Spectral and Biological Simulation Methods for the Design of Healthy Circadian Lighting

J. Alstan Jakubiec¹, Athina Alight¹

¹University of Toronto, Ontario, Canada

Abstract
We assess the state of the art in non-image forming effects (NIF) of light on human health, alertness and wellbeing as applied to the design of the built environment. There are many methods of calculating spectral daylighting weighted for its impact on circadian dynamics and alertness; however, all current analysis is based on a saturation effect. We add electric lighting to the calculation methods and implement a collection of photobiological models from medical literature to predict circadian dynamics, alertness, and melatonin levels due to light exposure. The new framework is tested under several different daylight, electric light, and monitor screen use scenarios.

Key Innovations
- We present a method of simulating high resolution timeseries spectral irradiance due to daylight, electric light, and monitor screens.
- Changes in light exposure due to daylight and electric light control systems can be calculated.
- Timeseries spectral irradiance is used to drive a photobiological model that predicts NIF effects of light: melatonin dynamics in the bloodstream, alertness, and circadian phase shifting.
- New metrics for assessment of NIF light are proposed and compared under a variety of design scenarios.

Practical Implications
A new framework is presented to directly predict the NIF physiological and alerting effects of light. These methods are reproducible using a new Python library we are sharing with the publication of this paper: https://github.com/C38C/NIF_Photobiology.

Introduction
Circadian rhythms are a key biological regulator that synchronize changes in our metabolism, behaviour, and hormone levels to the length of a day. The word circadian means about a day; however, light exposure is required to entrain the circadian system, synchronizing it to the actual length of a day (Minors et al., 1991). The response to light which entrains our circadian system is based on a photopigment within intrinsically photosensitive retinal ganglion cells (ipRGCs) throughout the retina called melanopsin (Provencio et al., 2000). Melanopsin is sensitive to bluer, shorter wavelengths of light (peak 480 nm) than the visual system’s cones (peak 555 nm) (Enezi et al., 2011; Lucas et al., 2014). Exposure to this ipRGC-influenced or melanopic light can advance or delay circadian rhythms depending on the time of exposure throughout the day, intensity, and duration (Panda et al., 2002; Rüger et al., 2013; Warman et al., 2003; Zeitzer et al., 2000). Human physiological responses to light are classified as non-image forming (NIF), because they are sensitive to shorter wavelengths of light than the visual system and because their impacts are on non-visual health and wellbeing factors.

Circadian rhythm influences alertness throughout the day, the onset of sleepiness, and the timing of metabolic activity. There are also short-term effects of NIF light exposure—neurophysiological stimulation (Cajochen et al., 2000) and suppression of the sleep hormone melatonin (Abeyrsuriya et al., 2018; Gooley et al., 2011) for example. It is critical for architectural lighting design to integrate these complex effects as our understanding of them rapidly develops.

NIF lighting analysis has rapidly emerged within architectural building simulation and performance analysis workflows. At first, the calculation of NIF light levels using equivalent melanopic lux (EML) was the primary concern of building performance researchers. Geisler-Moroder and Dür (2010) created a modified version of Radiance (Ward, 1994) to predict 81 channels of spectral irradiance; however, it did not extend to colored sky models and was never publicly released. Lark implements a 9-channel simulation methodology that accounts for spectral sky irradiation and material properties but not electric light (Inanici et al., 2015). ALFA implements a method for 81-channel spectral calculations and can account for light from the sun, sky and luminaires (Solemma, 2017). ALFA’s methods are described further on in this paper. Mardaljevic et al. (2014) and Konis (2019) describe methods for annual, climate-based spectral irradiance calculations using a custom tool and Lark respectively.

There has been much less emphasis on how to interpret this newfound light simulation capacity in terms of its NIF effects. Most design metrics rely on a saturation basis (Amundadottir et al., 2017; International Well Building Institute, 2020; Konis, 2017) but neglect time of exposure and translation into the photobiological effects described in the first paragraph. One move towards this is the...
method proposed by Andersen et al. (2012) and Mardaljevic et al. (2014) that separated light exposure into three times of day: morning advancing, midday alerting, and evening lighting to be avoided. Meanwhile in the medical literature, several photobiologically-driven models have been produced to assess circadian physiological effects of light exposure (Hilaire et al., 2007; Kronauer et al., 1999; Postnova et al., 2018; Zeitzer et al., 2000) as well as the short-term alerting effects of light exposure (Cajoche et al., 2000; Tekieh et al., 2020).

This paper describes a new framework to connect the high resolution spectral irradiance light simulation tool ALFA (Solemma, 2017) to timeseries annual calculations and physiologically-based measures of the circadian and short-term NIF effects of light exposure. First, we develop a workflow for the creation of timeseries spectral irradiance due to dynamic signals of daylighting, electric lighting, and light from monitor screens. Following this, a combined photobiological model based on medical literature is described. Finally, new measures for the evaluation of NIF light exposure are proposed and evaluated using a series of different lighting design strategies involving both daylight and electric light exposure.

Methodology

Within this manuscript, a model of the Ng Teng Fong hospital’s daylit wards are used for analysis, which is depicted in Figure 1. The model faces east and has a large potential to receive daylight. We highlight the results of a single view indicated by a red arrow.

![Figure 1: Example hospital ward model and view directions. The red arrow is the view used for analysis.](image)

A variety of possible material properties were assessed that could influence the resulting daylight and electric lighting spectral irradiances received at the eyes of persons within the ward: ones that provide blue-enriched light with a high melanopic to photopic sensitivity (M/P) ratio, with a neutral M/P ratio, and with a low, blue-depleted, M/P ratio. The spectral reflectance and transmission of these materials is illustrated in Figure 2. More details on these materials are present in a copublication (Alight & Jakubiec, 2021).

![Figure 2: Spectral material properties used in the simulation model.](image)

Timeseries Spectral Irradiance Calculations

The software ALFA (Solemma, 2017) is used to predict spectral irradiance based on 81-spectral channel raytrace simulations at 5 nm intervals between 380 nm and 780 nm. ALFA uses idealized sky models based on physics-based calculations performed with the libRadtran (Mayer & Kylling, 2005) atmospheric radiative transfer library. These skies are based on a atmospheric molecular profile measured by the Air Force Geophysics Laboratory (Anderson et al., 1986) with user-selectable aerosol profiles for clear and hazy (Shettle, 1990), variable ground albedo (Feister & Grewe, 1995), and an optional dense cloud layer. One-dimensional spectrally-specific radiative transfer calculations are solved using libRadtran for a grid of 181 x 181 sky directions and a specific solar zenith angle for each ALFA sky condition. While ALFA’s skies have not been validated directly, libRadtran-based skies have been shown to be highly accurate when compared to measured data (Bruneton, 2016).

ALFA performs point-in-time calculations using the physics-based raytrace engine Radiance (Ward, 1994), which utilizes only three colour channels: R, G, and B. To overcome this limitation and generate 81 channels, ALFA takes the approach of post-processing the entire Radiance ray tree (accessed by using the program rtrace with the -ot* option), applying spectral transmittance or reflectance information at each ray intersection.

A limitation of ALFA is its capacity to only perform point-in-time calculations; therefore, a method of extrapolating point-in-time simulations to an annual context was developed. The Lightsolve method (Kleindienst et al., 2008) was chosen. The Lightsolve method selects 56 simulation periods throughout the year to interpolate to annual results—seven times per day for eight days during the year. The times are selected to be equidistant from neighbouring simulation times and sunrise and sunset while days are selected to be equidistant from the first and last day of the year as well as subsequent or previous simulation days. These times for the Toronto (43.67° N, 79.63° W) sun path on March 9 are recorded in Table 1. Lighting conditions predicted at these 56 times and interpolated throughout the year based on prevailing climatic conditions can be used to interpolate the effects of light throughout the year with a high degree of accuracy (Kleindienst et al., 2008).
are illustrated in Figure 3.

Using the example view indicated in Figure 1, the neutral materials from Figure 2, and a sample day on March 9, spectral irradiances due to daylight were calculated and are illustrated in Figure 3.

Using the example view indicated under clear sky conditions.

Spectral irradiances are converted into α-opic irradiances using the methodology published by the CIE for assessing iPrGC-influenced (NIF) light responses (CIE, 2018). Specifically, melanopic irradiances are used as the inputs to our photobiological model, which will be the basis for the lighting units shared in the rest of this manuscript. Melanopic irradiance ($E_{mel}$, W/m$^2$) is proportional to equivalent melanopic illuminance (EML, lx) (Lucas et al., 2014), related by the constant factor, 1.0 W/m$^2$ $E_{mel} = 834.2$ lx EML.

One of the benefits of our method, which has not been implemented by other researchers or available commercial tools, is the ability to combine light from multiple sources such as daylight, luminaires, and monitor screens. Electric lights can be controlled in terms of their intensity—such as from daylight dimming systems—and in terms of their colour—such as with modern solid state LED lighting systems. Therefore, our spectral irradiance timeseries methods achieve reasonable annual results as well as the ability to adjust for realistic electric light exposures due to luminaires and screens and to predict the effects of control systems on exposure to light and subsequent photobiological effects.

**Photobiological Effects Model**

We implement a dynamic photobiological model of sleep/wake dynamics and alertness based on the work of Postnova et al. (2018). Postnova’s model is itself based on a variety of previous work of which only a few can be cited here (Hilaire et al., 2007; Kronauer et al., 1999). Blood melatonin levels are predicted based on Abeysuriya et al. (2018) and Tekieh et al. (2020). The instantaneous alerting effects of light are implemented based on Tekieh et al. (2020) for the prediction of subjective sleepiness.

We implement a dynamic photobiological model of sleep/wake dynamics and alertness based on the work of Postnova et al. (2018). Postnova’s model is itself based on a variety of previous work of which only a few can be cited here (Hilaire et al., 2007; Kronauer et al., 1999). Blood melatonin levels are predicted based on Abeysuriya et al. (2018) and Tekieh et al. (2020). The instantaneous alerting effects of light are implemented based on Tekieh et al. (2020) for the prediction of subjective sleepiness.

The basis of all these models is duelling homeostatic (H) and circadian (C) systems. The homeostatic system is increased during wake and the consequent utilization of wake-active monoaminergic neurons. The circadian system is modulated by sleep history as well as transient light exposure, and it inhibits sleep-active neurons. Alertness predictions such as subjective sleepiness and objective reaction time are largely determined based on the relative values of H and C during wake. Natural sleepiness will occur when the homeostatic drive periods of 6500 K CCT and 1900 K CCT, which are depicted in Figure 5.

<table>
<thead>
<tr>
<th>Hour</th>
<th>Altitude (degrees)</th>
<th>Azimuth (degrees)</th>
</tr>
</thead>
<tbody>
<tr>
<td>7.64</td>
<td>8.7</td>
<td>-74.2</td>
</tr>
<tr>
<td>9.24</td>
<td>24.4</td>
<td>-55.2</td>
</tr>
<tr>
<td>10.85</td>
<td>36.4</td>
<td>-30.9</td>
</tr>
<tr>
<td>12.46</td>
<td>41.2</td>
<td>-0.6</td>
</tr>
<tr>
<td>14.07</td>
<td>36.7</td>
<td>29.9</td>
</tr>
<tr>
<td>15.67</td>
<td>25.0</td>
<td>54.4</td>
</tr>
<tr>
<td>17.28</td>
<td>9.3</td>
<td>73.6</td>
</tr>
</tbody>
</table>

### Table 1: Simulated solar times and sun positions for March 9 (sunrise at 6.83 h, sunset at 18.08 h).

<table>
<thead>
<tr>
<th>Hour</th>
<th>Altitude (degrees)</th>
<th>Azimuth (degrees)</th>
</tr>
</thead>
<tbody>
<tr>
<td>7.64</td>
<td>8.7</td>
<td>-74.2</td>
</tr>
<tr>
<td>9.24</td>
<td>24.4</td>
<td>-55.2</td>
</tr>
<tr>
<td>10.85</td>
<td>36.4</td>
<td>-30.9</td>
</tr>
<tr>
<td>12.46</td>
<td>41.2</td>
<td>-0.6</td>
</tr>
<tr>
<td>14.07</td>
<td>36.7</td>
<td>29.9</td>
</tr>
<tr>
<td>15.67</td>
<td>25.0</td>
<td>54.4</td>
</tr>
<tr>
<td>17.28</td>
<td>9.3</td>
<td>73.6</td>
</tr>
</tbody>
</table>

### Table 2: Simulated solar times and sun positions for March 9 (sunrise at 6.83 h, sunset at 18.08 h).

<table>
<thead>
<tr>
<th>Hour</th>
<th>Altitude (degrees)</th>
<th>Azimuth (degrees)</th>
</tr>
</thead>
<tbody>
<tr>
<td>7.64</td>
<td>8.7</td>
<td>-74.2</td>
</tr>
<tr>
<td>9.24</td>
<td>24.4</td>
<td>-55.2</td>
</tr>
<tr>
<td>10.85</td>
<td>36.4</td>
<td>-30.9</td>
</tr>
<tr>
<td>12.46</td>
<td>41.2</td>
<td>-0.6</td>
</tr>
<tr>
<td>14.07</td>
<td>36.7</td>
<td>29.9</td>
</tr>
<tr>
<td>15.67</td>
<td>25.0</td>
<td>54.4</td>
</tr>
<tr>
<td>17.28</td>
<td>9.3</td>
<td>73.6</td>
</tr>
</tbody>
</table>
increases to the point that it surpasses the impact of the circadian drive to wakefulness.

While Postnova et al. (2018) indicates several alertness measures based on a regression against H, C and measured study data, we illustrate only two herein: the Karolinska sleepiness scale (KSS) (Åkerstedt & Gillberg, 1990) and the mean reaction time on a visual performance vigilance test (vPVTRT). KSS evaluates in a range from 1 (extremely alert) to 9 (extremely sleepy, fighting sleep); the median point on the KSS scale is 5 (neither alert nor sleepy). Our implementation of predicted KSS considers the instantaneous alerting effects of light exposure (Tekieh et al., 2020). Finally, melatonin blood plasma concentrations in pmol/L are calculated based on the driving forces for the circadian (C) system and short-term light exposure which suppresses melatonin synthesis (Abeysuriya et al., 2018; Tekieh et al., 2020).

We produced a Python library to process spectral irradiance files output by ALFA, convert them into E_{mel}, melanopic irradiance (CIE, 2018), interpolate them into an equally-spaced timeseries, implement the models described above, and post-process the results to generate relevant daily metrics which are described in the following subsection. The code is published via a Github repository which is shared in the front matter of this paper.

Some specifics of our implementation follow. The differential equations for the photobiological model are run at a time interval of 20 s. Before a light signal is provided to simulate a virtual person’s photobiological response, the person is entrained to a sleep schedule from 11:30 PM until 8:00 AM each day. They are exposed to 0.20 W/m² E_{mel} (168.6 lx EML) from 8:00 AM until 8:00 PM and 0.03 W/m² E_{mel} (27.0 lx EML) until sleep at 11:30 PM. In our implementation of the model, sleep can be allowed to occur naturally (when the mean voltage of the wake active neurons falls below a threshold (Postnova et al., 2018)) or, as is more common, on a schedule. For this paper, we implement a sleep schedule from midnight until 6:00 AM each day with wake from 6:00 AM until midnight. This represents a moderately poorly slept person. Furthermore, we run the simulation of moderately poor sleep and variable light exposure for five continuous identical days, to illustrate that of a typical work week. Variable light exposures due to weather, daylight and electric light control systems, or behaviour (Danell et al., 2020) can be calculated.

Figure 6 illustrates the dynamics of the photobiological model for days 2, 3 and 4 of the 5-day simulation period. H and C depict the duelling homeostatic and circadian systems. State illustrates the sleep-wake schedule we have assigned. Mel. irrad. displays the timeseries E_{mel}, melanopic irradiance due to daylight and electric light exposure; no monitor-based irradiance is included. KSS and vPVTRT show subjective and objective performance—sleepiness and mean reaction time respectively. Finally, melatonin displays the varying concentrations of melatonin present in the virtual person’s blood plasma. Lite grey lines show model photobiology dynamics in the absence of short-term light effects.

**New Photobiologically-derived Metrics**

Described in the introduction section of this manuscript, most photobiological architectural lighting metrics are saturation-based and intended to indicate the amount of light required for circadian entrainment, often calculated based on the percentage of hours in a year. When assessing actual photobiological effects, the timing of light exposure, sleep history, and light history are crucial. We generate metrics based on a time delta, for example over the course of a day or a week.

**Phase Shifting**— Daily phase shifting is calculated based on the time of peak melatonin or the predicted time of minimum core body temperature changing from one day to a subsequent day (Postnova et al., 2018).
Alertness – KSS and vPVTRT are calculated as the mean value during a working period—from 9:00 AM until 5:00 PM. It is important to not calculate reaction time or sleepiness shortly after the wake period, although it is displayed in Figure 6.

Melatonin Suppression – Melatonin suppression is simply calculated as the difference between the entrained period melatonin compared to any individual day using Equation 1 (Tekieh et al., 2020), where $\text{AUC}_{\text{day}}$ is the area under a single day’s blood plasma melatonin curve as displayed in Figure 6 and $\text{AUC}_{\text{entrainment}}$ is the same during the entrainment period conditions with minimal evening light exposure and 8.5 hours of sleep per day.

$$\text{Suppression} = 100 \times \frac{\text{AUC}_{\text{entrainment}} - \text{AUC}_{\text{day}}}{\text{AUC}_{\text{entrainment}}}$$ (1)

For example, for the photobiological system illustrated by Figure 6, the metrics presented in Table 2 are derived for each day (2, 3, and 4) presented. The light exposure, especially strong in the morning for the East-oriented test building, advances the circadian system although less each day. As a result, sleepiness and reaction time decrease during working hours, but increase in the evening prior to bed (see Figure 6). The amount of melatonin suppressed each day increases with phase shifting and a repeating daily light exposure.

Table 2: Daily performance metrics for the photobiological simulation presented in Figure 6.

<table>
<thead>
<tr>
<th>Metric</th>
<th>Day 2</th>
<th>Day 3</th>
<th>Day 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Phase Shift (min)</td>
<td>-30.3</td>
<td>-21.0</td>
<td>-14.7</td>
</tr>
<tr>
<td>Mean KSS</td>
<td>2.91</td>
<td>2.89</td>
<td>2.87</td>
</tr>
<tr>
<td>Mean vPVTRT (ms)</td>
<td>347</td>
<td>328</td>
<td>315</td>
</tr>
<tr>
<td>Melatonin Suppression (%)</td>
<td>16.2</td>
<td>19.9</td>
<td>22.7</td>
</tr>
</tbody>
</table>

Demonstrations of the Combined Time-Spectrum-Photobiological Model

To illustrate the applications of this model, we apply it to a set of lighting scenarios and report the total phase shift from baseline over a 5-day simulation period, and the 5th day measures of mean KSS, mean vPVTRT, and melatonin suppression for the representative view shown in Figure 1. Lightsolve method timed calculations are run using ALFA for clear sky conditions on 9 March, 7 June and 7 December. The scenarios we apply are described below:

1. Daylight with spectrum adjustment – Minimal electric lighting is present during dark, and three sets of material properties are tested: 1(a) bronze glazing and low M/P reflective materials, 1(b) grey glazing and neutral M/P materials, and 1(c) blue glazing and high M/P materials.

2. Daylight and constant electric lighting of varying CCT – Daylighting is calculated with neutral M/P materials (1(b) above) and electric lighting is calculated with varying CCT: 2(a) 4100 K, 2(b) 6100 K, and 2(c) 16000 K.

3. Daylight, colour changing electric lighting, and evening monitor screen use – Daylighting is calculated with neutral M/P materials but electric light that changes in intensity and colour throughout the day to be less intense and shifted towards warm 4100 K lighting in the evening. Two monitor screen scenarios are calculated: 3(a) with a blue-enriched screen throughout the evening and 3(b) with a screen which uses a night-time warm shift to reduce NIF effects.

Figure 7 illustrates the daily $E_{\text{mel}}$ melanic irradiance repeated over the course of five simulated days for all of the tested scenarios. For scenarios 1(a), 1(b), and 1(c) the effects of different glazing and material reflectances are illustrated. Scenarios 2(a), 2(b), and 2(c) show the differences between low (2(a)) and high CCT lamps (2(c)). Finally, scenarios 3(a) and 3(b) show that even with colour changing electric lamps, a blue enriched monitor screen (3(a)) can provide a similar effect to blue-enriched, high CCT lighting.

Figure 8 communicates the outcomes of the photobiological model for the three lighting scenarios. Melatonin suppression (Mel. Suppress.), KSS, and vPVTRT are all calculated on the fifth day of the scenario, while phase shifting is calculated cumulatively over five days of the same patterns of sleep and light exposure. KSS (Working) indicates mean sleepiness during working hours from 9:00 AM until 5:00 PM while KSS (Evening) indicates mean sleepiness during the last three hours of wake, from 9:00 PM until midnight.

Melatonin suppression increases with the amount of melanic irradiance naturally. Scenarios 2(b-c) (blue enriched electric lighting) and scenario 3(a) (blue enriched monitor screen) experience the most extreme suppression, higher than 30% during June clear sky days. The effect of a reduction in monitor colour temperature, 3(b), or blue depleted lighting, 2(a), clearly show benefits for levels of melatonin in blood plasma compared to scenarios 2(b), 2(c), and 3(a).

KSS during working hours, on the other hand, is marginally affected by design criteria; with the amount of daylight present being adequate to reduce sleepiness in all scenarios. Virtual occupants tend to be less sleepy during working hours during the brightest portions of the year, in June. Evening sleepiness (“KSS (Evening)”) shows a stronger impact where the short-term alerting effects are notable for scenarios with blue-enriched evening lighting (2(b-c) and 3(a)). A dimmed electric lighting scenario combined with a warm color shift to computer monitor use increases pre-bed evening sleepiness by nearly 1 KSS unit comparing 3(a) and 3(b). Mean reaction time on a performance vigilance test (vPVTRT) shows a similar range of effects to KSS during working hours.

Finally, all phase shifting in the tested scenarios was circadian phase-advancing due to the large amounts of morning daylight melanic irradiance present for the East-facing building. Phase shifting becomes less severe in the case of scenarios with significant evening light exposure and in the low M/P glazing and material scenario 1(a).
Discussion and Future Research Needs

What does the ability to simulate the NIF effects of light mean for the daylighting and electric lighting design industry? Clearly, the importance of the spectral colorimetric quality of light is revealed more directly than the rule of thumb to avoid high CCT lighting and blue-enriched screens in the evening could ever communicate. This alone allows the development of lighting control systems that can be tested directly in terms of their benefits with fewer assumptions.

The framework we present also allows assessment of the relative effect of different design strategies. For example, the predicted mean sleepiness during working hours for all sufficiently daylit spaces we tested were similar. The spectra of electric lighting choices in the evening notably reduced sleepiness as well as increased melatonin suppression. We should compare these relative impacts to inform design decisions and tailor them to the schedules and lighting conditions of different architectural programs and workspaces.

In the author’s opinion, it is important to bring together the most up-to-date knowledge on spectral light simulation and medical knowledge to help shape our built environment in terms of its health and wellbeing. This paper has attempted to do so; however, there is more work to do. We do not have enough knowledge on common sleep/wake practices nor on actual light exposure patterns for building occupants that are mobile.
Limitations

There are some notable limitations of the framework we present. One practical concern is that, currently ALFA is not easily extensible to timeseries or annual calculations (however in a separate paper we assess other means of achieving this (Alight & Jakubiec, 2021)). This is a target for future development or research. Furthermore, scheduling complex control systems for electric lighting, dynamic shading, behaviour (for example lunch breaks, walks), and screen use will require new software interfaces and baseline datasets which do not yet exist.

Another limitation is that the photobiological models we implement are based on highly controlled forced desynchrony and constant routine medical experiments. By inputting highly variable light exposure due to daylight, routine changes, or control systems, we cannot be certain that the model performs in a wholly realistic manner. More work is necessary in monitoring NIF lighting effects in natural environments.

Finally, some computational limitations arise. Because the photobiological model relies upon a system of differential equations run at a 20 s time interval, applying this to an annual lighting profile for 100’s or 1000’s of view directions is computationally expensive. Using graphics cards for processing, more efficient computation languages than Python, and parallel processing is expected to ameliorate this concern.

Conclusion

We demonstrated a significant step forward in the assessment of light’s NIF effects in the built environment. Our new model integrates spectral changes over time from daylight and electric light sources such as luminaires and monitor screens, which has not been demonstrated before. In addition, we implemented photobiological models from medical literature and generate novel metrics from them: melatonin suppression, mean subjective sleepiness, mean reaction time, and circadian phase shifting. This capacity will help designers and building simulation professionals help guide the design of lighting that supports health, alertness, and wellbeing.

Acknowledgement

The authors acknowledge funding support for Athina Alight from the University of Toronto Excellence Award. We further thank Dr. Steven Lockley, Dr. Svetlana Postnova, and Dr. Tahereh Tekieh for their comments on implementing the photobiological model.

References


