

Improving representation of riparian vegetation shading in a regional stream temperature model using LiDAR data

Loicq, Pierre; Moatar, Florentina; Jullian, Yann; Dugdale, Stephen J.; Hannah, David M.

DOI:

[10.1016/j.scitotenv.2017.12.129](https://doi.org/10.1016/j.scitotenv.2017.12.129)

License:

Creative Commons: Attribution-NonCommercial-NoDerivs (CC BY-NC-ND)

Document Version

Peer reviewed version

Citation for published version (Harvard):

Loicq, P, Moatar, F, Jullian, Y, Dugdale, SJ & Hannah, DM 2018, 'Improving representation of riparian vegetation shading in a regional stream temperature model using LiDAR data', *Science of the Total Environment*, vol. 624, pp. 480-490. <https://doi.org/10.1016/j.scitotenv.2017.12.129>

[Link to publication on Research at Birmingham portal](#)

Publisher Rights Statement:

Checked for eligibility: 28/02/2018
<https://doi.org/10.1016/j.scitotenv.2017.12.129>

General rights

Unless a licence is specified above, all rights (including copyright and moral rights) in this document are retained by the authors and/or the copyright holders. The express permission of the copyright holder must be obtained for any use of this material other than for purposes permitted by law.

- Users may freely distribute the URL that is used to identify this publication.
- Users may download and/or print one copy of the publication from the University of Birmingham research portal for the purpose of private study or non-commercial research.
- User may use extracts from the document in line with the concept of 'fair dealing' under the Copyright, Designs and Patents Act 1988 (?)
- Users may not further distribute the material nor use it for the purposes of commercial gain.

Where a licence is displayed above, please note the terms and conditions of the licence govern your use of this document.

When citing, please reference the published version.

Take down policy

While the University of Birmingham exercises care and attention in making items available there are rare occasions when an item has been uploaded in error or has been deemed to be commercially or otherwise sensitive.

If you believe that this is the case for this document, please contact UBIRA@lists.bham.ac.uk providing details and we will remove access to the work immediately and investigate.

Improving representation of riparian vegetation shading in a regional stream temperature model using LiDAR data

Pierre Loicq^{a,*}, Florentina Moatar^a, Yann Jullian^b, Stephen J. Dugdale^c, David M. Hannah^c

^a EA 6293 GÉHCO Géo-Hydrosystèmes Continentaux, Université François-Rabelais de Tours, Parc de Grandmont 37200 Tours, France

^b CaSciModOT, UFR Sciences et Techniques, Université François Rabelais, Parc de Grandmont 37200 Tours, France

^c School of Geography, Earth and Environmental Sciences, University of Birmingham, Edgbaston, Birmingham B15 2TT, United Kingdom

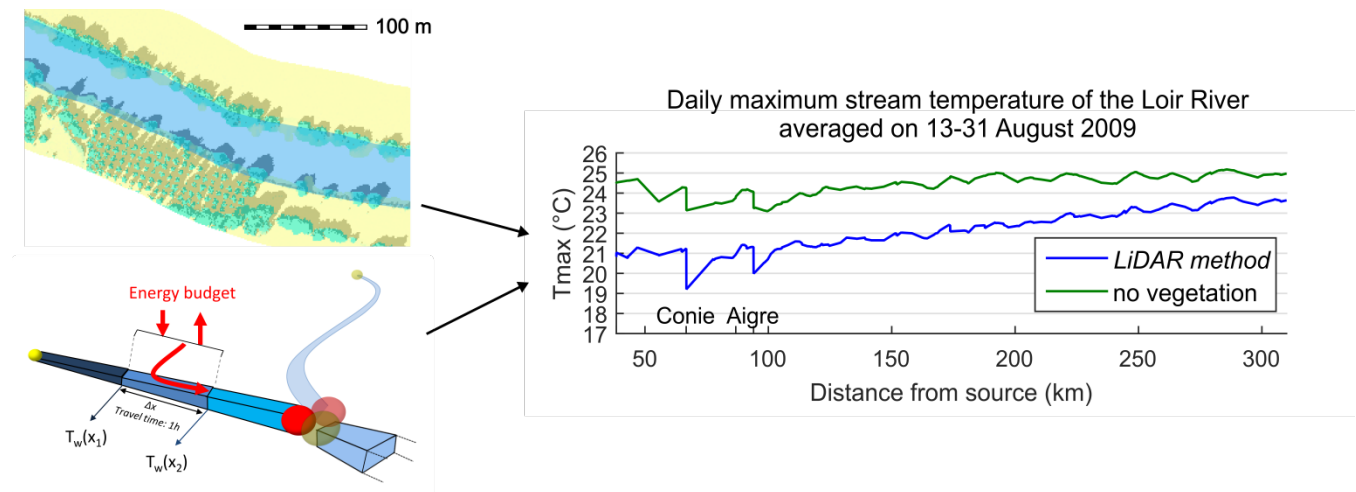
*Corresponding author. E-mail address: pierre.loicq@univ-tours.fr

Keywords: river temperature modelling, regional scale, riparian shading, LiDAR, Loir River.

Highlights:

- Riparian shading was characterised on a 270 km stream using LiDAR data.
- Shading data were injected in a regional stream temperature model.
- Vegetation's cooling effect ranges from -3.0 °C (upstream) to -1.3 °C (downstream).
- Model accuracy is improved compared to simpler shade characterisation methods.
- Riparian vegetation data's quality is a key factor for stream temperature modelling.

Graphical abstract:



Abstract

Modelling river temperature at the catchment scale is needed to understand how aquatic communities may adapt to current and projected climate change. In small and medium rivers, riparian vegetation can greatly reduce maximum water temperature by providing shade. It is thus important that river temperature models are able to correctly characterise the impact of this riparian shading. In this study, we describe the use of a spatially-explicit method using LiDAR-derived data for computing the riparian shading on direct and diffuse solar radiation. The resulting data are used in the T-NET one-dimensional stream temperature model to simulate water temperature from August 2007 to July 2014 for 270 km of the Loir River, an indirect tributary of the Loire River (France). Validation is achieved with 4 temperature monitoring stations spread along the Loir River. The vegetation characterised with the LiDAR approach provides a cooling effect on maximum daily temperature (T_{max}) ranging from 3.0°C (upstream) to 1.3°C (downstream) in late August 2009. Compared to two other riparian shading routines that are less computationally-intensive, the use of our LiDAR-based methodology improves the

30 bias of T_{\max} simulated by the T-NET model by 0.62°C on average between April and September. However,
31 difference between the shading routines reaches up to 2°C (monthly average) at the upstream-most station.
32 Standard deviation of errors on T_{\max} is not improved. Computing the impact of riparian vegetation at the hourly
33 timescale using reach-averaged parameters provides results close to the LiDAR-based approach, as long as it is
34 supplied with accurate vegetation cover data. Improving the quality of riparian vegetation data should therefore
35 be a priority to increase the accuracy of stream temperature modelling at the regional scale.

36

37 **1. Introduction**

38 Temperature is a major water quality parameter because it controls not only oxygen solubility (Moatar et al.,
39 2001) but also chemical and metabolic reactions (Haag and Westrich, 2002). Hence, it affects fish behaviour and
40 survival (Magnuson et al., 1979). River water temperature modelling is thus important for understanding the
41 distribution of aquatic species at regional scales, under present or future climatic conditions (Buisson et al.,
42 2008; Tisseuil et al., 2012; Boisneau et al., 2008; Brown et al., 2005). River temperature is already increasing
43 across French water courses, a trend which is expected to continue further under projected climate change
44 (Moatar and Gailhard, 2006; Bustillo et al., 2014; Hannah and Garner, 2015). Such a warming could have severe
45 consequences for a range of aquatic species, and adaptation measures are currently being sought with a view to
46 ensuring the continued survival of temperature sensitive fluvial organisms. In this context, riparian shade and
47 groundwater exchanges have been given increasing research attention, because of their ability to regulate river
48 temperature (Lalot et al., 2015; Leach and Moore, 2010). Indeed, many studies have shown that shade can
49 moderate water temperature of relatively small rivers (Moore et al., 2005; Garner et al., 2014). Conversely, in
50 larger rivers, Teti (2006) showed (using shade measurements acquired along an increasing-width stream) that
51 riparian vegetation has a limited impact on rivers larger than 30 m. DeWalle (2008) quantified the maximal
52 wetted width for which riparian vegetation can effectively reduce received solar radiation. However, no study
53 has yet quantified the impact of shading on temperature on rivers of intermediate width (>15 m and <30 m) or
54 at the regional scale.

55 Process-based river temperature models function by simulating the energy exchange processes heating
56 or cooling a river, in particular through the input of solar radiation. This solar radiation is composed of direct
57 (solar rays) and diffuse radiation (scattered by atmosphere), both of which are influenced in different ways by
58 the presence of riparian vegetation. The impact of riparian vegetation on the direct radiation can be quantified
59 by computing a shadow factor (SF), which is the proportion of a river being shaded at a given time. Several
60 methods have been proposed to compute it at an hourly time step. Chen et al. (1998) detailed a method to
61 compute riparian shade from GIS polygons of riparian vegetation. Their method used stream azimuth and tree
62 height (alongside solar position) to determine whether a section of stream channel was in shade. However, this
63 technique only accounted for the effect of vegetation located perpendicular to the stream centreline, and
64 furthermore, did not denote the fraction of the channel cross-section that was shaded. As a result, Li et al.
65 (2012) developed an enhanced version of the Chen et al. (1998) methodology, allowing for the determination of
66 the amount of channel cross-section covered by shade. This new method also enables the simulation of

67 overhanging vegetation, but like its predecessor, only considers the effect of vegetation located perpendicular
68 to the river reach. Approaches capable of simulating the effects of vegetation non-perpendicular to the reach
69 include that of Cox and Bolte (2007), who devised a methodology capable of simulating shadow cast by
70 vegetation located in 8 directions (steps of 45°) around each centreline node, and the Solar Analyst extension
71 for ArcGIS (Fu and Rich, 1999), which can compute shadow factor at much finer spatial and temporal scales.
72 Indeed, Johnson and Wilby (2015) applied this method to a small catchment in order to quantify the potential of
73 planting trees, without using a physically-based river temperature model.

74 The impact of riparian vegetation on diffuse radiation can be quantified by computing a sky view factor
75 (SVF). It is the ratio between the diffuse radiation actually reaching the water and the diffuse radiation that
76 would reach this surface with no vegetation around. In a lowland area where topographic shade can be
77 neglected, the tree view factor (TVF) can be defined as 1-SVF. Unlike SF, these view factors (VF) are constant in
78 time since they do not depend on the sun's position. For short reaches, a precise calculation can be achieved
79 through hemispheric photography. For larger areas, remote sensing products or vegetation polygons are
80 needed. Most previous studies (Chen et al., 1998, Cox and Bolte, 2007, Loinaz et al., 2013, Sun et al., 2015)
81 simply use the angle between the horizon and the tree in the directions perpendicular to the river, from one
82 fixed point of view (usually the centre of the river). Moore et al. (2014) introduced the computation of width-
83 averaged sky view factors, with equations considering infinitely long rivers, with or without overhanging trees.

84 With an approach similar to the one used to compute direct radiation, the Solar Analyst extension for
85 ArcGIS handles the computation of diffuse radiation by overlaying a viewshed and a discretised sky map. Two
86 different methods can be used to quantify the amount of radiation coming from each cell of the open sky
87 (uniform radiation or depending on the zenith angle). This method was modified and used by Sridhar et al.
88 (2004) to include the shading effects of near stream vegetation.

89

90 In order to quantify the impact of riparian shading, existing regional-scale stream temperature models
91 usually rely on theoretical values regarding vegetation characteristics (Sun et al., 2015; Loinaz et al., 2013), on
92 simplified assumptions regarding shading process (Haag and Luce, 2008; Cheng and Wiley, 2016), or incorporate
93 shading data from low-resolution DEMs (Cox and Bolte, 2007). Nowadays however, LiDAR can provide accurate
94 data at a large scale. In order to develop a tool for riparian shade inventories using LiDAR data, Guzy et al.
95 (2015) adapted the insolation module of the Heat Source model (Boyd and Kasper, 2003). They created
96 polygons of homogenous potential canopy height and extracted the 75th percentile of the computed frequency
97 distribution of canopy height provided by LiDAR. Greenberg et al. (2012) used LiDAR data and the r.sun module
98 of GRASS GIS to compute clear-sky solar radiation for three summer days in order to understand the impact of a
99 potential trees removal around a delta, without the use of a network based temperature model. Finally,
100 Wawrzyniak et al. (2017) used LiDAR data to compute the impact of riparian forest in a deterministic water
101 temperature model of a 21 km-long reach, during 5 days in summer 2010 and 2011. There is thus a range of
102 data sources and methods available to compute both SF and VF. However, there remains a lack of information
103 comparing the various methodologies, especially with regards to shading routines in regional-scale models.

Moreover, the use of LiDAR as a method for the computation of riparian shading is still in its infancy and has never been used to compute the impact of riparian vegetation in a large-scale stream temperature model, during a whole annual cycle.

The goal of this paper is therefore to test the influence of shadow and sky view factor computed from LiDAR data on the simulation of maximum daily water temperature (T_{max}) with the T-NET model, a dynamic physically based model for simulating stream temperature at the regional scale using the equilibrium temperature concept. We compute SF and VF based on a LiDAR-derived raster and incorporate these data into the radiative balance of a T-NET model of the Loir River (France) (see Beaufort et al., 2016). We then compare the T_{max} simulated with LiDAR data to two other methods used in the T-NET model for computing riparian shading at the regional scales. Model validation is achieved using data from 4 temperature monitoring stations that are spread over the Loir River.

2. Methods

2.1. Principles of T-NET model

T-NET is a 1D physically-based model designed to compute water temperature along the longitudinal dimension of a hydrographic network (a GIS polyline). Reaches of this network are limited by two confluences, or by a source and a confluence (for first order reaches). T-NET was designed and applied at the regional scale (110 000 km²) by Beaufort et al. (2016). T-NET runs at an hourly time step and is based on the equilibrium temperature concept, which is defined as the water temperature at which the net rate of heat exchange at the interface of a water body is null (Bustillo et al., 2014). The model considers six fluxes [$W \cdot m^{-2}$]: net solar radiation, atmospheric longwave radiation, longwave radiation emitted from the water surface, evaporative heat flux, convective heat flux, and groundwater heat inflow. To compute these terms, the model uses the following parameters as gridded input data: air temperature [$^{\circ}C$], specific humidity [$kg \cdot kg^{-1}$], wind velocity [$m \cdot s^{-1}$], atmospheric longwave radiation [$W \cdot m^{-2}$] and direct and diffuse solar radiation [$W \cdot m^{-2}$]. Parameters are allocated to each river reach as a function of the ratio between the length of the reach within a grid cell and the total reach length. All meteorological parameters except solar radiation are derived from the SAFRAN atmospheric reanalysis dataset (Vidal et al., 2010). These data are produced by Météo-France from both observations and modelling at an hourly time step and a spatial resolution of 8 km. Direct and diffuse solar radiation are derived from the Helioclim3-v5 dataset (Marchand et al., 2017), generated with the help of Meteosat satellite imagery at an hourly time step and a resolution of $\sim 3 \times 5$ km. Inputs pertaining to river discharge and groundwater contributions to river flow are also required by the model. These are computed at a daily time step with the semi-distributed hydrological model EROS (Thiéry and Moutzopoulos, 1992). Both parameters are modelled at the outlets of sub-basins for which river discharge observations are available for calibration. They are then scaled to the reaches inside each sub-basin using the partial area concept. T-NET simulates longitudinal variability in water temperature between the upstream and downstream nodes of each reach, with a spatial resolution depending on the travel time (Figure 1). Water velocity is given by the ratio between discharge and channel cross-section, which is computed using the ESTIMKART empirical model developed by Lamouroux et al. (2010). At the confluence of two reaches, the output temperature is defined as the sum of the product of the

two confluences' temperature and discharge divided by the sum of the discharge of the two confluences. T-NET was thus designed to be applied on well mixed streams and not on standing waters or large estuaries, where 2D (Cole and Wells, 2006; Becker et al., 2010; Ouellet et al., 2014) or 3D models (Maderich et al., 2008) are more suitable.

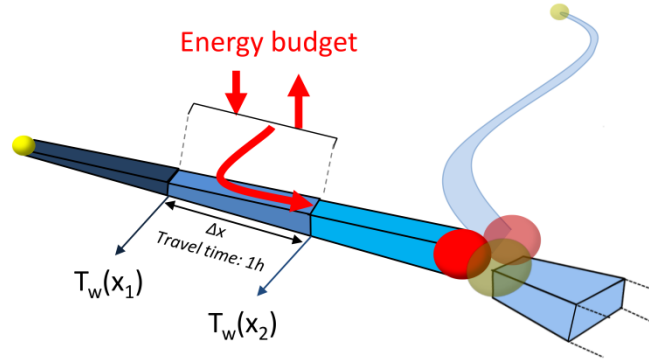


Figure 1: Principles of T-NET model

2.2. Net solar radiation calculation

In order to improve T-NET's ability to model the impact of riparian vegetation on solar radiation, modifications were made to the original model detailed by Beaufort et al. (2016). Similar to the approach of LeBlanc et al. (1997), net solar radiation (H_{ns}) is now computed as:

$$H_{ns} = R_{dir}(1 - \alpha_{dir})((1 - SF) + SF \tau) + R_{diff}(1 - \alpha_{diff})((1 - TVF) + TVF \tau) \quad (\text{Eq. 1})$$

Where R_{dir} and R_{diff} are the direct and diffuse solar radiation [$\text{W} \cdot \text{m}^{-2}$] derived from the Helioclim3-v5 product, α_{dir} and α_{diff} are the water surface albedo associated with direct and diffuse radiation respectively, τ is the transmissivity of riparian vegetation (i.e. the fraction of solar radiation that passes through the canopy), SF is the shadow factor and TVF is the tree view factor. α_{diff} was held at a constant of 0.09, following the recommendation of Sellers (1965) and α_{dir} was computed using the formulation of Anderson (1954):

$$\begin{aligned} \alpha_{dir} &= 1 & \text{if } \Psi < 1.24^\circ \\ \alpha_{dir} &= 1.18 * \Psi^{-0.77} & \text{otherwise} \end{aligned} \quad (\text{Eq. 2})$$

Where Ψ is the angle between the horizon and the sun in degrees.

τ was fixed at 50% in winter and 15% in summer. These values are the averages of global solar radiation transmissivities given by Cantón et al. (1994), Sattin et al. (1997) and Konarska et al. (2014) for deciduous tree species. Transitions between winter and summer values are described with an ascending and descending logistic regression whose equation is:

$$\tau = \frac{\kappa}{1 + \exp(\pm \gamma \cdot DoY - \beta)} + \mu \quad (\text{Eq. 3})$$

Where DoY is the day of year and κ , β , γ and μ are the parameters fitted by least squares adjustment to an averaged annual cycle of ground-based NDVI measured from oak trees during 2008-2012 (Soudani et al., 2012). These trees are located in the forest of Fontainebleau (60 km to the south of Paris and ~150 km away from the centre of the Loir catchment). Data from Lebourgeois et al. (2008) indicate that, for oak trees, there is little phenologic difference between Fontainebleau and the Loir catchment. However, remote sensing observations

from Muller (1995) show that, in 1987 and in the region of Toulouse (South of France), leaf emergence of riparian trees occurs about 15 days earlier than for oaks. In order to take into account this difference between oak and riparian species, we hence considered an enlarged growing season compared to oak's phenology (θ -15 days in spring, θ +15 days in autumn). After fitting the four parameters on NDVI values, κ and μ , representing the upper and lower values, are adjusted to fit the winter and summer values of transmissivity (50 and 15%, respectively).

2.3.Shadow factor and view factor calculations

In order to test the influence of different riparian shading algorithms on water temperatures simulated with T-NET, we used three approaches to compute both the shadow factor (SF) and the tree view factor (TVF).

In the first approach (hereafter referred to as the *constant* method), SF and TVF are held as coefficients that are constant in time but vary as a function of Strahler order based on the equation:

$$SF = TVF = vc \times k \quad (\text{Eq. 4})$$

where vc is vegetation cover (%) computed at the reach scale in a buffer of 10 m around the river, and k is a coefficient aiming to account for the influence of the reach width on shadow (where 1 (maximum impact) denotes a Strahler order of 1 and 0 (no impact) is associated with a Strahler order of 8). This approach is used in Beaufort et al. (2015, 2016).

In the second approach (hereafter referred to as the *variable* method), SF and TVF are derived from geometric calculations made at the reach scale, taking into account river width, tree height, vegetation cover, and position of the sun (for the shadow factor).

To compute SF at an hourly time step, the model of Li et al. (2012) was implemented in its simplest version, i.e. considering rectangular trees, located at the edge of the bank, without overhang:

$$SF = \frac{H \times \cot \Psi \times \sin \delta}{W} \times vc \quad (\text{Eq. 5})$$

where H is tree height, W is river width, Ψ is the solar elevation angle, δ is the angle between solar azimuth and the mean azimuth [0° - 180°] of each T-NET reach (computed by considering the first and last vertices of each reach).

To compute VF, we used the second model described in Moore et al. (2014). It provides SVF for channels of infinite length, without taking into account overhanging trees. For a channel with vertical banks and fixed tree height, the width- and reach-averaged tree view factor is computed as:

$$TVF = \left[1 - \frac{0.5}{W} \left(\sqrt{H^2 + W^2} + \sqrt{H^2 + W^2} - 2H \right) \right] \times vc \quad (\text{Eq. 6})$$

The third approach (subsequently referred to as the *lidar* method) is a spatially-explicit method that computes SF and TVF from a LiDAR-derived digital surface model (DSM). It requires a) a high-resolution digital surface model (~ 1 m) describing the elevation of riparian vegetation, b) information about the exact location of the river in order to define water and non-water pixels and c) polygons of river area, allowing the DSM pixels to be linked to a given T-NET reach.

206 To compute SF, we modified the r.sun module (Hofierka and Suri, 2002) of GRASS GIS (GRASS Development
 207 Team, 2015) to map per-pixel shade cast by the DSM. Using this algorithm, a water pixel is defined as being in
 208 shade if the elevation of the highest DSM pixel located along a 50 m track in the direction of the sun is greater
 209 than the solar elevation. Dividing the number of shaded pixels by the number of water pixels belonging to each
 210 river polygon thus provides a shadow factor for each T-NET reach. Because shading at a given hour vary slowly
 211 throughout the year, the computation was done every hour when the sun is above the horizon, every 15 days of
 212 a standard non-leap year, for every water pixel. A piecewise cubic interpolation is then applied to the SF of each
 213 hour separately in order to get a value for each day of the year.

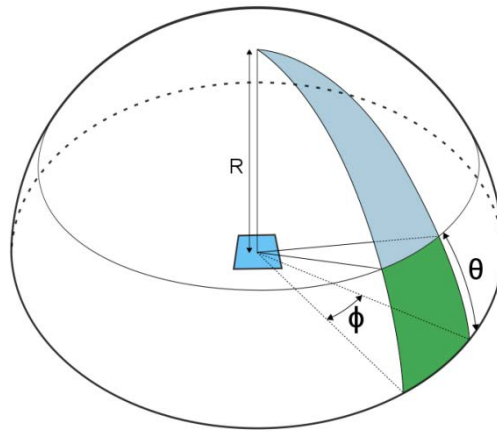
214 To compute SVF from the DSM, we represented the sky as a hemisphere of radius R centred on a water pixel (as
 215 in Essery et al. (2008), Johnson and Watson (1984) and Tung et al. (2006); Figure 2). We used the r.horizon
 216 module of GRASS GIS to calculate the angle θ between the horizon and the highest DSM pixel as seen from each
 217 water pixel at horizontal azimuth steps ϕ of 10° . The whole hemisphere is thus made of $n=36$ segments. The
 218 diffuse radiation emission is considered to be isotropic and the river surface to be horizontal. The SVF for each
 219 segment is computed from the sphere area formula:

$$\frac{R^2 \int_0^{\frac{\pi}{2}} \int_0^\phi \cos \theta \sin \theta d\phi d\theta}{R^2 \int_0^{\frac{\pi}{2}} \int_0^\phi \cos \theta \sin \theta d\phi d\theta} = \frac{1 + \cos 2\theta}{2} \quad (\text{Eq. 7})$$

221 It therefore follows that the SVF for the whole hemisphere is given by:

$$SVF = \frac{1}{2} + \frac{1}{n} \sum_{i=1}^n \cos 2\theta_i \quad (\text{Eq. 8})$$

223 An averaged TVF value (TVF=1-SVF) is subsequently attributed to each T-NET reach as the mean TVF value for all
 224 DSM pixels located within the reach.

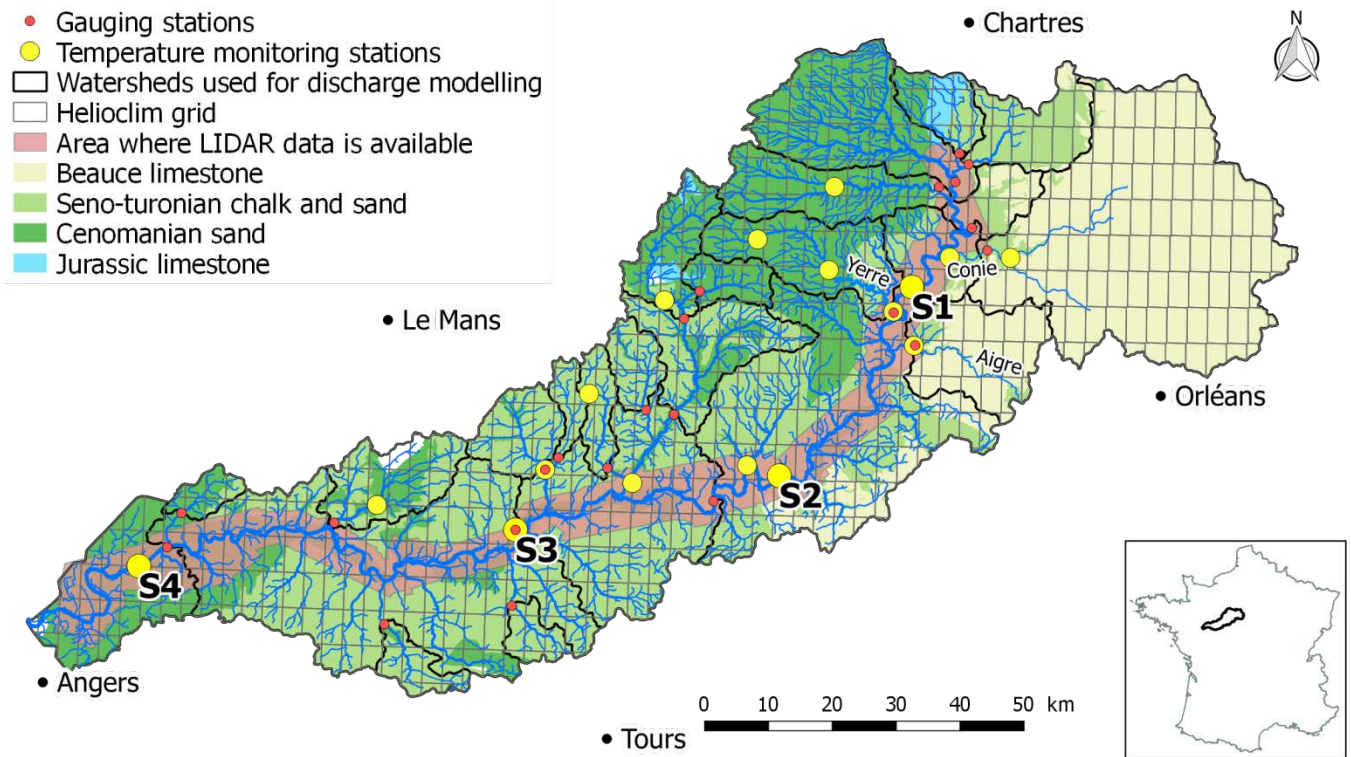


225
 226 **Figure 2: Calculation of a sky view factor from measures of θ , the angle between the horizon and**
 227 **the highest vegetation seen from a water pixel and with an angular step ϕ of 10° . R is the radius of the hemisphere**
 228

229 **2.4.Study site and water temperature observations**

230 The Loir River basin is an 8283 km^2 sub-catchment of the Maine River watershed located in central France
 231 (Figure 3). The river network of the Loir basin is 4420 km long, of which the Loir River itself is 316 km. The basin
 232 is generally low-lying, with altitudes ranging from 20 to 140 meters above sea level. As highlighted by the river
 233 network's variable drainage density (Figure 3), a calcareous aquifer with high permeability is present in the

234 north-east of the catchment. It feeds the river network with groundwater exchanges in its upstream sections
 235 (Baratelli et al., 2016). Channel slope (computed from a 25 m resolution digital terrain model of the watershed)
 236 ranges from 0.01% to 5%, with a median value of 0.5%. The main tributaries of the Loir are the Conie, the Yerre
 237 and the Aigre, with catchments areas of 530, 300 and 280 km² respectively. The mean discharge of the Loir at its
 238 downstream-most gauging station (1961-2015) is 31.8 m³·s⁻¹ (specific discharge = 4.0 l·s⁻¹·km⁻²). The flows of the
 239 Aigre (specific discharge = 5.4 l·s⁻¹·km⁻²) and the Conie (specific discharge = 3.4 l·s⁻¹·km⁻²) show little variation
 240 during the year, compared to the Loir. However, interannual fluctuations are much greater, driven by
 241 piezometric fluctuations of the Beauce aquifer.
 242 Eighteen temperature loggers allowing for the model validation are located in the catchment. They acquired
 243 data at an hourly time step with varying periods of availability (extending from summer 2008 to summer 2014).
 244 The loggers were generally placed at a depth greater than 1 meter (according to the mean interannual water
 245 level), and steps were taken to ensure than they were installed within well-mixed sections of the channel to
 246 avoid potential stratification biases. Four of these stations are located within the main stem of the Loir (S1 to
 247 S4), where LiDAR data are available. The period of measurement is different for each station and is given in
 248 Figure 4. The annual cycle of mean daily temperature of the Loir River ranges from 2 to 24 °C at station 1
 249 (between 08/2010 and 07/2011), while the annual amplitude of the Aigre and the Yerre are smaller because of
 250 the groundwater fluxes (5-21 °C and 4-16 °C on the same period, respectively). Temperature regime of the Conie
 251 River is strongly dependent on the groundwater level. Its variability can be similar to the Loir River (2009, 2010)
 252 or very limited (annual range of 8-14 °C in 2014).



253
 254
 255
 256

Figure 3: Map of the Loir catchment, with stream temperature monitoring stations, gauging stations, watersheds used for discharge modelling, LiDAR area, geologic formations, Helioclim grid.

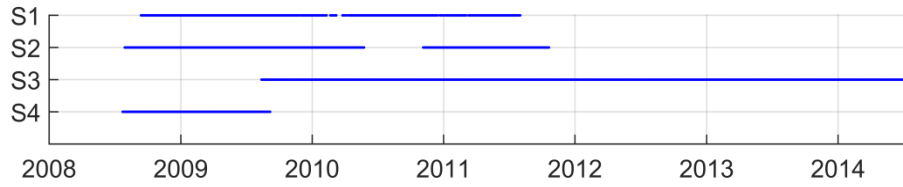


Figure 4: Period of availability of stream temperature observation at the four logger stations located on the Loir River

2.5.T-NET model implementation and criteria of model performance

The Loir River basin was implemented in the T-NET model. It consists of 2206 reaches, of which the Loir River itself is covered by 161 reaches. Simulated discharge and groundwater inputs used to drive T-NET (derived from the EROS hydrological model) were found to agree reasonably well with observed data. Nash-Sutcliffe (Nash and Sutcliffe, 1970) model efficiency coefficient (NSE) calculated against hydrometric observations ranged from 0.59 to 0.95 (1974-2012 period) for 21 of the 23 sub-basins of the Loir catchment. The remaining two sub-basins ($<0.10 \text{ m}^3 \cdot \text{s}^{-1}$; located in the upper portions of the watershed) yielded negative NSE values. In order to compare the three shading methods detailed in section 2.3, we ran the T-NET model three times on seven hydrologic years (from August 2007 to July 2014).

For the *constant* method, vegetation cover (*vc*) was derived from a dataset available at the national scale (Valette et al., 2012), which is based on river and vegetation polygons from the BD TOPO® database, provided by Institut national de l'information géographique et forestière (IGN).

For the *variable* method, *vc* was also derived from this dataset. Tree height *H* was fixed at 15m and river width *W* was estimated using the ESTIMKART empirical model (Lamoureux et al., 2010).

For the *lidar* method, the digital surface model (DSM) required for the shading computation was derived from a LiDAR survey conducted by IGN on approximately 270 km of the Loir River (85% of the total river length) on 26 May 2012. That day, average discharge was $25.5 \text{ m}^3 \cdot \text{s}^{-1}$ at the downstream-most gauging station (interannual average is $31.8 \text{ m}^3 \cdot \text{s}^{-1}$). The DSM was generated by gridding the LiDAR first returns at a resolution of 1 m^2 . LiDAR accuracy was assessed as $\sim 60 \text{ cm}$ in the horizontal and $\sim 20 \text{ cm}$ in the vertical components. Because water does not reflect the LiDAR pulses, no data was available for the water pixels (unless emergent aquatic vegetation was present), and we used this property to discriminate water vs. non-water pixels inside the river polygons of the BD TOPO database. Elevations for these water pixels as well as for other sporadic data gaps were computed by attributing values from a digital elevation model (DEM) to the no data pixels. This 1-m resolution DEM, built from LiDAR final returns, provides values above water by interpolation of altitudes between the river banks. Finally, polygons from BD TOPO were also used to attribute DSM pixels to each reach of the T-NET network. Because LiDAR data were not available on the tributaries and the headwaters of the Loir, the *constant* method was applied on these reaches. With this configuration, the *lidar* method takes less than 5 hours to run on a computer with 16 CPUs and 64 Gb of RAM. Finally, in order to compare the *lidar* method with a situation without riparian vegetation, a supplementary simulation was done with SF and TVF fixed at zero everywhere.

In order to characterise differences in vegetation cover between the DSM and that derived from the BD TOPO database (Valette et al., 2012), a DEM was also used to create a raster of vegetation height by subtracting

the DEM (ground) elevations from the DSM. A vegetation cover map was then extracted from the vegetation height raster, where vegetation cover was defined as all pixels with vegetation higher than 1 m. A LiDAR-derived river width was also extracted for analysis purposes by dividing the area of water pixel inside each polygon by the length of the T-NET reaches.

Three model performance metrics were used to quantify the accuracy of the different methods regarding the maximum daily temperature. The root-mean-square error (RMSE) was used as a global performance metric:

$$RMSE = \sqrt{\frac{\sum (T_{sim} - T_{obs})^2}{N}} \quad (\text{Eq. 9})$$

where N is the number of observations, T_{sim} is the simulated river temperature and T_{obs} is the observed river temperature. Bias (defined as the mean difference between simulated and measured temperatures) was used to quantify the mean over/underestimation of the model. Finally, the standard deviation of errors (SDE) quantifies the variability of daily biases in a given period. Because the temperature time series used for model validation were not concomitant (Figure 4), model performance was analysed using two methods. First, we compared model performance against all available validation data. This allows for comparison between the three shading methods detailed in section 2.3. Second, in order to compare spatial variability in the model's performance between the 4 temperature logger stations, we used temperature data from the period during which concurrent measures were available at all 4 stations (13th to the 31st August 2009).

3. Results

3.1.Characterisation of riparian vegetation cover

Analysis of vegetation cover extracted from the LiDAR data inside a single buffer of 10 m around the 270 km of river shows that 58% of the riparian zone is vegetated. The median vegetation height in this area is 10.0 m and the third quartile of the height (considered by Guzy et al., 2015) is 14.9 m, while the standard deviation is 6.5 m. Longitudinal profiles of vegetation cover, median and 3rd quartile of height are given in Figure 5. There is a slight but significant decreasing downstream trend for these three variables (p-value = 0.014). In comparison with the LiDAR-derived vegetation cover, vegetation cover derived from the BD TOPO database is overestimated everywhere with the exception of some small reaches (Figure 5). The median overestimation is 35% upstream of river km 160 and 22% downstream. This overestimation rises to more than 39% for 20% of the reaches.

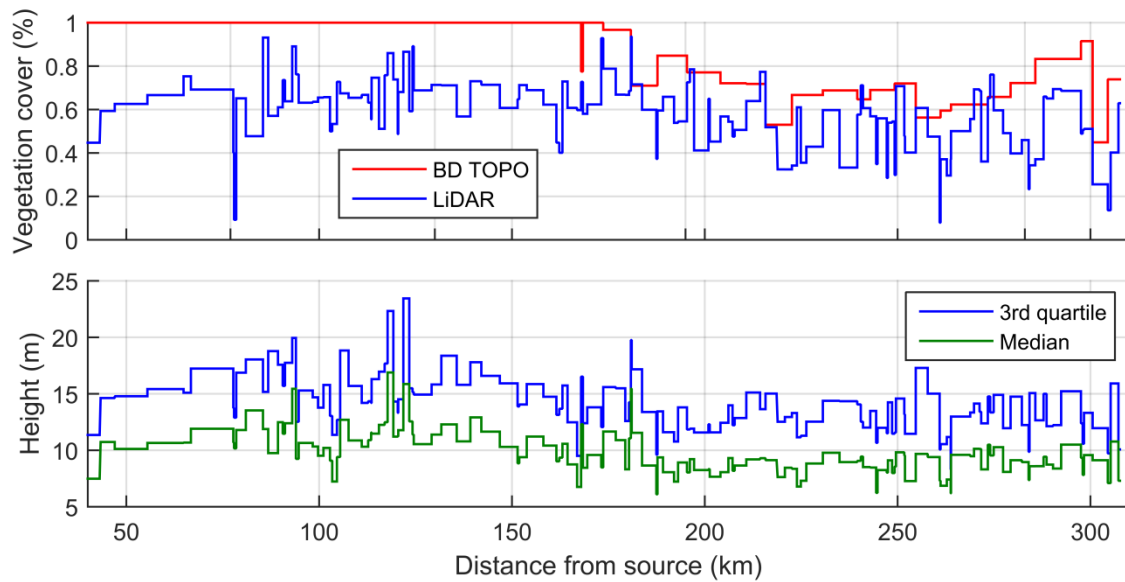


Figure 5: Characterisation of riparian vegetation for each T-NET reach (a) comparison of vegetation cover derived from the BD TOPO database (Valette et al., 2012) and LiDAR datasets (buffer of 10 m on both sides of the river polygons) (b) median and 3rd quartile vegetation heights from LiDAR data

3.2. Variation in riparian shading computed with the three methods

In the Loir catchment, direct and diffuse radiation comprise ~70% and ~30% respectively of the incoming solar radiation received at the river surface between 8 and 16h (period 2007-2014). This means that shadow factor has a greater impact on water temperature than view factor.

Figure 6 shows the longitudinal profile of SF on the Loir River for the three methods at midday on the summer solstice, when solar radiation is strongest. For the *constant* method, the reaches covered by LiDAR data have a uniform Strahler order of 5, so that the weighting coefficient k in this area is always equal to 0.4 (see section 2.3). The variation of SF is thus only dependent on the vegetation cover. The *variable* method varies strongly as a function of reach azimuth, even though the sun is at its highest elevation, while the *lidar* method shows smaller variations. The *lidar* method is thus less sensitive to reach azimuth, compared to the *variable* method.

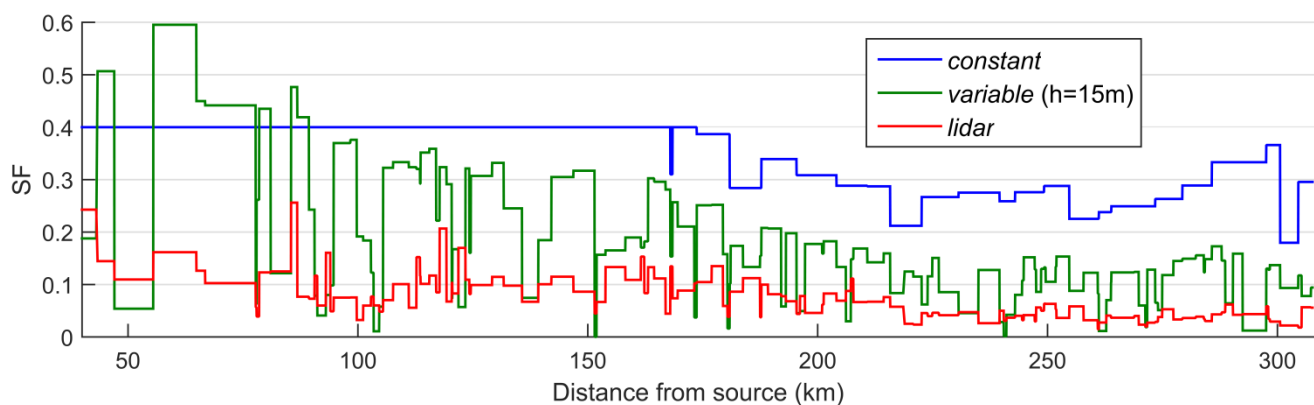


Figure 6: Longitudinal profile of shadow factor provided by the 3 methods on the Loir River at the summer solstice (21st June) at 12h UTC.

At noon, the Loir's SF computed with the *lidar* method lies between 0 and 0.3 in June (median=0.1; Figure 7a solid lines) and between 0.1 and 1 in December (median=0.5). There is thus more variability in winter than in summer, because reach azimuth has a much greater impact when the sun is low in the sky. Seasonal variability

in SF exhibits strong annual cyclicality, with SF minima centred on the summer solstice for every reach. Highest SF values are found on a reach located 85 km from the source, flowing East-West and bordered by persistent riparian forest cover (>20 m tall). Lowest SF values are found on a North-South oriented reach located 271 km from the source, explaining the weak annual cycle at noon (Figure 7a, pink solid line). Figure 7b shows the daily cycles at the summer solstice. The hour of minimum SF in a day is not always centred on noon because it depends on the reach orientation. SF obtained from the *variable* method is usually higher than that provided by the *lidar* method, except in winter and at noon for North-South oriented reaches (Figure 7a, dashed pink line). At the summer solstice, between 6 and 18h, the *variable* method yields higher SF than the *lidar* method 74% of the time, especially in the upstream parts of the watershed. Indeed, the *variable* method yields 184 occurrences of SF values equal to 1, while it only occurs 3 times with the *lidar* method.

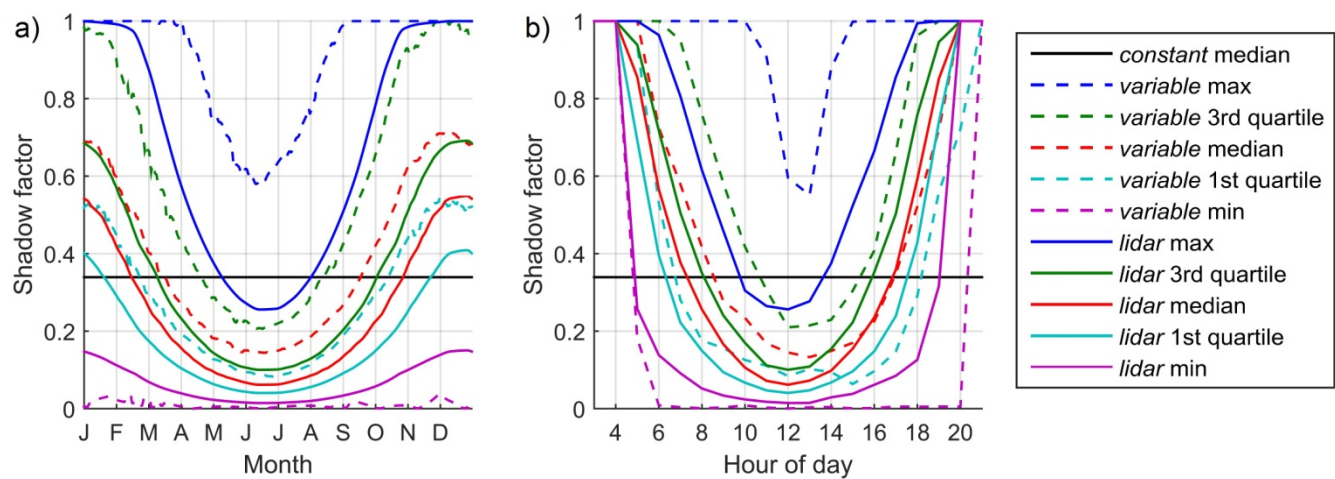


Figure 7: Percentiles of the SF distribution obtained with the three methods on the 135 T-NET reaches
(a) Annual cycles at noon (b) daily cycles at the summer solstice.

Figure 8 shows the longitudinal profile of TVF for the three methods. Mean values are 0.34, 0.38 and 0.26 for the *constant*, *variable* and *lidar* methods respectively. TVF computed with the *lidar* method comprises values between 0.47 and 0.11. Like for the SF, there is a significant ($p < 0.01$) decreasing trend due to both the increasing width of the river and the decreasing vegetation cover. The *variable* method overestimates TVF, especially for the upstream portion of the river. Indeed, the inter-method variability in computed TVF values decreases as the influence of vegetation on TVF reduces with increasing river width.

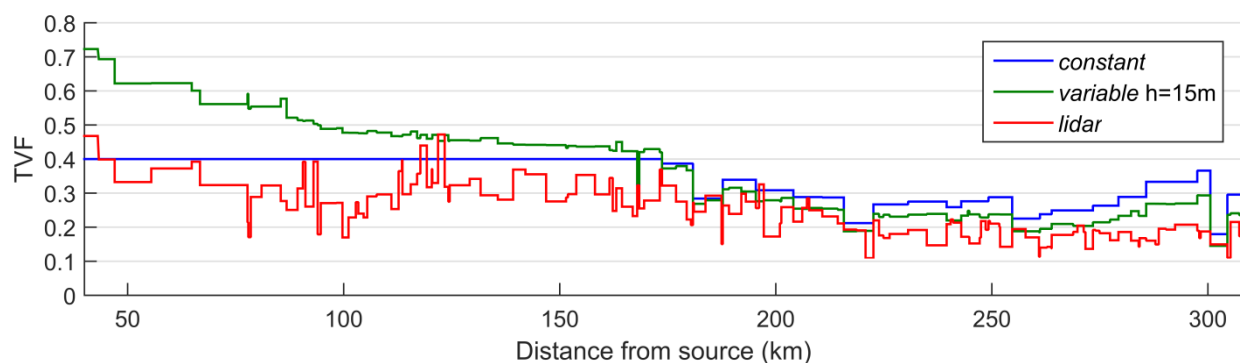


Figure 8: Longitudinal profile of tree view factor provided by the 3 methods on the Loir River.
Values from the *variable* method are averaged on 08/2007-07/2014

3.3.Impact of riparian shading method on annual and seasonal river temperature simulations

Results of this paper focus on the 4 temperature monitoring stations located on the Loir River, where LiDAR data are available. For the 14 other temperature monitoring stations located on the tributaries, the constant method provides a median annual RMSE on mean daily temperature at 1.69 °C (min=1.35 °C, max=2.89 °C). Seasonality in the accuracy is observed since median bias on mean daily temperature is -0.4 °C when computed for the full year but rises to 0.2 °C in summer. 67% of daily biases are comprised between ± 2 °C.

Biases, SDE and RMSE averaged on the four stations are shown in Table 1 for the April-September and the October-March periods. In the April-September period, the *lidar* method improves the mean bias by 0.62 °C in comparison with the *constant* method. The mean RMSE is improved by 0.22 °C although the mean SDE is increased by 0.10 °C. The three metrics show that the *constant* method provides better results than the *variable* method. During the October-March period, biases of the 3 methods are closer to zero. All criteria of the *constant* and the *lidar* methods are very similar because solar radiation is lower and vegetation transmissivity is high. However, the *variable* method is consistently colder than the other methods by ~ 0.3 °C.

Table 1: Model performance criteria for maximum daily temperature, averaged for the 4 stations located on the Loir River from April to September and from October to March (°C)

	April to September			October to March		
	Bias	SDE	RMSE	Bias	SDE	RMSE
<i>Constant</i> method	-1.44	1.61	2.17	-0.31	2.04	2.07
<i>Variable</i> method (h=15m)	-1.86	1.65	2.55	-0.60	2.09	2.18
<i>Lidar</i> method	-0.82	1.75	1.95	-0.33	2.05	2.08

Figure 9 shows the monthly biases ($T_{sim}-T_{obs}$) of maximum daily temperature (T_{max}) computed on available measured data (see Figure 4). At the four stations, the *lidar* method provides improved biases in comparison to both the *variable* and the *constant* method from April to September. Compared to the *variable* method, the maximum improvement occurs during the spring and autumn months (2 °C at S1; 1.5 °C at S2; 0.5 °C at S3; 0.7 °C at S4). Despite this improvement, the *lidar* method still underestimates river temperature by more than 1 °C during at least 2 months in summer at S1, S2 and S4. The *constant* method provides a consistently colder T_{max} than the *variable* (and *lidar*) methods at stations 3 and 4 from May to August, presumably because this method does not model the seasonal cycle of increasing and decreasing shadow length.

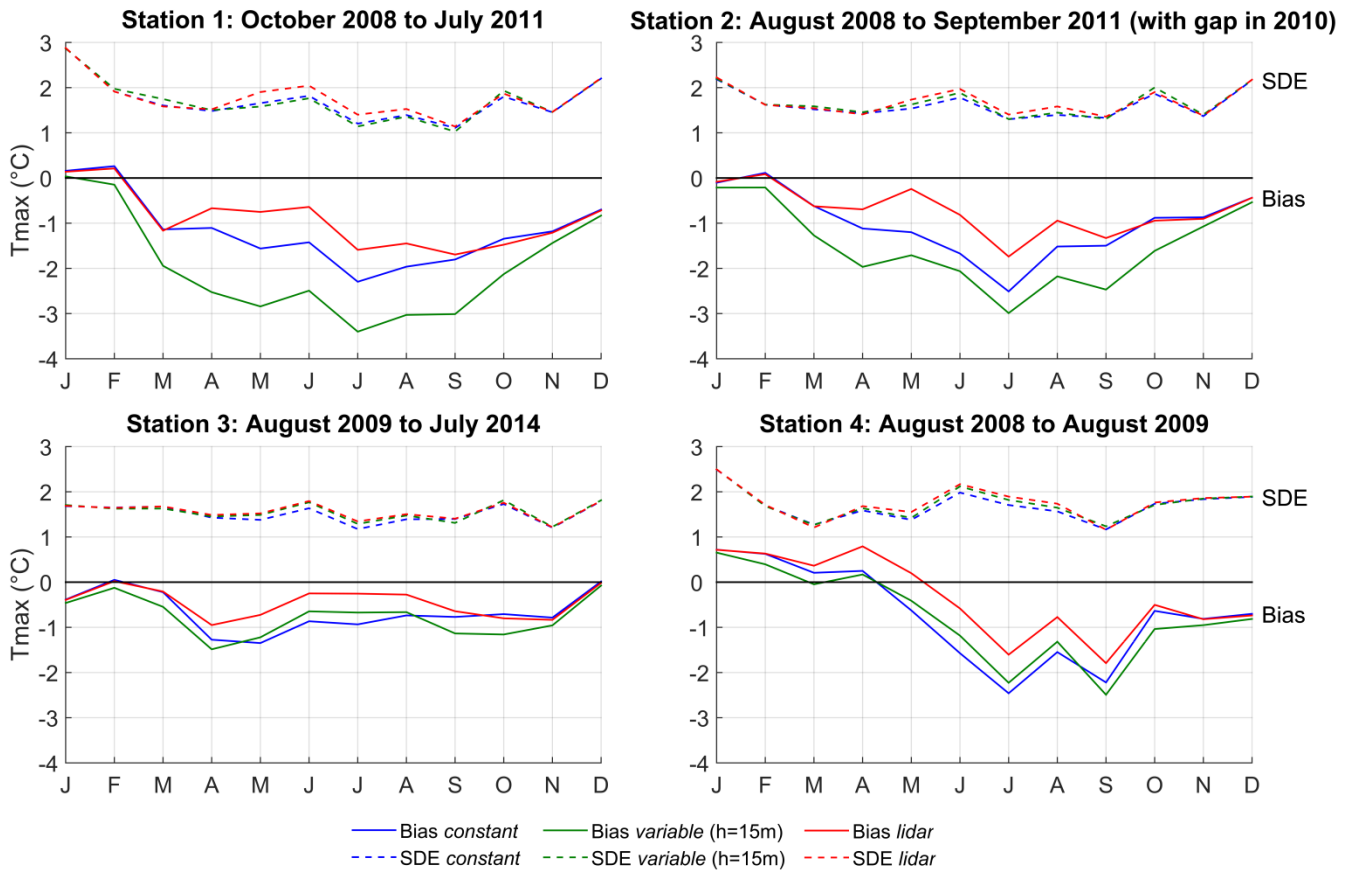


Figure 9: Monthly biases ($T_{sim}-T_{obs}$) and standard deviation of errors of maximum daily temperature provided by the 3 methods at the 4 stations (averaged annual cycles computed on available observed data)

Averaged annual cycles of SDE show little difference between methods and always stay above 1 °C (Figure 9). That means that simulated T_{max} is substantially more variable than observed data, whatever the method used.

3.4.Impact of riparian shading method on summer maximum daily temperature long profile

We analysed longitudinal profiles in summer by considering average maximum temperature between the 13th and the 31st August 2009. During this period, discharges were low ($<7 \text{ m}^3 \cdot \text{s}^{-1}$ at the downstream-most gauging station) and the averaged maximum daily air temperature in the catchment was relatively high (25.9 °C). The longitudinal profiles (Figure 10) exhibit discontinuities in the thermal signal that are driven by cool water inflows from the Conie and Aigre rivers, which drain the Beauce aquifer (Baratelli et al., 2016). Before entering the LiDAR-covered area (shown with a dashed vertical line), the *variable* method is colder than the *constant* method by more than 2.5 °C. This difference decreases slowly in a streamwise direction until it reverses and the *variable* method becomes warmer than the *constant*. Indeed, the three methods provide a persistent warming trend as a function of distance from source, but this trend is higher for the *variable* method (1.87 °C/100 km compared to 1.23 °C/100 km and 1.25 °C/100 km for the *constant* and *lidar* methods respectively). This difference in longitudinal trend persists across all summers in the 2007-2014 simulation period. On average between the 13th and 31st August 2009, the *lidar* methods provide warmer T_{max} than the two other methods all along the Loir, with biases close to zero at stations 3 and 4. However, T_{max} is still underestimated by 1.6 and 1.3 °C at stations 1 and 2. RMSE values are 1.99, 2.08, 1.43 and 1.79 °C on S1 to S4 respectively. Figure 10 also shows the simulation considering the absence of riparian vegetation. The difference between this output and the *lidar* method

reaches up to 3.0 °C just upstream of the Conie confluence, where sensitivity analysis shows that the *lidar* method simulation is no longer under the influence of the constant method applied upstream of the LiDAR area. This difference reaches a minimal value of 1.3 °C at the downstream-most point.

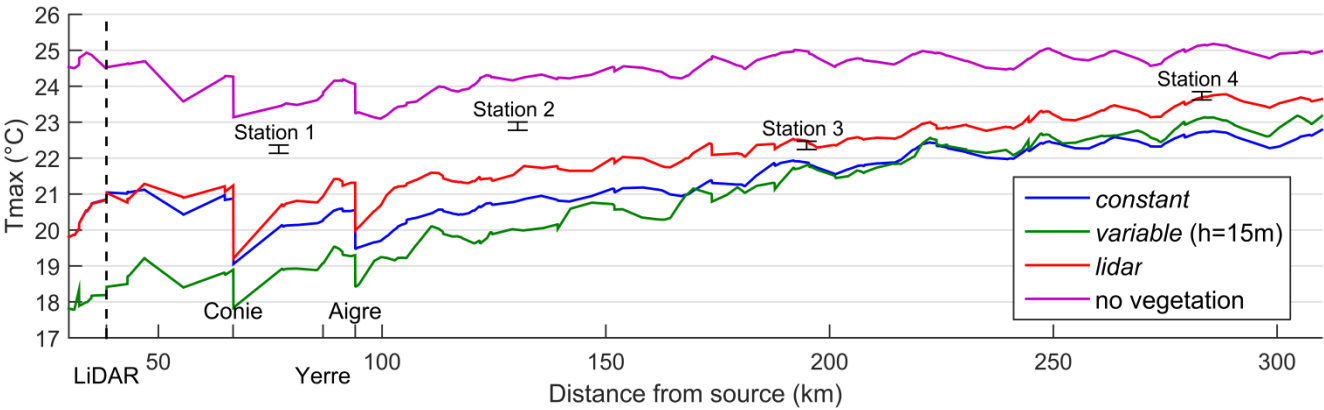


Figure 10: Longitudinal profile of maximum daily temperature (averaged between the 13 and the 31 August 2009) provided by the 3 methods and by a vegetation-free simulation. The vertical dashed line depicts the start of LiDAR cover. Conie, Yerre and Aigre are the main tributaries.

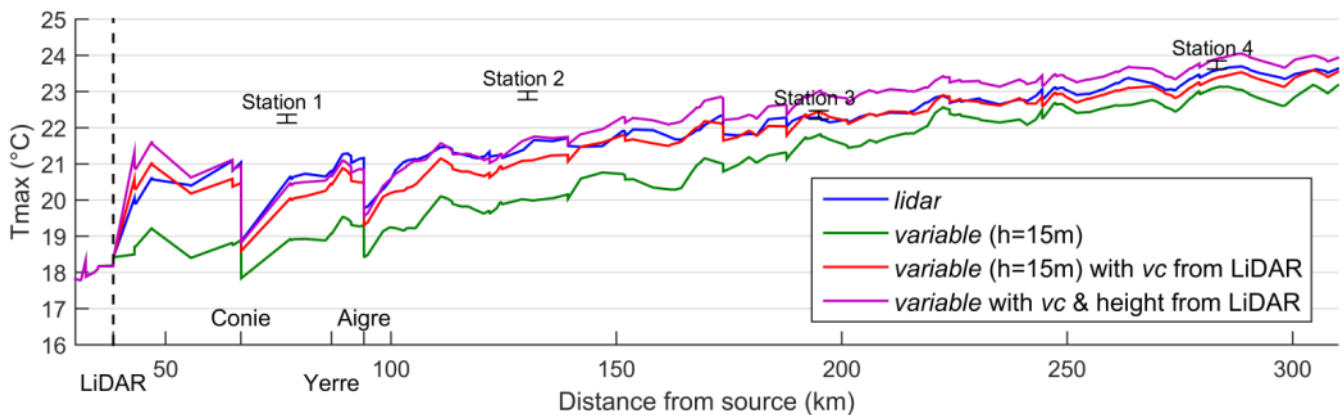
4. Discussion

4.1. Discrepancies in computed SF and TVF

The global overestimation of SF and TVF provided by the *variable* method compared to the *lidar* method can be explained by four key factors. First, the BD TOPO database that weights the results of the *variable* method clearly overestimates vegetation cover in relation to the LiDAR-derived values (discussed in section 3.1). Second, comparison of the wetted widths used in the *variable* method with LiDAR-derived river widths shows that the former are underestimated, especially upstream of ~150 km and downstream of ~250 km from the source. These width uncertainties drive an increase in SF (TVF) of 6% (4%) when averaged over the entire modelling period and 14% (9%) between 13th and 31st August 2009. Third, discrepancies may also arise from the fact that the *variable* method uses averaged stream azimuths while the *lidar* method intrinsically considers the position of vegetation in regard to the water surface. Indeed, reach azimuth impacts the timing of minimum SF (Li et al. 2012), the hourly amount of direct solar radiation and hence the maximum daily temperature (Garner et al., 2017). In order to quantify these discrepancies, we cut the Loir river GIS line in 50 m parts and compared azimuths of these small reaches with the original T-NET reaches azimuths. The mean absolute difference is 26° and R² is 0.66. Finally, the characterisation of vegetation cover and height at high resolution with the LiDAR data may not be reproducible in the *variable* method by taking an average of these data at the reach scale. Indeed, Greenberg et al. (2012) report that 28% of the change in insolation caused by removal of riparian vegetation characterised with LiDAR data could not be explained by considering averages at the reach scale. In our case, a multiple linear regression between LiDAR-derived TVF and LiDAR-derived tree height, vegetation cover and river width averaged at the reach scale provides R²=0.83. Hence, 17% of the TVF variance cannot be explained by these three variables when averaged at the reach scale.

4.2. Influence of shading routine on simulated river temperatures

443 In order to separate the influence of the *variable* method itself from the influence of the vegetation cover data
 444 used to drive it, we injected the vegetation cover computed from the LiDAR data (10 m buffers on each river
 445 bank for each reach) into the *variable* method. As a first step, tree height was kept at 15 m. The resulting
 446 longitudinal profile (13 to 31 August 2009 average) shows that, in this configuration, the *variable* method closely
 447 approximates the *lidar* method (Figure 11). The mean bias (computed against observed temperatures) between
 448 April and September is -1.19 °C, compared to -0.94 °C for the *lidar* method and to -1.86 °C for the *variable*
 449 method with the original vegetation cover. The median vegetation height computed from the LiDAR dataset was
 450 subsequently also injected into the *variable* method. In this case, mean bias is further reduced to -0.78 °C. Using
 451 the same approach with the *constant* method provides a profile that is warmer than the *lidar* method profile
 452 prior to river km 100 and colder after river km 200. Hence, a coefficient $k=0.4$ seems to be appropriate for a
 453 river width of 25-30 m, during the month of August.



454
 455 **Figure 11: Longitudinal profile of maximum daily temperature (averaged between the 13 and the 31 August 2009) provided by**
 456 **injecting the *variable* method with vegetation cover (vc) and median height from LiDAR data. The vertical dashed line depicts the**
 457 **start of LiDAR cover. Conie, Yerre and Aigre are the main tributaries.**
 458

459 **4.3. Performance of T-NET model on the Loir River**

460 Although the T-NET model of the Loir River (driven with the *lidar* method) provides relatively unbiased
 461 temperature at station 3, it still underestimates temperature at stations 1 and 2 and to a lesser extent at station
 462 4 (Figure 9). Sensitivity analyses show that uncertainty about the impact of vegetation on tributaries (because of
 463 the application of the *constant* method in areas where LiDAR data do not exist) cannot fully explain the
 464 underestimation of modelled temperatures on the Loir. Underestimation at station 1 is partly due to the
 465 underestimation of the Conie tributary. An impoundment located at the source of the river likely explains why
 466 the Conie is warmer than expected (Pedersen and Sand-Jensen, 2007; Dripps and Granger, 2013).
 467 Impoundments on several other tributaries may have the same effect and contribute to warming the Loir River
 468 and hence explain the negative biases at station 2. Station 4 is located just upstream of a small weir. There are
 469 more than 120 small weirs (height <3m) on the Loir River that may partially explain the temperature
 470 underestimation. Indeed, by increasing water depth, they increase travel time and thus sensitivity to air
 471 temperature. By decreasing water velocity, they can favour thermal stratification in summer (Torgersen et al.,
 472 2001) and since water is usually released by weir-overflow, warmer water may be selectively released. This
 473 process is not taken into account in T-NET because it only considers the longitudinal dimension. Other more
 474 complex hydrodynamic models (eg. Becker et al., 2010; Cole and Wells, 2006; Maderich et al., 2008; Deltares,

2014) would therefore be required to incorporate this process. The high temporal variability in modelled temperatures (compared to observed data) is likely due to modelled flow velocities that exceed real values. Unfortunately however, we have no observed values of travel time to compare with. Finally, it must be kept in mind that 1) computed model performances are dependent on the number of validation stations, which is limited to 4 in the current study and 2) that the T-NET model is driven with re-analysis data which are themselves subject to errors. In particular, the number of meteorological stations providing air temperature as input of the SAFRAN reanalysis in the Loir catchment is limited: approximately 10 stations are located upstream of S1 but only 2 stations located close to each other cover the rest of the basin (Quintana-Seguí et al., 2008). The density of stations is still lower for wind velocity and relative humidity but is higher for precipitations.

4.4. Implications, shading methods limitations and perspectives

Our results show that the *lidar* method has good potential for computation of SF and SVF at hourly timesteps on medium to large rivers and at large temporal and spatial scales. For small rivers (width < 10 m), whose precise location can be hard to determine using remote sensing due to obscuration by the tree canopy, the *variable* method may be more suitable, as long as it is fed with accurate vegetation cover data. Indeed, our results show that differences of modelled T_{max} can be large if the methods are used with inaccurate vegetation cover data. The quality of these input data is therefore highly important for improving stream temperature modelling. LiDAR covers of riparian zones are increasingly available, in particular because of their use for flood risk assessments. Furthermore, vegetation heights can also be obtained at the catchment scale by photogrammetric techniques (eg. Michez et al., 2017), while satellite and airborne high resolution imagery can provide accurate location of riparian vegetation (Tormos et al., 2014). These new techniques could potentially be valuable for improving future river temperature modelling efforts.

Our results show that in late August 2009, the Loir's vegetation decreases T_{max} up to 3 °C in the upstream part of the river and by 1.3 °C at the downstream-most reaches. This difference is caused by the increasing wetted width (from ~25 to ~50 m) but also by decreasing vegetation cover in the streamwise direction. These quantifications of the thermal impact of riparian vegetation are likely minimum values for two reasons. First, the impact of overhanging trees was neglected (as in all methods used in this paper) (Li et al., 2012; DeWalle, 2008). Secondly, the summer transmissivity value comes from publications studying single trees' transmissivity. However, because riparian buffers are often composed of several rows of trees, real world transmissivity values are likely to be lower, resulting in slightly cooler water temperatures (Duursma and Mäkelä, 2007; Dugdale et al., 2018). Beside this, further research is needed to validate the accuracy of shadows obtained with the *lidar* method against aerial imagery. As an example, Greenberg et al. (2012) reported an overall accuracy of 92%. Since their LiDAR data and ours were both acquired when trees were in leaf, a similar accuracy may be expected.

A wide range of values is reported in the literature regarding the cooling effect of vegetation (Moore et al., 2005), mainly for streams narrower than 10 m, for which the response of T_{max} to clear-cutting can range from 2 to 8°C (Gomi et al., 2006). For streams wider than 10 m, a modelling approach is usually used to quantify the

512 impacts of vegetation on stream temperature. Our results are in agreement with Woltemade and Hawkins
513 (2016), who modelled a cooling effect of vegetation of approximately 2 °C for a 14 m wide North-West/South-
514 East oriented stream flowing in a mountainous catchment of California (low-flow conditions). A topographic
515 shade of 17% was considered in the deforested scenario; their result would thus be higher in an environment
516 without mountains, like the Loir catchment. Using LiDAR data, Wawrzyniak et al. (2017) modelled a cooling
517 impact of 0.4 °C on T_{max} on a 22 km-long groundwater-fed river reach with a wetted width ranging from 50 to
518 120 m. The overall NNE-SSW orientation of this river is likely to decrease the impact of riparian vegetation, in
519 comparison with the Loir, which is globally east-west orientated. Other studies show that the impact of
520 vegetation decreases steadily as wetted width increases to about 30 m (Teti, 2006), 10 m (Davies-Colley and
521 Quinn, 1998) and 17 to 43 m for East-West to North-South oriented streams (DeWalle, 2008). Our results
522 suggest that the cooling effect can remain above 1 °C even for widths larger than 40 m.

523 Potential improvements to our *lidar* method include the incorporation of wetted widths related to the
524 discharge. Although this is possible at small spatial and temporal scales by using a hydraulic model (Wawrzyniak
525 et al., 2017), modelling wetted widths at regional scales can be very complex, especially without field measures
526 of hydraulic geometry. Channel morphology from bathymetric LiDAR data may be one potential solution to this
527 issue (eg. Hildale and Raff, 2008; Bailly et al., 2010). Another potential improvement to our methodology relates
528 to the use of Beer's law to model the extinction of solar rays through the tree canopy, as demonstrated by
529 several investigations using coarse vegetation data (Sun et al., 2015; Tung et al., 2007; Sridhar et al., 2004; Lee
530 et al., 2012). Transmission of light beneath the canopy of overhanging trees could also be modelled, but
531 requires information or hypotheses regarding the shape of trees. When aerial imagery is available, more
532 complex methods considering position of individual trees may be used in order to model the transmission of
533 light beneath the canopy (Essery et al., 2008).

534 Finally, this paper focuses on the impact of vegetation on solar radiation and hence on maximum daily
535 temperature (Johnson, 2004; Garner et al., 2017). Although the impact of vegetation on longwave radiation is
536 limited on sunny days (Leach and Moore, 2010; DeWalle, 2008), view factors computed in this paper could be
537 used to quantify the impact of vegetation on longwave fluxes at both regional scales and during a complete
538 annual cycle. LiDAR data could also be used to model the impact of vegetation on water temperature resulting
539 from decreased air temperature and wind velocity engendered by the riparian canopy. Indeed, forest canopies
540 can reduce daytime air temperature by 3 °C to more than 6 °C and wind velocity by 10-20 % in comparison with
541 open areas (Moore et al., 2005).

542

543 **5. Conclusion**

544 The main goal of this study was to understand the influence of using a LiDAR-derived digital surface model to
545 quantify the impact of riparian vegetation on 270 km of the Loir River. We demonstrated that the use of LiDAR
546 data improves the mean biases of simulated maximum daily temperatures (T_{max}) in summer, compared to two
547 other simpler methods for computing the effects of riparian shading at large scales. However, it did not improve

the standard deviation of errors on T_{max} , which is likely more influenced by the presence of weirs and impoundments.

The monthly-averaged difference in T_{max} computed by the various shading methods can reach up to 2 °C at the upstream-most station and 1 °C at the downstream-most station. However, this difference is mainly due to the overestimation of vegetation cover in the dataset used to compute shadow and view factors in the non-*lidar* methods. Indeed, injection of vegetation cover extracted from the LiDAR data into the shading method of medium complexity (*variable method*) decreased the largest difference at the upstream-most station to 0.8 °C, suggesting that this method is sufficient for the computation of SF and VF provided that it is supplied with accurate (high-resolution) data pertaining to vegetation cover. Improving the quality of riparian vegetation data should therefore be a priority for improving stream temperature modelling at the regional scale. The simplest method (*constant method*) may be appropriate to model mean daily temperature for a given period of the year, as long as vegetation cover is weighted with a coefficient depending on the river width.

We hope that the application and comparison of methods demonstrated in this paper will improve understanding of the strengths and limitations of other existing stream temperature models. Enhancing the ability of models to simulate the impact of riparian vegetation is of key importance for the development of climate change adaptation measures and understanding the fundamental processes responsible for spatio-temporal variability of river temperature.

565

566 **Acknowledgements**

This work forms part of a PhD thesis project supported by Agence française pour la biodiversité. Thanks are due to Météo-France for the SAFRAN database, to Transvalor for the Helioclim data, to D. Thiéry for the hydrological modelling, to A. Chandesris for the vegetation database, to K. Soudani for the NDVI data, to Direction régionale de l'environnement, de l'aménagement et du logement Pays de la Loire and to Fédération Départementale de Pêche d'Eure et Loir for the temperature data. This paper was improved thanks to the comments of two anonymous reviewers. We also thank the CaSciModOT federation (Calcul Scientifique et Modélisation Orléans Tours) as well as Yves Lansac and Enrick Olive (GREMAN UMR 7347) for providing the computing resources.

574

576 **References**

577

578 Anderson E. R. (1954) Energy budget studies, Part of Water Loss Investigations—Lake Hefner Studies. *US*
579 *Geological Survey. Professional Paper*, 269.

580 Bailly J.-S., Le Coarer Y., Languille P., Stigermark C.-J., Allouis T. (2010) Geostatistical estimations of bathymetric
581 LiDAR errors on rivers. *Earth Surface Processes and Landforms*, 35 (10), 1199–1210.

582 Baratelli F., Flipo N., Moatar F. (2016) Estimation of stream-aquifer exchanges at regional scale using a
583 distributed model: Sensitivity to in-stream water level fluctuations, riverbed elevation and roughness.
584 *Journal of Hydrology*, 542, 686–703.

585 Beaufort A., Curie F., Moatar F., Ducharne A., Melin E., Thiery D. (2016) T-NET, a dynamic model for simulating
586 daily stream temperature at the regional scale based on a network topology. *Hydrological Processes*,
587 2196–2210.

588 Beaufort A., Moatar F., Curie F., Ducharne A., Bustillo V., Thiéry D. (2015) River Temperature Modelling by
589 Strahler Order at the Regional Scale in the Loire River Basin, France. *River Research and Applications*,
590 597–609.

591 Becker A., Kirchesch V., Baumert H. Z., Fischer H., Schöl A. (2010) Modelling the effects of thermal stratification
592 on the oxygen budget of an impounded river. *River Research and Applications*, 26 (5), 572–588.

593 Boisneau C., Moatar F., Bodin M., Boisneau P. (2008) Does global warming impact on migration patterns and
594 recruitment of Allis shad (*Alosa alosa* L.) young of the year in the Loire River, France? *Hydrobiologia*, 602
595 (1), 179–186.

596 Bustillo V., Moatar F., Ducharne A., Thiéry D., Poirel A. (2014) A multimodel comparison for assessing water
597 temperatures under changing climate conditions via the equilibrium temperature concept: case study of
598 the Middle Loire River, France. *Hydrological Processes*, 28 (3), 1507–1524.

599 Cantón M. A., Cortegoso J. L., Rosa C. de. (1994) Solar permeability of urban trees in cities of western Argentina.
600 *Energy and Buildings*, 20 (3), 219–230.

601 Chen Y. D., Carsel R. F., McCutcheon S. C., Nutter W. L. (1998) Stream Temperature Simulation of Forested
602 Riparian Areas: I. Watershed-Scale Model Development. *Journal of Environmental Engineering*, 124 (4),
603 304–315.

604 Cheng S.-T., Wiley M. J. (2016) A Reduced Parameter Stream Temperature Model (RPSTM) for basin-wide
605 simulations. *Environmental Modelling & Software*, 82, 295–307.

606 Cole T., Wells S. (2006) CE-QUAL-W2: A Two-dimensional, Laterally Averaged, Hydrodynamic and Water Quality
607 Model, Version 3.5. *Civil and Environmental Engineering Faculty Publications and Presentations*.
608 Retrieved from http://pdxscholar.library.pdx.edu/cengin_fac/130

609 Cox M. M., Bolte J. P. (2007) A spatially explicit network-based model for estimating stream temperature
610 distribution. *Environmental Modelling & Software* Special section: Environmental Risk and Emergency
611 Management, 22 (4), 502–514.

612 Davies-Colley R. J., Quinn J. M. (1998) Stream lighting in five regions of North Island, New Zealand: Control by
613 channel size and riparian vegetation. *New Zealand Journal of Marine and Freshwater Research*, 32 (4),
614 591–605.

615 Deltares. (2014) Delft3D-FLOW: Simulation of Multidimensional Hydrodynamic Flows and Transport
616 Phenomena, including Sediments, User Manual. *Deltares Systems, Delft, The Netherlands*, 684 pp.

617 DeWalle D. R. (2008) Guidelines for Riparian Vegetative Shade Restoration Based Upon a Theoretical Shaded-
618 Stream Model. *JAWRA Journal of the American Water Resources Association*, 44 (6), 1373–1387.

619 Dripps W., Granger S. R. (2013) The impact of artificially impounded, residential headwater lakes on
620 downstream water temperature. *Environmental Earth Sciences*, 68 (8), 2399–2407.

621 Dugdale S. J., Malcolm I. A., Kantola K., Hannah D. M. (2018) Stream temperature under contrasting riparian
622 forest cover: Understanding thermal dynamics and heat exchange processes. *Science of The Total*
623 *Environment*, 610, 1375–1389.

624 Duursma R. A., Mäkelä A. (2007) Summary models for light interception and light-use efficiency of non-
625 homogeneous canopies. *Tree Physiology*, 27 (6), 859–870.

626 Essery R., Bunting P., Rowlands A., Rutter N., Hardy J., Melloh R., Link T., et al. (2008) Radiative Transfer
627 Modeling of a Coniferous Canopy Characterized by Airborne Remote Sensing. *Journal of*
628 *Hydrometeorology*, 9 (2), 228–241.

- Fu P., Rich P. M. (1999) Design and implementation of the Solar Analyst: an ArcView extension for modeling solar radiation at landscape scales. *Proceedings of the Nineteenth Annual ESRI User Conference*, 1–31.
- Garner G., Malcolm I. A., Sadler J. P., Hannah D. M. (2014) What causes cooling water temperature gradients in a forested stream reach? *Hydrology and Earth System Sciences*, 18 (12), 5361–5376.
- Garner G., Malcolm I. A., Sadler J. P., Hannah D. M. (2017) The role of riparian vegetation density, channel orientation and water velocity in determining river temperature dynamics. *Journal of Hydrology*. Retrieved from <http://www.sciencedirect.com/science/article/pii/S0022169417301695>
- Gomi T., Moore R. D., Dhakal A. S. (2006) Headwater stream temperature response to clear-cut harvesting with different riparian treatments, coastal British Columbia, Canada. *Water Resources Research*, 42 (8), W08437.
- GRASS Development Team. (2015) Geographic Resources Analysis Support System (GRASS GIS) Software, Version 7.1; Open Source Geospatial Foundation. Retrieved from <http://grass.osgeo.org>
- Greenberg J. A., Hestir E. L., Riano D., Scheer G. J., Ustin S. L. (2012) Using LiDAR Data Analysis to Estimate Changes in Insolation Under Large-Scale Riparian Deforestation. *JAWRA Journal of the American Water Resources Association*, 48 (5), 939–948.
- Guzy M., Richardson K., Lambrinos J. G. (2015) A tool for assisting municipalities in developing riparian shade inventories. *Urban Forestry & Urban Greening*, 14 (2), 345–353.
- Haag I., Luce A. (2008) The integrated water balance and water temperature model LARSIM-WT. *Hydrological Processes*, 22 (7), 1046–1056.
- Haag I., Westrich B. (2002) Processes governing river water quality identified by principal component analysis. *Hydrological Processes*, 16 (16), 3113–3130.
- Hannah D., Garner G. (2015) River water temperature in the United Kingdom: Changes over the 20th century and possible changes over the 21st century. *Progress in Physical Geography*, 39, 68–92.
- Hilldale R. C., Raff D. (2008) Assessing the ability of airborne LiDAR to map river bathymetry. *Earth Surface Processes and Landforms*, 33 (5), 773–783.
- Hofierka J., Suri M. (2002) The solar radiation model for Open source GIS: implementation and applications. *Proceedings of the Open source GIS-GRASS users conference*, 1–19.
- Johnson G. T., Watson I. D. (1984) The Determination of View-Factors in Urban Canyons. *Journal of Climate and Applied Meteorology*, 23 (2), 329–335.
- Johnson M. F., Wilby R. L. (2015) Seeing the landscape for the trees: Metrics to guide riparian shade management in river catchments. *Water Resources Research*, 51 (5), 3754–3769.
- Johnson S. L. (2004) Factors influencing stream temperatures in small streams: substrate effects and a shading experiment. *Canadian Journal of Fisheries and Aquatic Sciences*, 61 (6), 913–923.
- Konarska J., Lindberg F., Larsson A., Thorsson S., Holmer B. (2014) Transmissivity of solar radiation through crowns of single urban trees - application for outdoor thermal comfort modelling. *Theoretical and Applied Climatology*, 117 (3–4), 363–376.
- Lalot E., Curie F., Wawrzyniak V., Schomburgk S., Piegay H., Moatar F. (2015) Quantification of the Beauce's Groundwater contribution to the Loire River discharge using satellite infrared imagery. *Hydrol. Earth Syst. Sci. Discuss.*, 12 (2), 2047–2080.
- Lamouroux N., Pella H., Vanderbecq A., Sauquet E., Lejot J. (2010) Estimkart 2.0: Une plate-forme de modèles échohydrologiques pour contribuer à la gestion des cours d'eau à l'échelle des bassins français. Version provisoire. *Version provisoire. Cemagref, Agence de l'Eau Rhône-Méditerranée-Corse, Onema, Lyon (45 pp.)*.
- Leach J., Moore R. (2010) Above-stream microclimate and stream surface energy exchanges in a wildfire-disturbed riparian zone. *Hydrological Processes*, 24 (17), 2369–2381.
- LeBlanc R. T., Brown R. D., FitzGibbon J. E. (1997) Modeling the Effects of Land Use Change on the Water Temperature in Unregulated Urban Streams. *Journal of Environmental Management*, 49 (4), 445–469.
- Lebourgeois F., Pierrat J.-C., Perez V., Piedallu C., Cecchini S., Ulrich E. (2008) Phenological timing in French temperate forests - A study on stands in the Renecofor network. Retrieved from <http://hdl.handle.net/2042/19767>
- Lee T. Y., Huang J. C., Kao S. J., Liao L. Y., Tzeng C. S., Yang C. H., Kalita P. K., et al. (2012) Modeling the effects of riparian planting strategies on stream temperature: Increasing suitable habitat for endangered Formosan Landlocked Salmon in Shei-Pa National Park, Taiwan. *Hydrological Processes*, 26 (24), 3635–3644.
- Li G., Jackson C. R., Kraseski K. A. (2012) Modeled riparian stream shading: Agreement with field measurements and sensitivity to riparian conditions. *Journal of Hydrology*, 428, 142–151.

- Loinaz M. C., Davidsen H. K., Butts M., Bauer-Gottwein P. (2013) Integrated flow and temperature modeling at the catchment scale. *Journal of Hydrology*, 495, 238–251.
- Maderich V., Heling R., Bezhenar R., Brovchenko I., Jenner H., Koshebutskyy V., Kusch A., et al. (2008) Development and application of 3D numerical model THREE-TOX to the prediction of cooling water transport and mixing in the inland and coastal waters. *Hydrological Processes*, 22 (7), 1000–1013.
- Magnuson J. J., Crowder L. B., Medvick P. A. (1979) Temperature as an Ecological Resource. *American Zoologist*, 19 (1), 331–343.
- Marchand M., Al-Azri N., Ombe-Ndeffotsing A., Wey E., Wald L. (2017) Evaluating meso-scale change in performance of several databases of hourly surface irradiation in South-eastern Arabic Peninsula. *Advances in Science and Research*, 14, 7.
- Michez A., Piégay H., Lejeune P., Claessens H. (2017) Multi-temporal monitoring of a regional riparian buffer network (>12,000 km) with LiDAR and photogrammetric point clouds. *Journal of Environmental Management* Piégay & Lamouroux “Enlarging spatial and temporal scales for biophysical diagnosis and sustainable river management,” 202 (Part 2), 424–436.
- Moatar F., Gailhard J. (2006) Water temperature behaviour in the River Loire since 1976 and 1881. *Comptes Rendus Geoscience*, 338 (5), 319–328.
- Moatar F., Miquel J., Poirel A. (2001) A quality-control method for physical and chemical monitoring data. Application to dissolved oxygen levels in the river Loire (France). *Journal of Hydrology*, 252 (1–4), 25–36.
- Moore R. D., Leach J. A., Knudson J. M. (2014) Geometric calculation of view factors for stream surface radiation modelling in the presence of riparian forest. *Hydrological Processes*, 28 (6), 2975–2986.
- Moore R. D., Spittlehouse D. L., Story A. (2005) Riparian Microclimate and Stream Temperature Response to Forest Harvesting: A Review. *JAWRA Journal of the American Water Resources Association*, 41 (4), 813–834.
- Muller E. (1995) Phénologie forestière révélée par l’analyse d’images thématiques. *Comptes rendus de l’Académie des sciences. Série 3, Sciences de la vie*, 318 (9), 993–1003.
- Nash J. E., Sutcliffe J. V. (1970) River flow forecasting through conceptual models part I — A discussion of principles. *Journal of Hydrology*, 10 (3), 282–290.
- Ouellet V., Secretan Y., St-Hilaire A., Morin J. (2014) Daily Averaged 2d Water Temperature Model for the St. Lawrence River. *River Research and Applications*, 30 (6), 733–744.
- Pedersen N. L., Sand-Jensen K. (2007) Temperature in lowland Danish streams: contemporary patterns, empirical models and future scenarios. *Hydrological Processes*, 21 (3), 348–358.
- Quintana-Seguí P., Le Moigne P., Durand Y., Martin E., Habets F., Baillon M., Canellas C., et al. (2008) Analysis of near-surface atmospheric variables: Validation of the SAFRAN analysis over France. *Journal of applied meteorology and climatology*, 47 (1), 92–107.
- Sattin M., Milne R., Deans J. D., Jarvis P. G. (1997) Radiation interception measurement in poplar: sample size and comparison between tube solarimeters and quantum sensors. *Agricultural and Forest Meteorology*, 85 (3–4), 209–216.
- Sellers W. D. (1965) Physical climatology; University of Chicago Press.
- Soudani K., Hmimina G., Delpierre N., Pontailier J.-Y., Aubinet M., Bonal D., Caquet B., et al. (2012) Ground-based Network of NDVI measurements for tracking temporal dynamics of canopy structure and vegetation phenology in different biomes. *Remote Sensing of Environment*, 123, 234–245.
- Sridhar V., Sansone A. L., LaMarche J., Dubin T., Lettenmaier D. P. (2004) Prediction of stream temperature in forested watersheds; Wiley Online Library.
- Sun N., Yearsley J., Voisin N., Lettenmaier D. P. (2015) A spatially distributed model for the assessment of land use impacts on stream temperature in small urban watersheds. *Hydrological Processes*, 29 (10), 2331–2345.
- Teti P. (2006) Stream shade as a function of channel width and riparian vegetation in the BC southern interior. *Streamline Watershed Manag. Bull.*, (9), 10–15.
- Thiéry D., Moutzopoulos C. (1992) Un modèle hydrologique spatialisé pour la simulation de très grands bassins: le modèle EROS formé de grappes de modèles globaux élémentaires. *VIIIèmes journées hydrologiques de l’ORSTOM: Régionalisation en hydrologie, application au développement*, 285–295; ORSTOM Editions.
- Torgersen C. E., Faux R. N., McIntosh B. A., Poage N. J., Norton D. J. (2001) Airborne thermal remote sensing for water temperature assessment in rivers and streams. *Remote Sensing of Environment*, 76 (3), 386–398.
- Tormos T., Van Looy K., Villeneuve B., Kosuth P., Souchon Y. (2014) High resolution land cover data improve understanding of mechanistic linkages with stream integrity. *Freshwater Biology*, 59 (8), 1721–1734.

741 Tung C.-P., Lee T.-Y., Yang Y.-C. (2006) Modelling climate-change impacts on stream temperature of Formosan
742 landlocked salmon habitat. *Hydrological Processes*, 20 (7), 1629–1649.

743 Tung C.-P., Yang Y.-C. E., Lee T.-Y., Li M.-H. (2007) Modification of a stream temperature model with Beer’s law
744 and application to GaoShan Creek in Taiwan. *Ecological Modelling*, 200 (1–2), 217–224.

745 Valette L., Piffady J., Chandesris A., Souchon Y. (2012) SYRAH-CE: description des données et modélisation du
746 risque d’altération de l’hydromorphologie des cours d’eau pour l’Etat des lieux DCE. *Rapport final, Pôle*
747 *Hydroécologie des cours d’eau Onema-Irstea Lyon, MALY-LHQ, Lyon.*

748 Vidal J.-P., Martin E., Franchistéguy L., Baillon M., Soubeyroux J.-M. (2010) A 50-year high-resolution
749 atmospheric reanalysis over France with the Safran system. *International Journal of Climatology*, 30
750 (11), 1627–1644.

751 Wawrzyniak V., Allemand P., Bailly S., Lejot J., Piégay H. (2017) Coupling LiDAR and thermal imagery to model
752 the effects of riparian vegetation shade and groundwater inputs on summer river temperature. *Science*
753 *of The Total Environment*, 592 (Supplement C), 616–626.

754 Woltemade C. J., Hawkins T. W. (2016) Stream Temperature Impacts Because of Changes in Air Temperature,
755 Land Cover and Stream Discharge: Navarro River Watershed, California, USA. *River Research and*
756 *Applications*, 32 (10), 2020–2031.

757