A seasonally dynamic model of light at the stream surface

Philip Savoy1,2,6, Emily Bernhardt1,7, Lily Kirk3,8, Matthew J. Cohen4,9, and James B. Heffernan5,10

1Department of Biology, Duke University, 124 Science Drive, Durham, North Carolina 27708 USA
2United States Geological Survey, Earth System Processes Division, 12201 Sunrise Valley Drive, Reston, Virginia 20192 USA
3School of Natural Resources and Environment, Black Hall, University of Florida, Gainesville, Florida 32611 USA
4School of Forest Resources and Conservation, Newins-Ziegler Hall, University of Florida, Gainesville, Florida 32611 USA
5Nicholas School of the Environment, 9 Circuit Drive, Duke University, Durham, North Carolina 27710 USA

Abstract: Light is a primary constraint on primary production and drives many ecological processes in stream ecosystems, yet light regimes have received considerably less attention than other factors of the stream environment, such as hydrology or nutrient cycling. Light received by streams can be highly heterogeneous in both space and time resulting from changes in topography, channel characteristics, and riparian vegetation. Both the structure and phenology of riparian vegetation can be important determinants of the seasonality and magnitude of light reaching the stream surface, particularly in smaller forested streams. Despite the importance of riparian phenology on temporal patterns of stream light availability, existing models do not account for the seasonal dynamics of canopies. We developed a dynamic, biophysically based model (StreamLight) that incorporates canopy structure and phenology to predict light reaching the stream surface. We compared StreamLight to an existing model at 21 sites across the USA and found that, across sites, our biophysically based model produced light estimates that were more strongly correlated to observations and reduced the magnitude of errors in comparison to the existing model, particularly for streams that were relatively narrow compared to the height of riparian vegetation. Because smaller streams represent most global stream length, we expect that, in many smaller forested streams, the inclusion of canopy structure and phenology will enhance our ability to predict light regimes. We also used model simulations to examine the importance of controls on stream light environments and found that channel width was the strongest control on light environments. StreamLight represents an important incremental step forward in developing mechanistic models of river network productivity and in linking shifts in terrestrial vegetation structure and phenology to aquatic ecosystem productivity and thermal regimes.

Key words: stream light modeling, light regimes, riparian vegetation, channel geometry

Light drives a number of ecological processes in streams and rivers, including thermal regimes (Sinokrot and Stefan 1993, Webb and Zhang 1999), behavior of visual organisms (Lythgoe 1988), photodegradation of organic materials (Larson et al. 2007), and patterns of gross primary production (GPP) (Mulholland et al. 2001, Roberts et al. 2007, Izagirre et al. 2008, Heffernan and Cohen 2010). Stream light availability mediates ecosystem processes at both daily (Heffernan and Cohen 2010) and seasonal timescales (Rosemond et al. 2000, Roberts et al. 2007) as well as across river networks (Finlay 2011, Finlay et al. 2011). Despite the fundamental importance of light as a control on metabolism and biogeochemical processes (Boston and Hill 1991, Hill and Boston 1991), very few monitoring efforts capture stream light regimes. This scarcity of light monitoring stands in contrast to the widespread deployment of sensors that collect data on stream stage, temperature, oxygen, or nutrients. The lack of information about variation in stream light regimes over the temporal timescales and spatial extents relevant to ecosystem processes is likely to constrain our ability to understand how light shapes the ecology of flowing waters.
The light environment of streams is often poorly characterized, which may be a limiting factor in mechanistic studies of stream ecosystem processes. For example, periodic fisheye or hemispherical photographs are often used to estimate the amount of light reaching a stream (Davies-Colley and Payne 1998, Garner et al. 2017), but stream light environments can be highly variable across many scales of both space and time (Julian et al. 2008b). A few high-frequency datasets of light at the stream surface do exist, notably at Walker Branch in Oak Ridge, Tennessee (Hill et al. 1995, Roberts et al. 2007), and more recently, the StreamPULSE (https://data.streampulse.org) and National Ecological Observatory Network (NEON) projects have increased the number of sites where high-frequency light sensors are deployed for stream ecosystem research. Capturing temporal dynamics of stream light regimes is an important and necessary step toward mechanistic study of how light interacts with other variables to influence stream ecosystem processes. Indeed, there are many existing datasets of stream ecological processes that could benefit from information on stream lighting conditions. Furthermore, as we begin to consider how light influences stream ecology at network or continental scales, it becomes infeasible to sufficiently characterize the spatiotemporal dynamics of light regimes through in-situ measurements alone. One potential way to address these issues is to model light estimates based on the processes mediating stream light regimes.

Light availability in streams results from a combination of proximal and distal controls. Broadly, incident shortwave radiation varies with geographical location due to sun–earth geometry and atmospheric absorption by ozone and water vapor (Lacis and Hansen 1974). Within this context, there are a series of potentially important proximal controls on stream light availability. Both topography and channel features, such as canyon walls or deeply incised banks, can limit the period of time that streams receive radiation inputs (Yard et al. 2005). Channel geometry influences the amount of direct radiation at the stream surface through a combination of channel width, azimuth, and vertical elements of banks or adjacent riparian vegetation (Li et al. 2012). Light is attenuated by riparian vegetation, and the strength of this attenuation depends on the structure of the canopy, such as the density and orientation of leaves (Campbell 1986, Monsi and Saeki 2005). Because canopy development varies seasonally, the phenology of adjacent riparian canopies can exert strong control on the light regimes of streams, particularly in small, forested headwater streams (Roberts et al. 2007). From the stream surface to the benthos, light may be further attenuated by changes in water depth or clarity (Julian et al. 2013).

Previous models have focused on estimating stream shading (Davies-Colley and Rutherford 2005, DeWalle 2008, 2010, Li et al. 2012), primarily for use in planning restoration efforts or for predicting stream temperatures, and the complexity of the representation of riparian canopy attenuation varies considerably among these models. At the most basic, canopies are simplified as non-transmitting planes (DeWalle 2008). Other models consider the extinction of light as a function of path length through a rectangular riparian buffer (DeWalle 2010), as a constant fraction (Li et al. 2012), or through the determination of an empirically derived shading coefficient (Julian et al. 2008b). However, all of these models suffer from 2 primary limitations in the way that they represent riparian vegetation. First, they do not adequately represent how light transmission through canopies is influenced by the density and structure of canopies at a given time. Second, although riparian phenology influences observed light regimes (Roberts et al. 2007), existing models do not account for the seasonal dynamics of canopies.

Our objective was to develop and test a simple model for predicting light at the stream surface that explicitly considers how canopy structure and phenology influence light transmission. The resulting model (StreamLight) has a biophysically based representation of light transmission and produces temporally dynamic light estimates. Modeled outputs reflect the scale of data inputs and could be used to make estimates at multiple scales. Our estimates are representative of average lighting conditions for a stream segment because we relied on several remotely sensed data products in this study. Rather than focusing on increased precision at any 1 site, we opted to assess the contribution of a dynamic and biophysically based representation of canopy light transmission across many sites with varying channel sizes, climates, and canopy characteristics. Through a series of model simulations, we also sought to use our model to better understand how stream light regimes are influenced by latitude, channel properties, and the structure and phenology of riparian canopies.

**METHODS**

**Model conceptual framework**

Given that a combination of channel characteristics and riparian vegetation influences stream light regimes, the structure of a model for predicting light at the stream surface can be conceptualized as 2 components. The 1st component consists of estimating the proportion of the water surface that receives full light and the portion shaded by features such as banks or riparian canopies. The SHADE2 model (Li et al. 2012) served as the basis for estimating this component within our modeling framework. The 2nd component deals with the transmission of light through canopies to the portion of water shaded by vegetation. In SHADE2, the influence of canopies on light transmission is represented by a fixed density term. However, in reality the transmission of light through canopies varies depending on factors including the orientation and density of leaves and the position of the sun (Campbell 1986, Campbell and Norman 1998). We replaced the simple approximation of canopy transmission in SHADE2 with a...
biophysically based radiative transfer model (Campbell and Norman 1998) to create a single model capable of estimating the average lighting conditions across a channel (Fig. 1A, B). We focused on estimating photosynthetically active radiation (PAR) because it is directly related to the conversion of solar energy by autotrophs via photosynthesis, and we expressed these estimates in terms of the quanta of light in PAR (µmol m\(^{-2}\) s\(^{-1}\)), otherwise referred to as the photosynthetic photon flux density (PPFD). The model produces estimates of PPFD at the same temporal resolution as that of our chosen light inputs (hourly), but we used daily PPFD integrals (mol m\(^{-2}\) d\(^{-1}\)) to assess model performance. The specific details of the 2 components of our model are outlined below.

**Estimating shade**

Li et al. (2012) developed SHADE2 to predict the percentage of channel shaded based on both channel characteristics and riparian vegetation. SHADE2 was based on the work of Chen et al. (1998) but included more complex representation of canopy structure, flexibility in temporal resolution of estimates, and improvements in computational efficiency. SHADE2 captures shading from channel geomorphology and geometry through the effects of channel width, channel azimuth, bank height, and bank slope.

Shading from riparian vegetation is represented by simplifying canopy geometry to account for both canopy height and overhang into the channel as well as the position of vegetation relative to the channel. The percentage of channel that is shaded can be computed at any time step and accounts for changes in solar altitude, azimuth, and declination (Li et al. 2012). SHADE2 first calculates a shadow length and then translates this value to a shadow length perpendicular to the stream bank to derive a percentage of channel shaded based on the contributions from stream banks and riparian vegetation:

\[
r = \frac{B_L + B_R + S_L \times D_L + S_R \times D_R}{W}
\]

(Eq. 1),

where \(r\) is the shading ratio (%); \(B_L\) and \(B_R\) are the shading lengths (m) on the water surface from left and right banks, respectively; \(S_L\) and \(S_R\) are the shading lengths (m) on the water surface from left and right bank vegetation, respectively; \(D_L\) and \(D_R\) are the left and right bank vegetation crown densities (%); and \(W\) is the channel width (m). We multiplied the unshaded portion of the channel (1 - \(r\)) by incoming PPFD so that SHADE2 could be used to estimate the weighted mean PPFD at the stream surface (\(I_{shd}\), µmol m\(^{-2}\) s\(^{-1}\)). Because SHADE2 served as the foundation

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**Figure 1.** A simplified model schematic highlighting the major components of the StreamLight model. The relationship between channel azimuth (\(\phi\)) and solar azimuth (\(\Phi\)) is used to estimate the unshaded (\(U\)) and shaded (\(S\)) portions of the water surface perpendicular to the bank based on the SHADE2 model (Li et al. 2012) (A). The length of shading will depend on bank height, height of riparian vegetation, and the solar elevation angle (\(\alpha\)) (B). Total incoming shortwave irradiance (\(Q_o\)) is partitioned into the beam (\(I_{ob}\)) and diffuse components (\(I_{od}\)) and converted to photosynthetically active radiation. \(I_{ob}\) and \(I_{od}\) are transmitted through the canopy as a function of the solar zenith angle (\(\Psi\)), leaf area index (LAI), and other canopy structural properties. The transmitted beam and diffuse components are then summed together to get total photosynthetic photon flux density (PPFD) transmitted through the canopy (\(I_i\)). Total incoming PPFD (\(I_o\)) and \(I_i\) are then weighted by \(U\) and \(S\) to generate a weighted mean PPFD at the stream surface.
of our model, we recoded SHADE2 in R (version 4.0.3; R Project for Statistical Computing, Vienna, Austria), which we used for all subsequent modeling.

A biophysical model of canopy light transmission

The inclusion of a radiative transfer model to estimate light transmission through the canopy improves upon previous models that have completely omitted canopy transmission, represented canopies as opaque (DeWalle 2008), or included a simplified calculation of canopy transmission (Julian et al. 2008b, DeWalle 2010, Li et al. 2012). Here, we based our radiative transfer model on that of Campbell and Norman (1998). Global total incoming shortwave irradiance \( Q_o \) at the surface of the earth is used as an input for the model. This incoming irradiance consists of both diffuse and direct beam components, and tree canopies attenuate beam and diffuse radiation differently. To account for this difference, we partitioned \( Q_o \) into beam and diffuse components following Spitters et al. (1986). Because leaf absorptivity varies with the spectrum of light, we partitioned beam and diffuse radiation into PAR (Goudriaan 1977).

The fraction of incident beam radiation transmitted through the canopy, \( \tau_b(\psi) \), varies with the solar zenith angle \( \psi \) and can be estimated by accounting for 1) the absorptivity of leaves for PAR (\( \tau_b \)), 2) the amount of leaves in the canopy as quantified by the leaf area index (LAI, \( m^2/m^2 \)), and 3) a beam light extinction coefficient, \( K_{be}(\psi) \). These elements can be combined into a formalized expression that models radiative transfer (Campbell and Norman 1998):

\[
\tau_b(\psi) = \exp\left( -\sqrt{\alpha_p} \times K_{be}(\psi) \times \text{LAI} \right) \quad \text{(Eq. 2)}
\]

The extinction coefficient varies based on the ratio of vertical and horizontal projections of canopy elements (x). Effectively, x is a parameter that considers the influence of the distribution of leaf angles within the canopy. In the limit, if all leaves were completely vertical and the sun was directly overhead (\( \psi = 0^\circ \)), then all incoming light would be transmitted through the canopy. In reality, leaves are not oriented completely vertically, and most canopies can be approximated by \( x = 1 \) (Campbell and Norman 1998), which is the value we assumed throughout our analysis. Specifically, \( K_{be}(\psi) \) is the ratio of projected area to hemisurface area for an ellipsoid (Campbell and Norman 1998):

\[
K_{be}(\psi) = \frac{\sqrt{x^2 + \tan^2 \psi}}{x + 1.774(x + 1.182)^{-0.733}} \quad \text{(Eq. 3)}
\]

Unlike beam radiation, diffuse radiation comes from all directions. The transmission of diffuse radiation can be estimated similar to beam radiation (Eq. 2), but \( K_{be}(\psi) \) must be replaced with an extinction coefficient that considers the omni-directional nature of diffuse radiation. If diffuse radiation is treated as a series of beams, then a diffuse transmission coefficient \( (\tau_d) \) can be calculated by numerical integration over all solar zenith angles from horizontal to vertical:

\[
\tau_d = 2 \int_0^{\pi/2} \tau_b(\psi) \times \sin \psi \times \cos \psi \times d\psi \quad \text{(Eq. 4)}
\]

where \( \tau_b(\psi) \) is the beam extinction assuming that all light is absorbed by leaves (i.e., black leaves), which is calculated by setting \( \tau_p = 1 \) in Eq. 2. The diffuse light extinction coefficient \( (K_d) \) can then be estimated (Eq. 5). We estimated the transmission of diffuse radiation \( (\tau_d) \) by replacing \( K_{be}(\psi) \) in Eq. 2 with \( K_d \):

\[
K_d = \frac{-\log(\tau_d)}{\text{LAI}} \quad \text{(Eq. 5)}
\]

We multiplied PAR in beam \( (I_{ob}) \) and diffuse \( (I_{od}) \) components by their respective transmission equations and summed them to obtain the total PPFD transmitted through the canopy \( (I_t, \mu\text{mol m}^{-2}\text{s}^{-1}) \):

\[
I_t = I_{ob} \times \tau_b(\psi) + I_{od} \times \tau_d \quad \text{(Eq. 6)}
\]

Estimating light with StreamLight

We combined the SHADE2 model (Li et al. 2012) and the radiative transfer model of Campbell and Norman (1998) to produce our final model, hereafter referred to as StreamLight. StreamLight estimates the average PPFD at the water surface along a cross section of the stream \( (I_d, \mu\text{mol m}^{-2}\text{s}^{-1}) \):

\[
I_d = \frac{S \times I_t + U \times I_o}{W} \quad \text{(Eq. 7)}
\]

where \( S \) is the total length of shading on the water surface perpendicular to the bank (m) that is caused by vegetation, \( U \) is the total length of unshaded water surface perpendicular to the bank (m), \( I_o \) is the total incoming PPFD (\( \mu\text{mol m}^{-2}\text{s}^{-1}) \), and \( W \) is the channel width (m).

The final model is capable of making predictions at any time step. We implemented this model in a new open-source R package named StreamLight (version 0.1.0; Savoy 2021), and specifically the model is executed using the stream_light() function. Model input parameters include latitude (decimal degrees), longitude (decimal degrees), channel width (m), channel azimuth (degrees from north), bank height (m), bank slope (dimensionless), water level (m), tree height (m), canopy overhang (m), height of canopy overhang (m), and the ratio of vertical and horizontal projections of canopy elements (x).

We made several assumptions to simplify the process of model parameterization. First, we assumed that both banks were identical, although SHADE2 allows for individual parameterization of the characteristics of each bank and its associated riparian vegetation. Additionally, because our primary objective was improved representation of canopy...
elements, we controlled for bank geometry by parameterizing the model with steeply sloped banks (100), short bank heights (0.1 m), and a fixed water level equal to the bank height (0.1 m). This combination of bank height, steep slopes, and water level essentially assumed bankfull conditions and minimized the influence of bank geometry. Finally, without detailed canopy geometry data available, we assumed canopy overhang to be 10% of tree height and the height of maximum canopy overhang to be 75% of tree height. Latitude, longitude, channel azimuth, channel width, and tree height varied by site as described below.

**Study sites and observational data**

**Light observations** For model validation, we compiled available high-frequency (15–30 min intervals) measurements of light at the stream surface or bank from StreamPULSE, NEON (NEON.DOM.SITE.DP1.20042.001, https://data.neonscience.org/data-products/DP1.20042.001), and long-term measurements from Walker Branch (W. Hill, personal communication). We only used days where all time steps had observations because we assessed model performance in terms of daily integrals. Our resulting dataset consisted of 21 sites with a total of 54 site years of data and 9988 d (Table 1). Of the 54 site years in our dataset, only 23 site years of data had complete daily coverage for at least ½ of the year. Within these 23 site years, there were data from 14 different sites, but Walker Branch (WALK) alone accounted for ~½ of the site years. Only 12 site years had complete daily records for at least 90% of the year, and 4 of these site years were from WALK. Data support varied across sites, ranging from 21 d at Lewis Run (LEWI) to 2660 d at WALK, with a median of 392 d.

Because we acquired the data from various sources, some data processing was required to achieve a standardized dataset for model validation. Data were either recorded with HOBO® PAR sensors as PPFD (μmol m\(^{-2}\) s\(^{-1}\)) or with small pendant light sensors (Onset®, Bourne, Massachusetts) that record light in lux (lm/m\(^2\)). Because lux captures the intensity of light perceived by the human eye, rather than its influence on photosynthetic efficiency, it was necessary to estimate PPFD from lux data. It is not possible to directly convert lux data to PPFD, so we used the approximate conversion from lux to irradiance at peak luminous efficacy (555 nm) (Williamson 1983) to estimate PPFD. If multiple sensors had been deployed, then we calculated a single mean value for each time step.

Table 1. Site names, abbreviations, and derived model parameter values. All sites are either part of the StreamPULSE or NEON observation networks as indicated by their data source. The site location (decimal degrees), channel width (m), channel azimuth (°), and riparian tree height (m) are listed for each site. * indicates sites where light detection and ranging estimates from Simard et al. (2011) of 0 m were replaced with a landcover-informed weighted mean tree height.

| Site name              | Site ID  | Data source | Latitude (°) | Longitude (°) | Width (m) | Azimuth (°) | Tree height (m) |
|------------------------|----------|-------------|--------------|--------------|-----------|-------------|-----------------|
| Arikaree River         | ARIK     | NEON        | 39.76        | -102.45      | 5.20      | 75          | 7.12*           |
| Oak Creek              | AZ_OC    | StreamPULSE | 34.86        | -111.76      | 25.75     | 13          | 18              |
| Como Creek             | COMO     | NEON        | 40.03        | -105.54      | 5.30      | 331         | 24              |
| Lower Hop Brook        | HOPB     | NEON        | 42.47        | -72.33       | 7.90      | 49          | 24              |
| Kings Creek            | KING     | NEON        | 39.11        | -96.60       | 6.80      | 290         | 12              |
| Lewis Run              | LEWI     | NEON        | 39.10        | -77.98       | 5.50      | 319         | 17              |
| Martha Creek           | MART     | NEON        | 45.79        | -121.93      | 8.20      | 49          | 29              |
| Mayfield Creek         | MAYF     | NEON        | 32.96        | -87.41       | 5.35      | 359         | 25              |
| McRae Creek            | MCRA     | NEON        | 44.26        | -122.17      | 4.65      | 32          | 32              |
| Mud Tributary          | NC_Mud   | StreamPULSE | 36.00        | -78.97       | 6.99      | 7           | 24              |
| New Hope Creek         | NC_NHC   | StreamPULSE | 35.99        | -79.05       | 18.90     | 330         | 23              |
| Stony Creek            | NC_Stony | StreamPULSE | 36.03        | -79.08       | 20.10     | 292         | 22              |
| East Eno River         | NC_UEno  | StreamPULSE | 36.14        | -79.16       | 10.10     | 348         | 17              |
| Upper New Hope Creek   | NC_UNHC  | StreamPULSE | 35.98        | -79.00       | 21.30     | 320         | 23              |
| Posey Creek            | POSE     | NEON        | 38.89        | -78.15       | 4.00      | 335         | 27              |
| Pringle Creek          | PRIN     | NEON        | 33.38        | -97.78       | 6.80      | 91          | 13.5*           |
| Sycamore Creek         | SYCA     | NEON        | 33.75        | -111.51      | 7.50      | 353         | 3.76*           |
| Walker Branch          | WALK     | NEON        | 35.96        | -84.28       | 3.30      | 52          | 31              |
| Black Earth Creek      | W1_BEC   | StreamPULSE | 43.11        | -89.64       | 7.64      | 305         | 10              |
| Brewery Creek          | W1_BRW   | StreamPULSE | 43.13        | -89.64       | 8.82      | 10          | 8.8*            |
| West St Louis Creek    | WLOU     | NEON        | 39.89        | -105.92      | 2.20      | 70          | 23              |
Representativeness of light observations  The estimates of light presented in this study are approximately at the scale of stream reaches, but most sites only had a single light sensor. SHADE2 was previously validated for 7 reaches by using in-situ photographs of shading, and the model was well correlated to those measurements of instantaneous shading (Li et al. 2012). As a tradeoff to obtaining light measurements with much higher temporal resolution, the measurements used in this study were not as spatially integrative as the in-situ photographs used by Li et al. (2012). To help address this issue, we deployed an array of HOBO light sensors along a 400-m reach at our New Hope Creek (NC_NHC) and Upper New Hope Creek (NC_UNHC) sites in North Carolina to characterize spatial heterogeneity in reach-level light environments (Appendix S1). The inter-quartile range of daily observations from sensors in the array at each site tended to be small. At NC_NHC, median values from the array generally tracked measurements from the single long-term sensor at the monitoring site, but at NC_UNHC, values observed at the monitoring site were higher than the upper quartile of values from the array during a portion of the spring (Fig. S1). Because similar reach-scale observations were not available for other sites, we could not quantify light environment heterogeneity for all sites used in this study. Our decision to rely on sites with single light sensors for validation data was based on the desire to use the most widely available data sources so light estimates could be compared across a diverse set of sites and for the longest near-continuous records possible. However, the implications of this decision should be considered when interpreting the results presented in this study.

Model parameters and drivers

A combination of site parameters and model driver data, such as downwelling shortwave radiation (W/m²) and LAI (m²/m²), are required to run the model. A companion open-source package in R, StreamLightUtils (Savoy 2020), is available to aid in the production of model driver and validation files for the data products and methods described below.

Site parameters  We determined tree height, channel azimuth, and bankfull channel width for each site in our dataset. At each site, we extracted tree heights from 1-km light detection and ranging (LiDAR) derived estimates of Simard et al. (2011). Several of our sites had tree heights that were estimated to be 0 m, and we replaced these values by considering land cover at the site. We used global 1-km landcover information (Tuanmu and Jetz 2014), and, for each landcover type, we calculated median tree heights using the Simard et al. (2011) data for all pixels in the contiguous US that were primarily composed of that landcover type. We then calculated a weighted mean tree height based on the fractional coverage of each landcover type for the pixel that contains the site. We compared our landcover-informed estimated tree heights directly to the Simard et al. (2011) height data for all pixels in the contiguous US, and the results indicated a strong correlation ($r = 0.83$). We derived channel azimuth from aerial imagery in Google Earth Pro (https://www.google.com/earth; Google, Mountain View, California). Field estimates of bankfull channel width were available for StreamPULSE sites (https://data.streampulse.org) and for NEON sites from stream morphology data (NEON.DP4.00131). If multiple in-situ bankfull width measurements were available, then we calculated the median value for each site.

Model drivers  We used hourly surface downwelling shortwave radiation (W/m²) from the North American Land Data Assimilation System (NLDAS) (Xia et al. 2012) as our estimates of $Q_{sw}$. We downloaded NLDAS data from the NASA Goddard Earth Sciences Data and Information Services Center Data Rods Explorer (Teng et al. 2016). We calculated $I_s$, used in Eq. 7 by converting NLDAS shortwave radiation to PPFD (µmol m⁻² s⁻¹) using the coefficients from Britton and Dodd (1976).

To capture seasonal changes in canopy development, we used the Moderate Resolution Imaging Spectroradiometer (MODIS) 4-d 500 m composite LAI product (MCD15A3Hv006) (Myneni et al. 2015). We downloaded single pixel time series at each site through the Application for Extracting and Exploring Analysis Ready Samples (AppEEARS), courtesy of the NASA EOSDIS Land Processes Distributed Active Archive Center, United States Geological Survey Earth Resources Observation and Science center (https://lpdaacsvc.cr.usgs.gov/appeears/). To get daily values of LAI, we smoothed and gap-filled MODIS LAI data to extract the seasonal phenological signal following the approach of Gu et al. (2009) and using the phenoR package (Kong et al. 2020). During this process, individual days were weighted according to their 5-level quality control confidence score provided by the quality control layer of the dataset. An estimate of crown density is required for SHADE2, and we used yearly estimates of % tree cover derived from the MODIS vegetation continuous fields product (MOD44Bv006) (Dimiceli et al. 2015), downloaded through AppEEARS, to generate an estimate of crown density for each site year of data.

The use of the various remotely derived datasets described above resulted in estimates that we consider to be representative of stream segments. The median National Hydrography Dataset Plus version 2 reach length, derived from McManamay and DeRolph (2019) for ~2.6 million reaches, is 1.54 km, and the datasets used to characterize tree heights and LAI had spatial resolutions of 1 km and 500 m, respectively. Therefore, we would expect the approximate spatial scale of estimates generated in this study to represent between 500 m and 1.5 km.
Model validation

We compared the performance of StreamLight and SHADE2 in terms of 3 different fitting statistics with complementary error assessment properties. Because we assessed model performance in terms of total daily sums of light, we only used days where all time steps had observations of observed light \( I_{\text{obs}} \) \( \text{mol m}^{-2} \text{d}^{-1} \). We assessed the correlation between predicted and observed values by using Pearson’s correlation coefficient \( r \) and followed the guidelines for interpreting the strength of these correlations (e.g., weak, moderate) suggested by Evans (1996). Two series may be highly correlated despite differences in magnitudes; therefore, we calculated 2 additional measures of model performance. We calculated the normalized root mean squared error (NRMSE) to assess the accuracy of model predictions while accounting for differences in total overall light received across sites. There are multiple conventions for normalizing RMSE, and we chose to use the mean of observations, similar to the calculation of the coefficient of variation. Finally, we calculated mean bias to determine systematic model over- or underestimation of PPFD.

We report fitting statistics at several levels. For study-wide level statistics, we pooled observations across all sites to calculate fitting statistics. Next, we examined if differences in model performance were related to site conditions. Because channel width and the height of riparian trees both influence lighting conditions, we used a channel width to tree height ratio to separate sites into 2 groups such that all sites with a ratio >0.5 were placed into the 1st group and the remainder of sites were placed into the 2nd group. We then calculated fitting statistics separately for each group. Finally, we calculated site level fitting statistics separately for each site.

Sensitivity analyses

We performed 2 separate model sensitivity analyses, a single factor analysis and a fully factorial analysis. These 2 analyses served different purposes. Factorial designs are useful for examining a wide range of parameter space, but they are not able to finely investigate changes across parameter space (Box 1978).

Single factor sensitivity analysis  
Our 1st sensitivity analysis examined the effect of single parameters with respect to their expected influence on modeled light. This approach provided insight into how the model can be expected to behave with respect to varying parameters. In this single factor analysis, we varied a single variable at a time while keeping other variables constant, and we quantified the parameter sensitivity with a sensitivity index \( SI \) (Hamby 1994):

\[
SI = \frac{\text{max} - \text{min}}{\text{max}} \tag{Eq. 8}
\]

where \text{max} and \text{min} are the maximum and minimum predicted values obtained by varying a single given parameter over its range of values. We used the geographic coordinates of Walker Branch and based all calculations requiring a solar zenith angle on the solar zenith angle at solar noon on the summer solstice for 2003 (day of year = 172). We parameterized bank height, bank slope, and water level to reduce the effects of bank geometry and effectively mimic bankfull conditions.

We examined the sensitivity of the model to changes in channel azimuth and LAI by running a series of model simulations. Because increasing channel width and tree height have countervailing impacts on light availability, we calculated values of \( SI \) across a range of width to height ratios from 0 to 10 in 0.25 increments rather than by varying width or height alone. We varied azimuth from 1 to 90° and 270 to 360° in 1° increments to capture a full range of values. We assessed the sensitivity of the model to azimuth for 3 different LAI scenarios (0.1, 1.35, and 5.85 m²/m²). We chose these LAI values because they represent the points where transmission through the canopy is 95, 50, and 5%, respectively. For the sensitivity analysis of LAI, we varied LAI between 0.01 and 9.00 m²/m². Because transmission asymptotically approaches 0% with increasing LAI, we chose a value of 9.00 m²/m² for our upper limit because only 1% of light is transmitted at that LAI value. We assessed model sensitivity to changes in LAI under 3 different azimuth scenarios (0, 45, and 90°).

Factorial sensitivity analysis  
Our 2nd sensitivity analysis used a full factorial design to examine the influence of several factors on stream light availability. This analysis is akin to the factorial experimental design that a researcher would use to examine the effect of combinations of factors on a specific response. In our case, we conducted a model-based experiment to examine how potential drivers of light availability (latitude, channel azimuth, channel width, tree height, maximum LAI, and the timing of spring and autumn phenological transition dates) influenced annual sums of PPFD (kmol m⁻² yr⁻¹). The factors chosen are not all defined specifically as parameters in the model structure. For example, maximum LAI and the timing of phenology are not model inputs in a strict sense. However, by abstracting the concept of canopy seasonality to these components, we could individually vary and assess how the timing and magnitude of canopy dynamics affect annual patterns of light reaching the surface of the stream. Each of the 7 factors had 2 levels resulting in a 2⁷ factorial design with a total of 128 combinations. Because the variation of individual factors differs, we selected values for the 2 levels of each factor based on the 25th percentile \( (P_{25}) \) and 75th percentile \( (P_{75}) \) of observed values within the contiguous US to capture a similar range in variation for each factor (Table 2, Appendix S2).
Our aim was to assess the influence of each factor on cumulative annual PPFD, so we needed to have a 1-y driver file for each of the 128 model simulations. We created a model driver file containing a year-long time series of $Q_0$ and LAI for each permutation of parameters. A daily time series of LAI was simulated with a double logistic function (Bauer et al. 2017) where the maximum LAI as well as the height of riparian trees (width:height ½) were both strongly correlated to LAI observed ($r = 0.26$, NRMSE $= 3.44$ mol m$^{-2}$ d$^{-1}$; bias = 9.70 mol m$^{-2}$ d$^{-1}$). In contrast, for sites where channel width was >½ the height of riparian trees (width:height >0.5) ($n = 11$), the correlations between model predictions and observed values for $I_d$ and $I_{shd}$ were more similar: $I_d$ ($r = 0.70$, NRMSE = 1.21 mol m$^{-2}$ d$^{-1}$; bias = 9.65 mol m$^{-2}$ d$^{-1}$) and $I_{shd}$ ($r = 0.61$, NRMSE = 1.93 mol m$^{-2}$ d$^{-1}$; bias = 17.35 mol m$^{-2}$ d$^{-1}$).

We calculated fitting statistics for each site to assess how model performance varied by site and found there was a fairly large range in the strength of correlations between predicted and observed values for both $I_{shd}$ (0.02–0.96) and $I_d$ (0.26–0.97) across sites (Fig. 2A–C). Although $I_d$ predictions did not always have a stronger correlation to observations than did $I_{shd}$, NRMSE was less for $I_d$ at 19/21 sites. Both $I_{shd}$ and $I_d$ tended to overestimate $I_{obs}$ at the site level, but the temporal patterns of this overestimation differed between the 2 models. Examining the temporal patterns of predictions across all sites showed that the tendency of $I_d$ towards overestimation is largely from time periods at the start and end of the season when LAI is relatively low (Fig. 3A), whereas, for $I_{shd}$, the greatest overestimation occurred during the middle portion of the year (Fig. 3E). Example timeseries from site years with the most observations highlight some key differences between $I_d$ and $I_{shd}$. At the Arikaree River, $I_d$ underestimated peak $I_{obs}$, while $I_{shd}$ captured the upper bounds (Fig. 3B–F). However, at both the East Enosh River (Fig. 3C–G) and Walker Branch (Fig. 3D–H) $I_d$ more closely resembled the timing and magnitude of $I_{obs}$ particularly in the middle of the year.

Single factor sensitivity analysis

The sensitivity of the model to changes in azimuth peaked then decreased with increasing channel width to...
The sensitivity of the model to changes in azimuth also varied under the 3 different LAI scenarios, with the peak model sensitivity increasing with increasing LAI (Fig. 4A). The peak sensitivity also occurred at different width to height ratios depending on the LAI. Peak sensitivity occurred at a width to height ratio of 0.6 when LAI = 0.1 m²/m² but occurred at a ratio of 0.4 when LAI = 1.35 or 5.85 m²/m². When LAI was 5.85 m²/m², model sensitivity remained >0.5 until a width to height ratio of 0.8, but all 3 scenarios converged toward low values with increasing width to height ratios. Model sensitivity to LAI decreased nonlinearly with increasing width to height ratios for all 3 azimuth scenarios (Fig. 4B). However, model sensitivity to LAI was consistently the highest when channel azimuth was 0°.

Factorial sensitivity analysis

Factorial analysis allowed us to take a more holistic view on the effect of parameters. The mean annual PPFD across all 128 parameter combinations was 11.47 kmol m⁻² y⁻¹. Increasing channel width had the strongest positive effect (ME = 10.35) out of the factors tested. The only other positive ME was going from a channel azimuth of 0° to an azimuth of 90° (ME = 0.86). Increasing latitude had the strongest negative effect (ME = −2.73), followed by the effect of increasing riparian tree height (ME = −1.33). Factors related to canopy status all reduced annual PPFD as a function of increasing maximum LAI (ME = −0.9), earlier onset of SOS (ME = −0.46), and later EOS (ME = −0.31).

Within the suite of controls examined by the factorial sensitivity analysis, changes in phenological timing had comparatively small effects on total annual light received by the stream. However, varying phenological timing for a given set of site conditions altered the timing and magnitude of cumulative light reaching the stream surface (Fig. 5). For example, for a fixed set of simulated site conditions (latitude = 43.17°; maximum LAI = 6.46 m²/m²; channel azimuth = 0°; channel width = 3.88 m; tree height = 22 m) changing phenology from the shortest growing season (SOS = 117; EOS = 296) to the most extended growing season (SOS = 91; EOS = 325) resulted in a 32% reduction in total annual light reaching the stream surface. Despite changing SOS and EOS by approximately the same number of days (26 and 29 d, respectively), changes in SOS led to a 22% reduction in total annual light, whereas changes in EOS only resulted in a 10% reduction.

**DISCUSSION**

We developed a model for predicting light at the stream surface that includes the influence of canopy structure and phenology on the transmission of light. The foundation of this effort was an existing modeling framework (SHADE2) that considers the effects of channel characteristics and riparian vegetation geometry and density on light transmission. We replaced the static approximation of canopy light transmission within SHADE2 with a dynamic, biophysically based model. Our resulting final model (StreamLight) incorporates remotely sensed data products that enable
application across broad spatial extents. We tested both StreamLight and SHADE2 across sites with varying conditions, and to our knowledge, this paper represents the largest and most extensive dataset of in-situ light measurements ever used to validate models of stream light regimes. At the study-wide level, light estimates from StreamLight were more strongly correlated to observations and had reduced magnitude of errors in comparison to SHADE2. Riparian vegetation exerts stronger control on light availability when channel width is relatively small compared to the height of riparian vegetation, and the performance of StreamLight was substantially better than SHADE2 at sites where channel width was ≤½ the height of riparian trees. To place this finding in context, based on estimates of global mean tree height (16.9 m) (Simard et al. 2011), this channel width to tree height ratio would include streams of ≤8.5 m wide, and streams of this size constitute a substantial portion of global stream length (Downing et al. 2012). Therefore, we expect that the inclusion of biophysically based canopy light transmission will be important for many streams with forested riparian zones.

Model sensitivity
To better understand potential drivers of stream light environments, we used a series of model simulations to
examine the influence of various factors on light reaching the stream surface. By isolating other factors, we showed that the sensitivity of light regimes to changes in channel azimuth reaches a peak when channel width is ~½ as wide as the height of riparian vegetation. Previous findings indicate that channel meandering has minimal impact on lighting conditions when streams are very narrow or wide relative to the height of riparian vegetation (Rutherford et al. 2018a), and our results also suggest a similar pattern of the importance of channel orientation for stream lighting conditions. Additionally, this sensitivity was influenced by LAI, with more dense canopies increasing the model sensitivity to azimuth. These results support previous findings that the influence of channel azimuth depended on channel width or canopy closure (Julian et al. 2008b). Our factorial model analysis of controls on stream light availability indicated that, out of the factors we examined, channel width exerted the strongest control on stream light environments. This result suggests that local factors, such as channel characteristics, are more important for determining the light environment of streams than are broad-scale patterns in light associated with latitude. Results from our sensitivity analyses lend further support for both the role of channel width (Vannote et al. 1980, Davies-Colley and Quinn 1998) and the relationship between channel width and canopy height (Rutherford et al. 2018a, b) in mediating stream light environments.

Including dynamic canopy phenology in StreamLight allowed us to examine how temporal dynamics of riparian vegetation influence stream light regimes. Changes in the timing of canopy phenology had small effects on total annual light when compared to other factors, such as channel width, but altering the timing of canopy phenology did influence the seasonal timing of peak light and substantially reduced total annual light (Fig. 5). These results support the importance of canopy phenology for regulating the magnitude and temporal dynamics of light observed in small and mid-sized forested streams (Roberts et al. 2007). The ranges in SOS and EOS we used to vary phenology in our factorial sensitivity analysis reflected spatial variability in long-term averages of phenological timing across the contiguous US. However, our calculated ranges in SOS (26 d) and EOS (29 d) also fall within observed interannual

![Figure 4](image-url)  
Figure 4. Results from a single factor sensitivity analysis of light estimates produced by the StreamLight model. The sensitivity of modeled light estimates to changes in channel azimuth (ψ) (A) are expressed for 3 values of leaf area index (LAI, m²/m²). The sensitivity of modeled estimates to changes in LAI (B) are expressed for 3 values of ψ.

![Figure 5](image-url)  
Figure 5. An example of changes in a light regime in response to changes in the timing of canopy phenology for a given set of site conditions (latitude = 43.17°; maximum leaf area index = 6.46 m²/m²; channel azimuth = 0°; channel width = 3.88 m; tree height = 22 m). These estimates were generated as part of the factorial sensitivity analysis for the StreamLight model. Incoming photosynthetic photon flux density (PPFD) (I₀, mol m⁻² d⁻¹) is shown in addition to modeled light at the stream surface for short and extended terrestrial growing seasons. The short growing season has start and end of season dates of 117 and 296 (day of year), respectively. The extended growing season has start and end of season dates of 91 and 325 (day of year), respectively.
variation of phenological transition dates for temperate deciduous forests (Melaas et al. 2013), which suggests that both intra-annual and interannual patterns of terrestrial phenology could have important impacts on stream light availability.

Model limitations

There are several ways in which the structure of our biophysical model could be refined. For example, to simplify our model, we did not include the effects of topographic shading and minimized the influence of bank shading, and this simplification presents an area for future model development. In some landscapes, local topography can be a strong control on light availability (Yard et al. 2005), and including topographic shading in the model should improve light estimates in these locations. The model we used to calculate stream shading (SHADE2) descends from the SHADE model (Chen et al. 1998) that accounted for topographic shading, and these effects could be integrated into our current model structure. Similarly, we did not include the effects of shading from woody plant elements. The tendency for StreamLight to overestimate light at the stream surface, particularly at the start and end of the year when LAI is low, suggests that including these other sources of shade could be particularly important at these times of the year. However, the tendency toward overestimation could also be related to the fact that light sensors are generally located along stream banks and likely underestimate the integrative light profile for a channel cross-section.

In this study, we focused our efforts on predicting light at the surface of the stream, yet the light regime for benthic organisms is further influenced by light attenuation in the water column through the influence of depth and optical water clarity (Davies-Colley and Smith 2001, Hall et al. 2015). Vi- able models of benthic light availability exist (Davies-Colley and Nagels 2008, Julian et al. 2008b) and could be incorporated into our modeling framework by establishing relationships between measured factors influencing water clarity (e.g., fluorescent dissolved organic matter, turbidity, discharge, and the exponential decay of light through the water column). Of the multiple refinements that might improve our stream light model, the addition of light transmission through the water column stands out as the most notable insofar as the goal is to predict light regimes experienced by aquatic organisms. Water column light attenuation exerts disproportionate influence on light regimes as streams widen, because of the diminished influence of canopy (Vannote et al. 1980). Additionally, water clarity decreases along the river continuum because of the accumulation of light attenuating constituents (Julian et al. 2008a), suggesting that the water column is the primary control on light attenuation downstream of forested headwaters (Julian et al. 2008c). Moreover, anthropogenic influences from land use (Glendell and Brazier 2014) and nutrient enrichment (Hilton et al. 2006) increase particulate loads in streams and rivers. Quantification of benthic light regimes (i.e., integrating canopy and water column light attenuation) greatly improves predictions of stream primary production (Kirk et al. 2020) and enables investigation of the role that changing light regimes play in modulating benthic community structure and function (Grubisic et al. 2017, Bengtsson et al. 2018).

Applying StreamLight at different scales

When considering refining data sources to be used as model inputs, it is necessary to consider the desired scale of light estimates. Our modeling framework does not necessitate the input of any specific data sources, and thus as new and higher quality datasets become available, they could be incorporated to either improve estimates at specific locations or to allow for generating estimates at broader spatial scales.

There are several ways of improving estimates at fine spatial scales. For example, instead of using moderate resolution remotely sensed products, in-situ measurements of tree heights and canopy structure could be used. Alternatively, using finer-scale remote products could also improve model estimates or reduce uncertainty. For example, cameras can be deployed at sites to capture high frequency estimates of water width (Leduc et al. 2018) or LAI (Ryu et al. 2012, Macfarlane et al. 2014). Because structural complexity of canopies can influence light transmission (Warren et al. 2013), studies modeling stream conditions have also characterized canopies using finer resolution Li- DAR data (Greenberg et al. 2012, Bode et al. 2014, Bachiller-Jareno et al. 2019) or drone-based photogrammetry (Dugdale et al. 2019). To appropriately assess such fine-scale estimates, it would also be necessary to deploy a sufficient number of sensors, preferably PAR sensors, to capture heterogeneity of the light environment over the spatiotemporal scales of the associated light estimates.

Using the highest quality in-situ data may improve light estimates at individual locations, but the lack of continuous spatial coverage of these products prohibits making light predictions at watershed to continental scales. As they come available, new datasets with continuous spatial coverage should be explored to aid making spatially extensive estimates of light. Other approaches include estimating channel widths by using predictive models to extrapolate observed widths to reaches without measurements (McManamay and DeRolph 2019) or as a function of hydraulic geometry coefficients and discharge (Gomez-Velez et al. 2015). The sensi- tivity of light estimates to errors in channel width estimates will depend on other factors, such as LAI or tree height, and researchers should consider the implications of using empirically derived widths for their particular application. Finer resolution LiDAR data is increasingly available, such as the growing compilation of nationwide data curated through the National 3D Elevation Program.
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Broader implications
The ability to predict stream light regimes provides opportunities to draw new insights about the role of light in mediating ecosystem processes. Light availability is correlated to GPP across streams (Mulholland et al. 2001), and this influence on primary production has a number of implications. For example, light availability can influence stream nutrient dynamics (Quinn et al. 1997, Hall and Tank 2003, Finlay et al. 2011). Light may also influence assemblage composition of macrophytes (Julian et al. 2011) as well as periphyton and invertebrate taxa (Quinn et al. 1997). Light is also important for driving stream thermal regimes (Sinoikrot and Stefan 1993, Webb and Zhang 1999), and watershed-scale estimates of stream temperature require both basin-wide characterization of riparian vegetation and dynamic estimates of riparian shading (Chen et al. 1998). Evidence suggests altered patterns of forest phenology (Menzel and Fabian 1999, Menzel et al. 2006, Jeong et al. 2011), and phenology can be particularly relevant to the light dynamics of small streams (Roberts et al. 2007). Remotely sensed measures of LAI are now of sufficient duration that we could estimate long-term patterns of light to examine if changes in phenology are altering stream light regimes. Both the inter- and intra-annual dynamics of existing datasets on other light-mediated ecosystem processes could also be examined to improve our empirical knowledge of how strongly light controls these processes. While we maintain that collecting high frequency in situ measurements of light is important, models that can predict the full seasonal dynamics of stream light availability will allow stream ecologists to expand the spatial and temporal scales over which they investigate the implications of changing light conditions on stream ecosystem processes.

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