this moment?” The 9-point scale was discrete and presented vertically in order to fit on a mobile phone screen. Participants received eight notifications per day according to a semi-random schedule, with at least 30 minutes between each notification. Four notifications were delivered in the morning (between 08:30 and 12:30) and four in the afternoon (between 13:00 and 17:00).

2.3.3. Light measurements
Luminous exposure was tracked using a light logger (Martin 2015). Participants were asked to wear it continuously and the storage rate was set to 200 seconds. Participants received instructions that if they were not wearing the light logger, they should place them upside down on a surface. All observations <10 lx were coded as missing (as this could indicate not wearing the sensor or the sensor being covered by a jacket) and a calibration correction was applied (Peeters et al. 2020). Based on the participants’ individual light logger data TaT and MLiT were computed, in line with work by Pattinson et al. (2016), and Reid et al. (2014). For each of these metrics, we explored 41 threshold levels, equally distributed on a logarithmic scale ranging from 20–1995 lx. (10^1.30 until 10^3.30 with 0.05 power increments), hence employing a similar range as employed in the dose-response studies by Smolders et al. (2018) and Lok et al. (2018b).

2.3.4. Time above threshold (TaT)
The TaT values were computed using Matlab R2017B. Two versions of TaT were computed: TaT_{day} and TaT_{30min}; TaT_{day} counted the time above threshold during working hours (08:30–17:00), for every workday of every participant, and TaT_{30min} computed the time above threshold over the 30 minutes before completing the experience sampling questionnaire, for every trigger of every participant during working hours. For reliable TaT_{day} computations, we allowed no more than 30% of missing data in that morning and no more than 30% missing data in that afternoon. If these conditions were not met, the TaT_{day} was marked as missing. For TaT_{30min}, a maximum of 50% missing data over the 30 minutes was allowed.

Per threshold level, the number of measurements above and below that given level were counted. Based on this information, the percentage of measures above this threshold for the given time period was computed. The resulting TaT indicates the percentage of the time that the measured illuminance was above the specific threshold level across the workday (ranging from 0% to 100%), for example, TaT_{day}^{500} reflects the percentage of time that the light measurements of a given participant were above 500 lx (close to the eye) on a given workday. The Matlab Script for computing the TaT values is available from github.com/STPeeters/TaTMLiT.

2.3.5. Mean light timing above threshold (MLiT)
The MLiT values were computed based on the TaT_{day} output in Matlab R2017B. For every light logger measurement marked as above threshold, the timestamp at which this occurred was recorded. To compute the MLiT, the average of all these time points was calculated and saved. This routine was repeated for every participant, for every threshold level, for every day. The output is a numeric average timestamp for which the specified TaT occurred on a given day. For instance, MLiT^{500} indicates the average of all TaT_{day}^{500} timestamps on a given day. If the threshold was never met, the MLiT was marked as missing. The MLiT metric was only computed for the full workday, and not for the small 30-min windows. The Matlab Script for computing the MLiT values is available from github.com/STPeeters/TaTMLiT.

2.4. Statistical analysis
The data were analyzed using R version 3.5.0, using the packages lme4, ggplot2, sjplot and plyr. Given the nested structure of the data, a linear mixed modeling (LMM) approach was used. The TaT and MLiT for the different threshold levels were used individually as a predictor for the dependent variables. The resulting estimates for all thresholds were then plotted per dependent variable. For these sensitivity analyses, an α of .05 was used as the cutoff value for statistical significance – the analyses should hence be
regarded as exploratory rather than confirmatory. The data for spring and winter were analyzed separately. The R Script for creating the sensitivity plots is available from github.com/STPeeters/TaTMLiT.

2.4.1. Sleep
In the models pertaining to sleep, the variables Person and Week (1–3; nested within person) were included as random intercepts. For every threshold, the respective TaT and MLiT values were included as covariates. Besides the models with either TaT or MLiT as predictor, interactions between these metrics were explored as well in additional models. Additionally, two covariates were included: Day (mon – fri) and PSQI (sleep quality score).

2.4.2. Subjective alertness
For the models predicting subjective alertness, the variables Person, Week (1–3; nested within Person) and Day (1–5; nested within Week and Person) were included as random intercepts. The respective TaT threshold was included as a covariate. One additional covariate was included here as well: PSQI (sleep quality score).

As an extra exploration for subjective alertness, sensitivity analyses were also performed per individual participant. For this, the variables Week (1–3) and Day (1–5; nested within Week) were included as random intercepts.

2.4.3. Sensitivity plots
Per outcome variable, and per covariate (TaT, MLiT, and TaT x MLiT), sensitivity plots were made. The x-axis represents all the different threshold levels, while the y-axis represents the unstandardized parameter estimates (based on the outcome of the respective mixed model). In the plots, the significance (p < .05) is indicated and the Standard Errors (SE) are included. Based on the sensitivity plots it is possible to determine which thresholds are potential candidates for TaT or MLiT to influence either sleep or subjective alertness.

In the sensitivity analyses, boundaries were set to account for reliability of the analysis. At the lower threshold levels (of, for example, 20 lx), the large majority of the data will be above the given threshold, particularly as we are only taking into account the time frame between 08:30 and 17:00. At the higher threshold levels, however, chances are high that the thresholds are not, or only rarely, met. This is acceptable until only a handful of observations above threshold can predict the outcome measure, or when virtually every observation is above threshold, and hence little variance is observed for the specific threshold. Therefore, two rules were applied based on the TaT\textsubscript{day} outcomes, to make clear which areas should be regarded as not reliable (these areas will be shaded in gray in the sensitivity plots).

1. For the lower thresholds: If more than 50% of the cases included had a TaT\textsubscript{day} above 75%, these were marked as not reliable.
2. For the higher thresholds: If more than 50% of the cases included had a TaT\textsubscript{day} below 5.88% (which is equal to 30 minutes of exposure) these were marked as not reliable.

For the TaT\textsubscript{30min} gray areas, slightly different boundary rules were employed.

1. For the lower thresholds: If more than 75% of the cases had a TaT\textsubscript{30min} above 75%, these were marked as not reliable (similar to TaT\textsubscript{day})
2. For the higher thresholds: If more than 75% of the cases never met the threshold, these were marked as not reliable.

3. Results
In this section, we present sensitivity plots over the full range of thresholds, but only the white parts are of sufficient reliability – the areas that are marked gray do not fulfil the requirements as formulated in Section 2.4.3 and hence reflect findings based on too few data points or too many above threshold. In view of the aims of the current manuscript, the main interest is in whether clear ranges of thresholds emerge that meaningfully predict outcome variables; individual significant estimates are less relevant, especially also in view of multiplicities.

3.1. Sleep
3.1.1. Time above threshold
The sensitivity plots using TaT values as a predictor for the various sleep markers (duration, midsleep timing, and sleep onset, estimated both from self-
reports and from Actiwatch data), for both spring and winter are presented in Figs. 1 and 2. Graphs on the left present the analyses on data from the sleep diaries, those on the right present similar analyses, but based on the actigraphy data.

In Fig. 1, it can be observed that there are two significant thresholds for subjective sleep duration in spring. For subjective sleep duration, $\text{TaT}_{\text{day}}^{282−562}$ predicted a shorter sleep duration with more time above the range of 282–562 lx in the vertical plane close to the eye during daytime working hours, respectively (B ranged between −0.014 and −0.022, average $R^2_{\text{marginal}} = .27$). As for the winter data, two of the outcome variables showed significant relationships for specific TaTs. For subjective sleep duration, the analysis suggests that a higher $\text{TaT}_{\text{day}}^{126−200}$ predicted shorter sleep (B ranged between −0.011 and −0.012, average $R^2_{\text{marginal}} = .28$). Subjective sleep onset was significantly predicted by $\text{TaT}_{\text{day}}^{158−316}$, suggesting later sleep onset with more time above these thresholds (B ranged between < 0.01 and 0.01, average $R^2_{\text{marginal}} = .06$). Sensitivity plots were also created for subjective sleep quality, as can be observed in Fig. 3. No reliable, statistically significant estimates were observed for the prediction of sleep quality.

3.1.2. Mean light timing above threshold

Figures 4 and 5 show the sensitivity plots for the relation between the different sleep measures and the MLiT for the various thresholds. Again, graphs on the left present the analyses on data from the
**Fig. 2.** Sensitivity plots for the relation between TaT and sleep outcomes per threshold in winter. Whiskers represent the standard error. Significant (p < .05) unstandardized parameter estimates are printed in black. The gray shaded areas represent the areas that should not be regarded as reliable.

**Fig. 3.** Sensitivity plots for the relation between TaT and subjective sleep quality per threshold in both seasons. Whiskers represent the standard error. Significant (p < .05) unstandardized parameter estimates are printed in black. The gray shaded areas represent the areas that should not be regarded as reliable.
sleep diaries, those on the right present similar analyses based on actigraphy data.

When observing the spring data (Fig. 4), there seems to be no statistically significant relationship which falls in the reliable zone. In winter (Fig. 5), some thresholds showed a significant relationship between the MLiT and subjective sleep measures. These suggested that if the mean timing of light exposure above thresholds of roughly 70 to 200 lx (at eye level) fall later on the workday (so a higher MLiT), this will lead to a longer sleep duration ($B = 0.16$, $R^2_{\text{marginal}} = .28$), earlier midsleep ($B$ ranged from $-0.09$ to $-0.14$, average $R^2_{\text{marginal}} = .21$) and earlier onset ($B$ ranged from $-0.15$ to $-0.19$, average $R^2_{\text{marginal}} = .08$). Sensitivity plots were also created for the relationship between MLiT thresholds and subjective sleep quality as can be seen in Fig. 6. No reliable significant relations were observed here for either season.

### 3.1.3. Interactions

Sensitivity plots for the relation between the different sleep measures and the interaction $\text{TaT}_{\text{day}} \times \text{MLiT}$ are shown in Figs. 7 and 8 for the different thresholds. Again, graphs on the left present the analyses on data from the sleep diaries, those on the right present similar analyses based on actigraphy data.

The estimates in this case represent the estimates for the interaction, though with only this estimate it is difficult to interpret the meaning of the interactions. Therefore, additional plots are

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**Fig. 4.** Sensitivity plots for the relation between TaT and subjective sleep quality per threshold in both seasons. Whiskers represent the standard error. Significant ($p < .05$) unstandardized parameter estimates are printed in black. The gray shaded areas represent the areas that should not be regarded as reliable.
shown to demonstrate the implications of significant interaction effects.

When observing the spring data, several significant interactions were statistically significant. For midsleep (both subjective ($R^2_{marginal} = .21$) and Actiwatch-based (average $R^2_{marginal} = .34$)), sleep onset (both subjective (average $R^2_{marginal} = .10$) and Actiwatch-based (average $R^2_{marginal} = .23$)) and sleep duration (only Actiwatch-based (average $R^2_{marginal} = .21$)), some significant interactions were observed (see Fig. 7). These mainly occurred at the lower thresholds (around 89–126 lx at eye level) in the trusted area. For all Actiwatch-based data, however, there was also one significant interaction for the higher thresholds ($TaT_{day}^{891} \times MLiT^{891}$). In winter, there were some significant interaction effects for all measures, except for subjective midsleep. Most interactions occurred around the range of 251–316 lx at eye level (average $R^2_{marginal} = .15$, range = .09 – .31). Figure 9 shows similar sensitivity plots, but with subjective sleep quality as an outcome measure. In neither season, significant interactions were found to predict subjective sleep quality.

Figures 10 and 11 show the interactions plots for some of the statistically significant $TaT \times MLiT$ interactions. Figure 10 shows the interaction plots for AW midsleep for the thresholds of 100 lx and
891 lx at eye level, with the purpose of comparing a value in the lower range with the value in the higher range of the significant thresholds. The figure clearly shows that the threshold of 100 lx was met more often than the 891 lx threshold. The data points presented in the graph for TaT<sup>891</sup> become scarcer for more time above the threshold. This should be kept in mind when interpreting and comparing these interactions. The direction of the relationship is the same for both thresholds, suggesting that more time above these thresholds resulted in an earlier midsleep when the luminous exposure occurred, on average, earlier during the workday (earlier MLiT), while more time above these thresholds led to a later midsleep when the luminous exposure occurred later during the workday (later MLiT).

**Figure 6.** Sensitivity plots for the relation between MLiT and subjective sleep quality per threshold in both seasons. Whiskers represent the standard error. Significant (p < .05) unstandardized parameter estimates are printed in black. The gray shaded areas represent the areas that should not be regarded as reliable.

3.2. Subjective alertness

Figure 12 shows the sensitivity plot for the relation between the various TaT<sub>30min</sub> values and subjective alertness. As can be clearly seen, no significant relationship emerged for any of the threshold levels, in either season. To explore whether inter-individual differences were potentially causing these null effects, the same sensitivity plots were created for each participant separately. These plots also mainly showed null effects only, with substantial overlap between the individuals. To improve the legibility of Fig. 13, due to the large overlap between individuals, only three individuals (one average and two most “extreme” in terms of parameter estimates) are shown in each graph, together roughly representative for the profiles found in the full sample.

4. Discussion

Field research is crucially important for the lighting domain, but complicated, and correct quantification of light is one major challenge (de Kort 2021; Houser and Esposito 2021). In this study, we explored the use of TaT and MLiT metrics as an alternative quantification of light in terms of intensity, duration and timing with a relatively small dataset. Sensitivity analyses were performed to test their utility in modeling the relation between luminous exposure and sleep and alertness markers in the field. TaT and MLiT metrics in combination with sensitivity analyses for varying threshold levels were first proposed by Reid et al. (2014). We expanded their methodology in
various ways. First, our analyses included a more fine-grained range of threshold levels. Second, we investigated the relevance of this strategy not only for modeling circadian effects on sleep parameters, but also of acute alerting effects. Third, for circadian effects, we explored not only main effects of TaT and MLiT metrics, but also included their interaction to explore timing-dependent moderations in the predictive strength of light dosage for sleep-related markers. Last, for acute effects, we employed this strategy for exploring interindividual differences in light sensitivity for acute alerting effects.

4.1. Modeling circadian light effects

The emergence of pronounced optimal ranges for TaT or MLiT metrics in the prediction of sleep-related measures would support the existence of a sigmoidal or step-shaped dose–response relationship for field-based light exposure data, similar to that established in laboratory studies (Cajochen et al. 2000; Zeitzer et al. 2000). This finding would motivate the favoring of a time-over-threshold metric approach over a linear averaging of (log-transformed) light levels. Relationships between TaT_{day} and self-reported sleep duration reached significance in a small range in spring (between

Fig. 7. Sensitivity plots for the relation between the interaction TaT x MLiT and sleep outcomes per threshold in spring. Whiskers represent the standard error. Significant (p < .05) unstandardized parameter estimates are printed in black. The gray shaded area represents the areas which should not be regarded as reliable.
282 and 562 lx at eye level) and in winter (between 126 and 200 lx at eye level). In winter, \( TaT_{day} \) additionally emerged as a significant predictor of self-reported sleep onset. In the remaining analyses (on self-reported midsleep, sleep quality, and all objective sleep markers) \( TaT_{day} \) did not render statistically significant parameter estimates. Parameter estimates for \( TaT_{day} \) as predictor for sleep duration were negative in both seasons. This implies that longer light exposure above these specific thresholds during working hours was related to shorter sleep. In winter, exposure to more light during working hours was related to a later sleep onset. The average timing of moments above threshold, similarly, only emerged as a significant predictor in some occasions: only for self-reported midsleep and onset (plus one threshold for duration), and both only in winter. Again, the most relevant threshold range was between 100 and 200 lx at eye level in winter. A later timing of the luminous exposure above these levels led to a longer sleep duration, earlier midsleep and earlier sleep onset (only for subjective measures).

We also explored the interaction between dosage (\( TaT \)) and timing (MLIT) metrics, and these analyses rendered patterns that were quite consistent across self-reported and objectively measured sleep variables (duration, midsleep and sleep onset). Most

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Fig. 8. Sensitivity plots for the relation between the interaction \( TaT \times MLIT \) and sleep outcomes per threshold in winter. Whiskers represent the standard error. Significant \((p < .05)\) unstandardized parameter estimates are printed in black. The gray shaded area represents the areas which should not be regarded as reliable.
significant predictions by the TaT x MLiT interaction emerged for thresholds around 100 lx in spring (plus the 891 lx threshold) and around 200–300 lx in winter. These interactions revealed that light-induced moderations in sleep depend on the combined effect of timing, duration, and intensity of light exposure.
In spring, more time above the threshold toward the beginning of the workday (so high TaT_{day} in combination with early MLiT), was related to an earlier midsleep and longer sleep; a high light dosage received later on the workday resulted in relatively later midsleep and less sleep. In winter, interestingly the relationship between light exposure and sleep duration was reversed (though not for midsleep timing). A later timing during the workday of higher doses of light, led to a positive relation with sleep, leading to, for example, a longer sleep duration (as measured with the Actiwatch). A possible explanation here could be that this exposure to light at the end of the workday led to a lowered sensitivity to brighter light in the evening. Hints for this were also found in other studies, where early evening exposure to bright light reduced the potential negative effects of bright light exposure in the late evening (Münch et al. 2012; Te Kulve et al. 2019). In winter, people are generally exposed to less daylight and for a shorter timeframe, while in spring exposure to daylight is higher and during a longer timeframe, see also Peeters et al. (2020). Therefore, it could be that in winter, people will benefit more from a later timing of light exposure during the day, because this lessens the sensitivity to light in the evening, resulting in positive effects on sleep. In contrast, the timing of the light in spring is more relevant in the morning, due to more exposure to daylight throughout the day. This shows how important it is to take timing into account, as well as the complex interaction with intensity and duration.

4.2. Acute alerting effects

We also attempted to model the relationship between the amount of light in the 30 minutes prior to completing the short experience sampling questionnaire and self-reported alertness. These analyses rendered a very different picture. None
of the thresholds for TaT resulted in a significant parameter estimate. The fact that we had many more datapoints for modeling this relationship (multiple time points per day) allowed us to explore whether these null effects could perhaps be explained by the fact that, although we were modeling personal luminous exposure and individually reported alertness, the above analyses still assume a similar dose-response relationship (and hence sensitivity threshold) for the entire sample. We therefore also performed sensitivity analyses per individual – expecting to see significant estimates emerge for individuals, although perhaps at different levels. This was not the case: the individual analyses also resulted in consistent null-findings across the full range of thresholds.

4.3. General reflection

Based on our analyses, we hoped to be able to recognize a clear sigmoidal dose–response relationship between luminous exposure and circadian or acute alerting responses. For the circadian effects, the general trend in our results did suggest specific threshold ranges of more relevant (more significant) estimates. These generally occurred around the lower thresholds (around 100–300 lx). These findings do align more with a stepwise or sigmoidal dose–response relationship than with a linear one. Also, they quite nicely align with the laboratory-based dose–response curves established for night time, with phase resetting occurring around 100 lx (Zeitzer et al. 2000). However, parameter estimates across the board were extremely small and the overall models performed only slightly better than those employing linear averaging across the workday (Peeters et al. 2021). Note that these analyses had rendered only scarce and modest relationships between light and sleep-related indicators, and none for alertness. The average improvement in marginal R², as compared to the light logger models for sleep in Peeters et al. (2021), was 3%, ranging from <1% to 9%. In a few cases, the models performed slightly worse (R² decreased 1% on average, ranging from <1% to 1%.), or were similar. We should again note that the dataset was relatively small and only included measurements during office hours. Perhaps with a bigger sample, and 24/7 measurements, a clear optimal range would emerge. Yet, even though the improvement is modest, the employed method does provide more insight in the relationship as opposed to only focusing on average intensity.

The fact that the interaction between TaT and MLiT rendered the most consistent parameter estimates across measures and seasons, underlines that we should not focus on intensity, duration, or timing individually, but should take into account all three simultaneously. The interactions found for circadian effects in the current analysis suggest that the timing at which exposure occurs impact the direction of effects. The importance of the timing of a light pulse has also been observed in earlier phase response curves (Khalsa et al. 2003). For acute effects, the current analyses rendered no indications for sensitivity thresholds, which is in line with earlier attempts to construct a dose–response curve for acute alerting effects during daytime (Lok et al. 2018b; Smolders et al. 2018). The most important insight is that we need the complex interaction of timing, intensity and duration to understand the relationship between light and circadian effects. We should not be focusing on those metrics in isolation.

The current study was intended as a proof of concept, exploring the feasibility and potential of the method of employing the TaT and MLiT metrics as well as their interaction with actual field data. Though fits and parameter estimates of our models were relatively low, possibly due to the size of our dataset and a limited number of observations for multiple thresholds, the more detailed quantification of light did provide more insights in potential relationships and which factors were important, in this case the intensity, duration, and timing as opposed to an average over a certain time frame.

4.4. Limitations

In the current analysis, we explored a novel approach to quantify light, yet the study has obvious limitations, the most urgent one being the size of the data set. Even though the data were based on two longitudinal studies in two separate seasons, the number of participants in the sample was limited, and all participants worked in the same office. Moreover, the light measurements only pertained to daytime working hours.
In the current analyses, we explored thresholds ranging from 20 to 2000 lx in order to predict circadian and acute effects of light in the field, employing a similar range as employed in Smolders et al. (2018) and Lok et al. (2018b), and quite similar to the one used in a nocturnal dose–response exploration (Cajochen et al. 2000; Zeitzer et al. 2000). In the current dataset, though measured over three weeks, it is clear that data in the higher illuminance ranges is rather scarce (as also reflected in the gray areas in the figures), leading to a limited number of datapoints to be included in the analyses. Observations above 891 lx in spring and above 316 lx in winter were scarce. Furthermore, only linear relationships were explored. Moreover, there was little variance in the time above low thresholds (also reflected in the gray areas that were employed in the visualizations). Important to note also is that, in the current study, only luminous exposure during office hours was included, possibly contributing to the restricted variance in these lower and upper ranges, making it difficult to interpret both main effects and the interactions. Additionally, luminous exposure outside of office hours play a role in the effects on sleep (Khalsa et al. 2003; Münch et al. 2017; Te Kulve et al. 2019).

Another point of interest, which was not investigated in the current article, is the differential effect of constant versus intermittent exposure. Due to adaptational processes, one would expect the latter to be relatively stronger than the former, as shown by several studies (Gronfier et al. 2004; Najjar and Zeitzer 2016; Rimmer et al. 2000), but no metric was employed to account for this effect. Others have also shown that light history can play a role (Chang et al. 2011; Chang et al. 2013). With the current measures we take into account intensity, duration, and average timing, however it is difficult to say whether TaT was spread over time, or if, for example, TaT was more bundled in time, mainly occurring at the beginning and the end of the workday. A metric to take this temporal pattern into account, however, is not yet available, something which should be investigated by future studies.

As mentioned in the introduction, CCT levels or spectrum can have an influence on both sleep measures as well as subjective alertness (Viola et al. 2008). However, the type of light logger employed in the current study only measures the light intensity, and is not able to measure the spectrum accurately. This is not only the case for our light logger, but most light loggers currently available. In future studies, we hope that wearable light sensors could be used that are able to record the spectral information accurately and continuously, providing more insights in the predictive strength of spectrum in both circadian effects and acute alerting effects.

Using intensity and duration as a predictor for acute alertness in this study did not render any significant relationships. A possible reason could be the resolution of measuring the light. In this case, the sampling rate was set to 200 seconds, providing 9 light samples per 30 minutes, i.e., the period that was used as a predictor. So as opposed to using a full 8.5 hour TaT, the computed TaT_{30min} is based on far fewer datapoints, which makes the influence of individual data points larger. For future studies employing this method, it would be strongly recommended to make use of higher measurement resolutions, or longer prediction periods.

### 4.5. Implications

Real-life light exposure is highly dynamic and unpredictable, which poses quite a number of challenges in terms of quantification of light in the field. In the present study, one of them was addressed: sensible and accurate quantification of such exposure patterns for the prediction of sleep and sleepiness. Based on the current literature, a threshold-based approach to the quantification of light would perhaps be more suitable than linear average-based metrics. Moreover, threshold-based metrics reflect both intensity and duration, and allow for elegant integration of timing. However, to date, the choice of a specific threshold is rather arbitrary, which limits the utility of such an approach. Sensitivity analyses such as those presented here may pave the way for the detection of relevant thresholds in naturalistic conditions.

After relevant threshold detection, metrics, such as TaT and MLIT, and potentially their interaction, may better reflect the nature and impact of naturalistic light measurements in the field than linear averages. For future studies it would be good to explore this method further, especially in combination with larger data sets, and extend it with
metrics to quantify the temporal dynamics in the luminous exposure.

4.6. Conclusion

The goal of this study was to see whether clear optimal ranges of threshold levels would emerge in sensitivity analyses employing multiple light threshold levels when modeling light’s effects during working hours on sleep timing, duration and quality, and on momentary alertness. The aim was not to determine such threshold levels for the field based on our two studies: for this, the sample size should be considered too limited. Rather, the aim was to test the general utility of such an approach for testing circadian and acute light effects in naturalistic conditions as a proof of concept. In other words, the goal was to learn whether this alternative way of quantifying light would present a promising avenue for future studies.

The current study has led to the insight that this alternative way of quantifying light can lead to more insights in the relationship between light and circadian effects. We need to take into account the interactions between timing, intensity, and duration in order to understand the impact of luminous exposure in the field. Limitations of the dataset make it hard to draw any firm conclusions on threshold levels that should be considered relevant in field studies. We do, however, consider the approach taken in this study potentially promising and would advocate that this would be continued in larger, potentially combined, naturalistic field data sets.

Disclosure statement

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Open science statement

Due to restrictions in the informed consent the authors cannot share data via a public repository. Individual researchers can, however, request access to the data via osf.io/sm7wz. The Matlab Script for computing the TaT values is available from github.com/STPeeters/TaTMLiT; The R Script for creating the sensitivity plots is available from github.com/STPeeters/TaTMLiT.

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