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Pierre Loicq, Florentina Moatar, Yann Jullian, Stephen J. Dugdale, David M. Hannah. Improving representation of riparian vegetation shading in a regional stream temperature model using LiDAR data. *Science of the Total Environment*, 2018, 624, pp.480–490. 10.1016/j.scitotenv.2017.12.129 . hal-02377286

**HAL Id: hal-02377286**

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DOI:

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

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*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>

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

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

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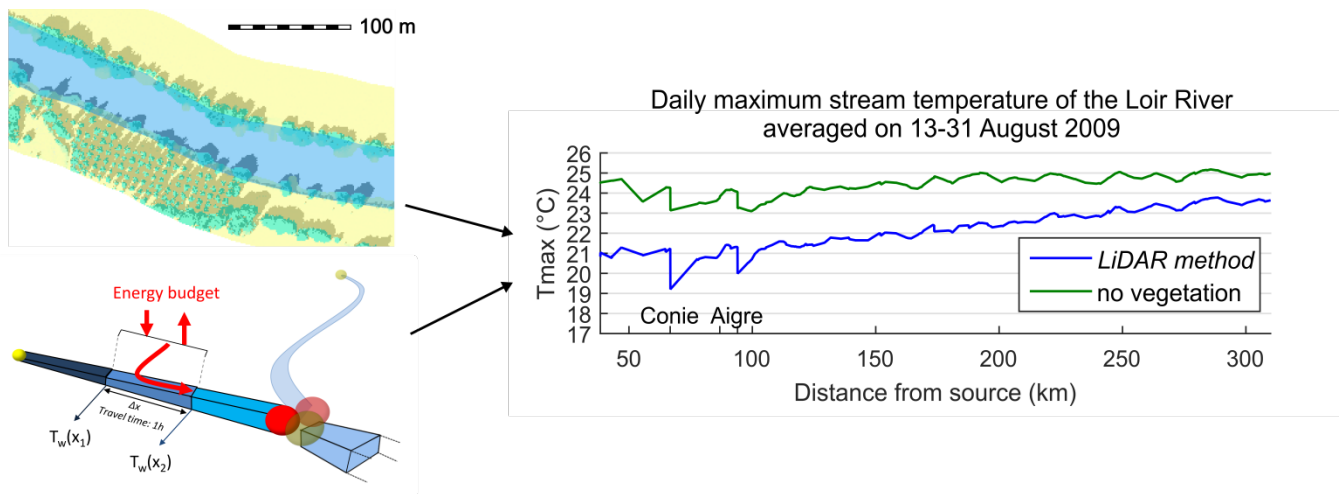
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Keywords: river temperature modelling, regional scale, riparian shading, LiDAR, Loir River.

## 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 75<sup>th</sup> 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.

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

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

## 115 **2. Methods**

### 116 **2.1. Principles of T-NET model**

117 T-NET is a 1D physically-based model designed to compute water temperature along the longitudinal dimension  
118 of a hydrographic network (a GIS polyline). Reaches of this network are limited by two confluences, or by a  
119 source and a confluence (for first order reaches). T-NET was designed and applied at the regional scale (110 000  
120 km<sup>2</sup>) by Beaufort et al. (2016). T-NET runs at an hourly time step and is based on the equilibrium temperature  
121 concept, which is defined as the water temperature at which the net rate of heat exchange at the interface of a  
122 water body is null (Bustillo et al., 2014). The model considers six fluxes [ $W \cdot m^{-2}$ ]: net solar radiation, atmospheric  
123 longwave radiation, longwave radiation emitted from the water surface, evaporative heat flux, convective heat  
124 flux, and groundwater heat inflow. To compute these terms, the model uses the following parameters as  
125 gridded input data: air temperature [ $^{\circ}C$ ], specific humidity [ $kg \cdot kg^{-1}$ ], wind velocity [ $m \cdot s^{-1}$ ], atmospheric longwave  
126 radiation [ $W \cdot m^{-2}$ ] and direct and diffuse solar radiation [ $W \cdot m^{-2}$ ]. Parameters are allocated to each river reach as  
127 a function of the ratio between the length of the reach within a grid cell and the total reach length. All  
128 meteorological parameters except solar radiation are derived from the SAFRAN atmospheric reanalysis dataset  
129 (Vidal et al., 2010). These data are produced by Météo-France from both observations and modelling at an  
130 hourly time step and a spatial resolution of 8 km. Direct and diffuse solar radiation are derived from the  
131 Helioclim3-v5 dataset (Marchand et al., 2017), generated with the help of Meteosat satellite imagery at an  
132 hourly time step and a resolution of  $\sim 3 \times 5$  km. Inputs pertaining to river discharge and groundwater  
133 contributions to river flow are also required by the model. These are computed at a daily time step with the  
134 semi-distributed hydrological model EROS (Thiéry and Moutzopoulos, 1992). Both parameters are modelled at  
135 the outlets of sub-basins for which river discharge observations are available for calibration. They are then  
136 scaled to the reaches inside each sub-basin using the partial area concept. T-NET simulates longitudinal  
137 variability in water temperature between the upstream and downstream nodes of each reach, with a spatial  
138 resolution depending on the travel time (Figure 1). Water velocity is given by the ratio between discharge and  
139 channel cross-section, which is computed using the ESTIMKART empirical model developed by Lamouroux et al.  
140 (2010). At the confluence of two reaches, the output temperature is defined as the sum of the product of the

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

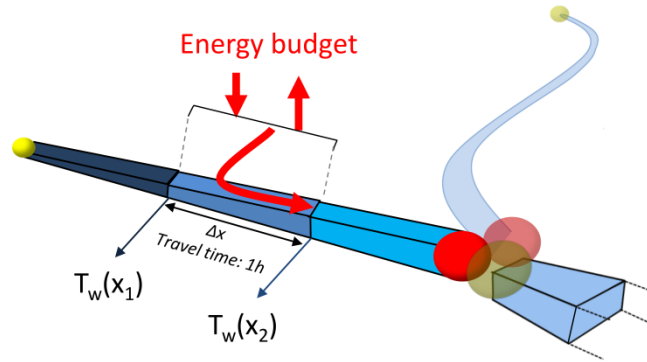


Figure 1: Principles of T-NET model

145  
 146  
 147

## 148 2.2. Net solar radiation calculation

149 In order to improve T-NET's ability to model the impact of riparian vegetation on solar radiation, modifications  
 150 were made to the original model detailed by Beaufort et al. (2016). Similar to the approach of LeBlanc et al.  
 151 (1997), net solar radiation ( $H_{ns}$ ) is now computed as:

$$152 H_{ns} = R_{dir} (1 - \alpha_{dir}) ((1 - SF) + SF \tau) + R_{diff} (1 - \alpha_{diff}) ((1 - TVF) + TVF \tau) \quad (\text{Eq. 1})$$

153 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,  $\alpha_{dir}$   
 154 and  $\alpha_{diff}$  are the water surface albedo associated with direct and diffuse radiation respectively,  $\tau$  is the  
 155 transmissivity of riparian vegetation (i.e. the fraction of solar radiation that passes through the canopy),  $SF$  is the  
 156 shadow factor and  $TVF$  is the tree view factor.  $\alpha_{diff}$  was held at a constant of 0.09, following the recommendation  
 157 of Sellers (1965) and  $\alpha_{dir}$  was computed using the formulation of Anderson (1954):

$$158 \begin{aligned} \alpha_{dir} &= 1 && \text{if } \Psi < 1.24^\circ \\ \alpha_{dir} &= 1.18 * \Psi^{-0.77} && \text{otherwise} \end{aligned} \quad (\text{Eq. 2})$$

159 Where  $\Psi$  is the angle between the horizon and the sun in degrees.

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

$$164 \tau = \frac{\kappa}{1 + \exp(\pm \gamma \cdot DoY - \beta)} + \mu \quad (\text{Eq. 3})$$

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

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

### 177 2.3.Shadow factor and view factor calculations

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

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

$$182 \quad SF = TVF = vc \times k \quad (\text{Eq. 4})$$

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

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

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

$$192 \quad SF = \frac{H \times \cot \Psi \times \sin \delta}{W} \times vc \quad (\text{Eq. 5})$$

193 where  $H$  is tree height,  $W$  is river width,  $\Psi$  is the solar elevation angle,  $\delta$  is the angle between solar azimuth and  
 194 the mean azimuth [ $0^\circ$  -  $180^\circ$ ] of each T-NET reach (computed by considering the first and last vertices of each  
 195 reach).

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

$$199 \quad TVF = \left[ 1 - \frac{0.5}{W} \left( \sqrt{H^2 + W^2} + \sqrt{H^2 + W^2} - 2H \right) \right] \times vc \quad (\text{Eq. 6})$$

200  
 201 The third approach (subsequently referred to as the *lidar* method) is a spatially-explicit method that  
 202 computes SF and TVF from a LiDAR-derived digital surface model (DSM). It requires a) a high-resolution digital  
 203 surface model ( $\sim 1$  m) describing the elevation of riparian vegetation, b) information about the exact location of  
 204 the river in order to define water and non-water pixels and c) polygons of river area, allowing the DSM pixels to  
 205 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.

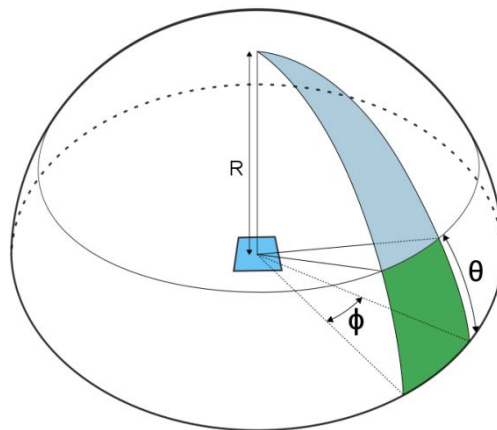
214 To compute SVF from the DSM, we represented the sky as a hemisphere of radius R centred on a water pixel (as  
 215 in Essery et al. (2008), Johnson and Watson (1984) and Tung et al. (2006); Figure 2). We used the r.horizon  
 216 module of GRASS GIS to calculate the angle  $\theta$  between the horizon and the highest DSM pixel as seen from each  
 217 water pixel at horizontal azimuth steps  $\phi$  of  $10^\circ$ . 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:

$$220 \frac{R^2 \int_0^{\frac{\pi}{2}} \int_0^\phi \cos \theta \sin \theta d\phi d\theta}{R^2 \int_0^{\frac{\pi}{2}} \int_0^\phi \cos \theta \sin \theta d\phi d\theta} = \frac{1 + \cos 2\theta}{2} \quad (\text{Eq. 7})$$

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

$$222 SVF = \frac{1}{2} + \frac{1}{n} \sum_{i=1}^n \cos 2\theta_i \quad (\text{Eq. 8})$$

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.



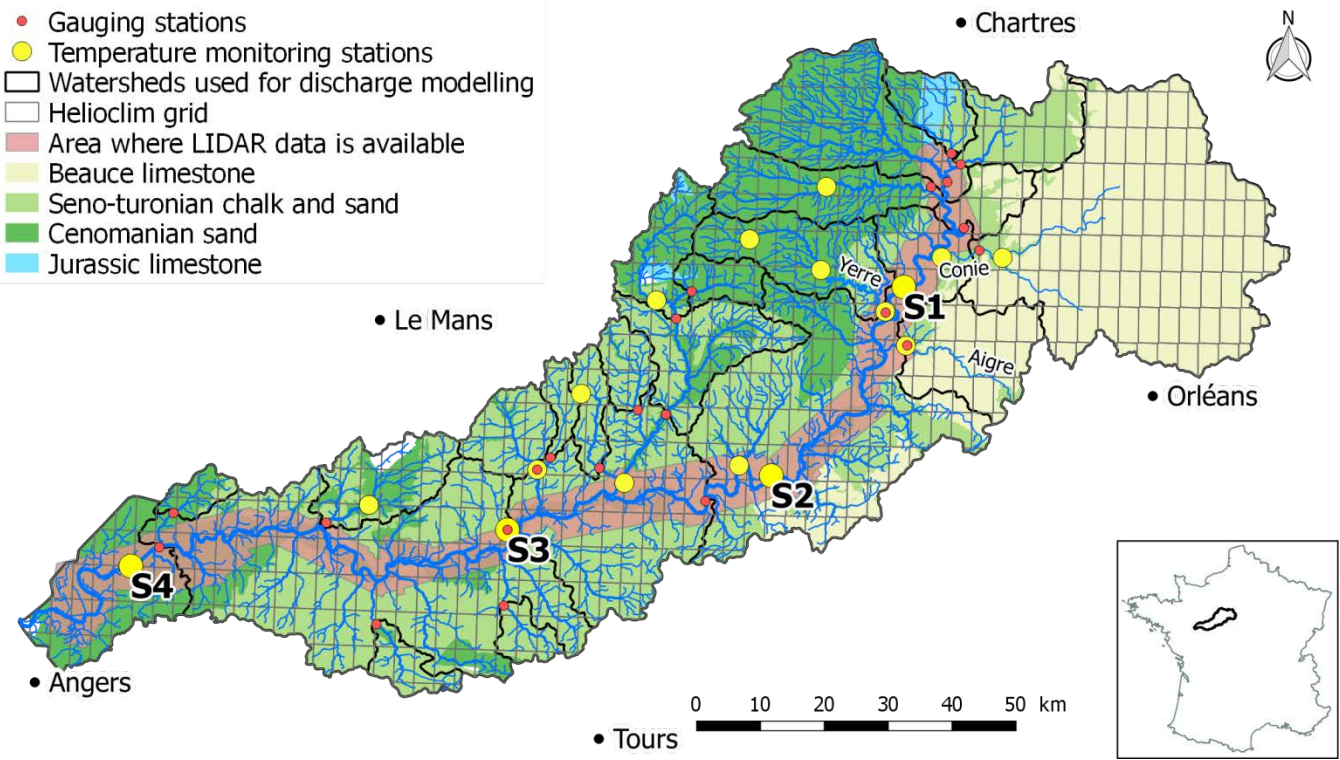
225  
 226 **Figure 2: Calculation of a sky view factor from measures of  $\theta$ , the angle between the horizon and**  
 227 **the highest vegetation seen from a water pixel and with an angular step  $\phi$  of  $10^\circ$ . R is the radius of the hemisphere**  
 228

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

230 The Loir River basin is an 8283 km<sup>2</sup> 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 km<sup>2</sup> respectively. The mean discharge of the Loir at its  
 238 downstream-most gauging station (1961-2015) is 31.8 m<sup>3</sup>·s<sup>-1</sup> (specific discharge = 4.0 l·s<sup>-1</sup>·km<sup>-2</sup>). The flows of the  
 239 Aigre (specific discharge = 5.4 l·s<sup>-1</sup>·km<sup>-2</sup>) and the Conie (specific discharge = 3.4 l·s<sup>-1</sup>·km<sup>-2</sup>) 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 that 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  
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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.

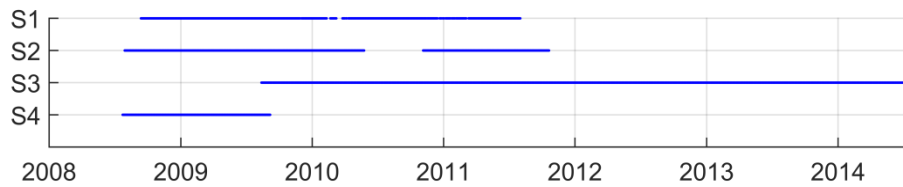


Figure 4: Period of availability of stream temperature observation at the four logger stations located on the Loir River

## 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 (Lamouroux 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  $1 \text{ m}^2$ . 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

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

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

$$298 \text{ RMSE} = \sqrt{\frac{\sum(T_{sim} - T_{obs})^2}{N}} \text{ (Eq. 9)}$$

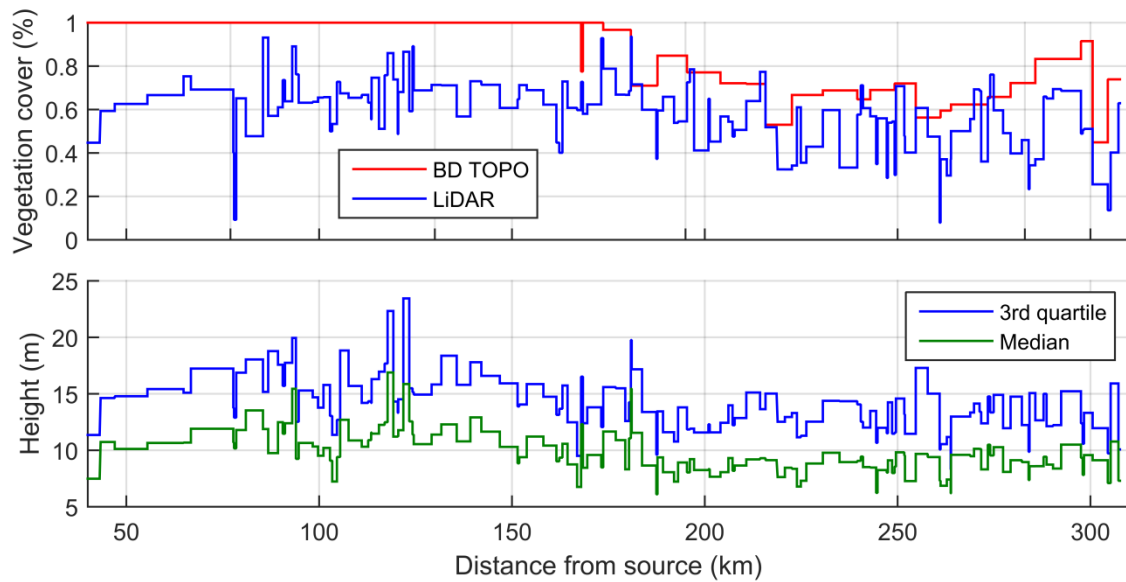
299 where N is the number of observations,  $T_{sim}$  is the simulated river temperature and  $T_{obs}$  is the observed river  
300 temperature. Bias (defined as the mean difference between simulated and measured temperatures) was used  
301 to quantify the mean over/underestimation of the model. Finally,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

308

### 309 3. Results

#### 310 3.1. Characterisation of riparian vegetation cover

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

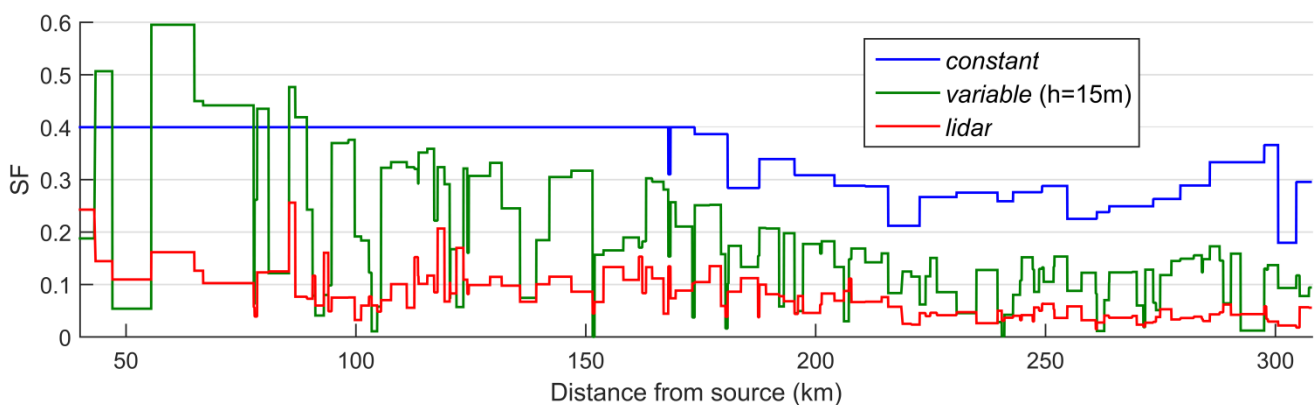


319  
 320 **Figure 5: Characterisation of riparian vegetation for each T-NET reach (a) comparison of vegetation cover derived from the BD TOPO**  
 321 **database (Valette et al., 2012) and LiDAR datasets (buffer of 10 m on both sides of the river polygons) (b) median and 3<sup>rd</sup> quartile**  
 322 **vegetation heights from LiDAR data**  
 323

### 324 3.2. Variation in riparian shading computed with the three methods

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

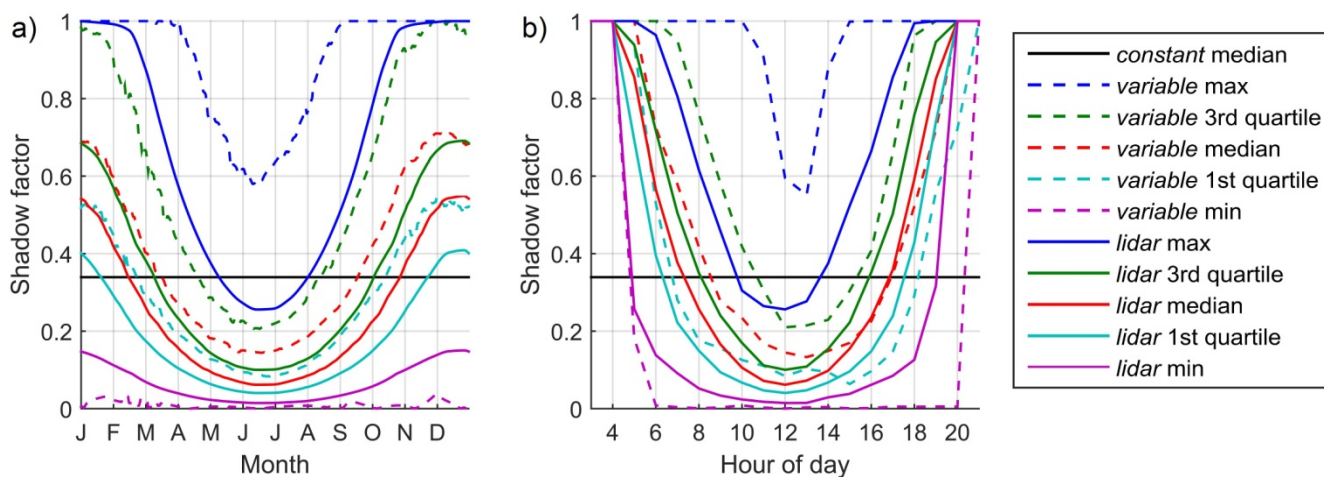
328 Figure 6 shows the longitudinal profile of SF on the Loir River for the three methods at midday on the summer  
 329 solstice, when solar radiation is strongest. For the *constant* method, the reaches covered by LiDAR data have a  
 330 uniform Strahler order of 5, so that the weighting coefficient  $k$  in this area is always equal to 0.4 (see section  
 331 2.3). The variation of SF is thus only dependent on the vegetation cover. The *variable* method varies strongly as  
 332 a function of reach azimuth, even though the sun is at its highest elevation, while the *lidar* method shows  
 333 smaller variations. The *lidar* method is thus less sensitive to reach azimuth, compared to the *variable* method.



334  
 335 **Figure 6: Longitudinal profile of shadow factor provided by the 3 methods on the Loir River**  
 336 **at the summer solstice (21<sup>st</sup> June) at 12h UTC.**  
 337

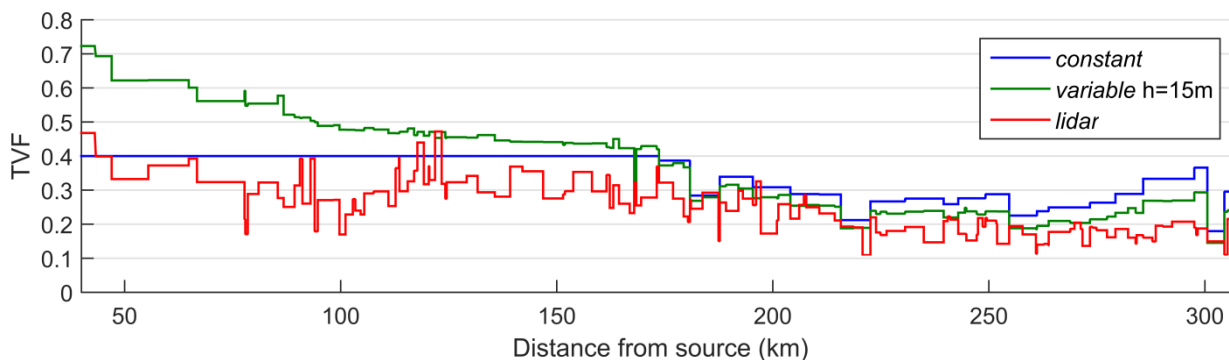
338 At noon, the Loir's SF computed with the *lidar* method lies between 0 and 0.3 in June (median=0.1; Figure 7a  
 339 solid lines) and between 0.1 and 1 in December (median=0.5). There is thus more variability in winter than in  
 340 summer, because reach azimuth has a much greater impact when the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

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



351  
 352 **Figure 7: Percentiles of the SF distribution obtained with the three methods on the 135 T-NET reaches**  
 353 **(a) Annual cycles at noon (b) daily cycles at the summer solstice.**  
 354

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



361  
 362 **Figure 8: Longitudinal profile of tree view factor provided by the 3 methods on the Loir River.**  
 363 **Values from the *variable* method are averaged on 08/2007-07/2014**  
 364

365 **3.3. Impact of riparian shading method on annual and seasonal river temperature simulations**

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

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

378  
 379

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

380

381 Figure 9 shows the monthly biases ( $T_{sim} - T_{obs}$ ) of maximum daily temperature ( $T_{max}$ ) computed on available  
 382 measured data (see Figure 4). At the four stations, the *lidar* method provides improved biases in comparison to  
 383 both the *variable* and the *constant* method from April to September. Compared to the *variable* method, the  
 384 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  
 385 °C at S4). Despite this improvement, the *lidar* method still underestimates river temperature by more than 1 °C  
 386 during at least 2 months in summer at S1, S2 and S4. The *constant* method provides a consistently colder  $T_{max}$   
 387 than the *variable* (and *lidar*) methods at stations 3 and 4 from May to August, presumably because this method  
 388 does not model the seasonal cycle of increasing and decreasing shadow length.

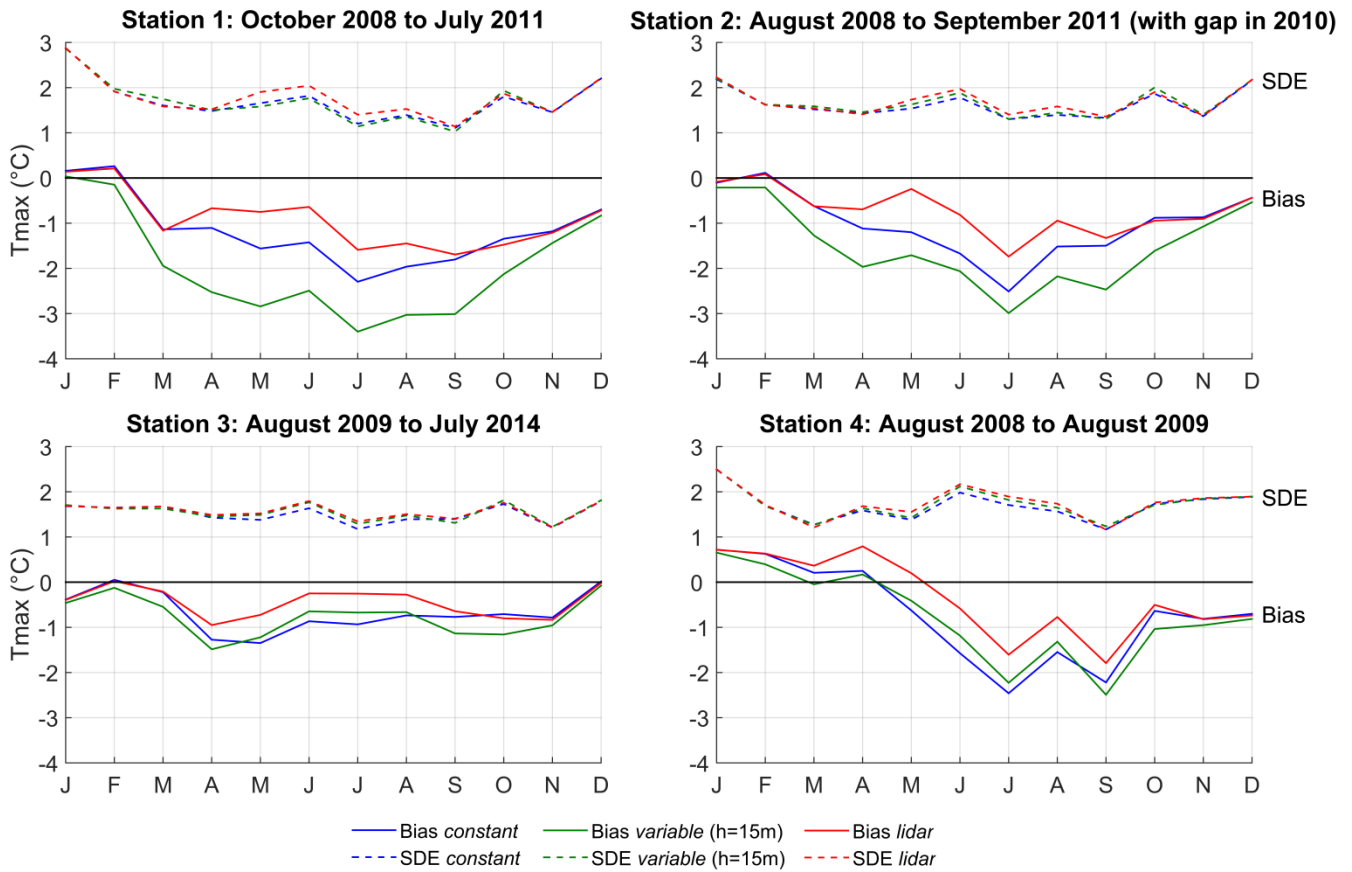


Figure 9: Monthly biases ( $T_{sim}-T_{obs}$ ) and standard deviation of errors of maximum daily temperature provided by the 3 methods at the 4 stations (averaged annual cycles computed on available observed data)

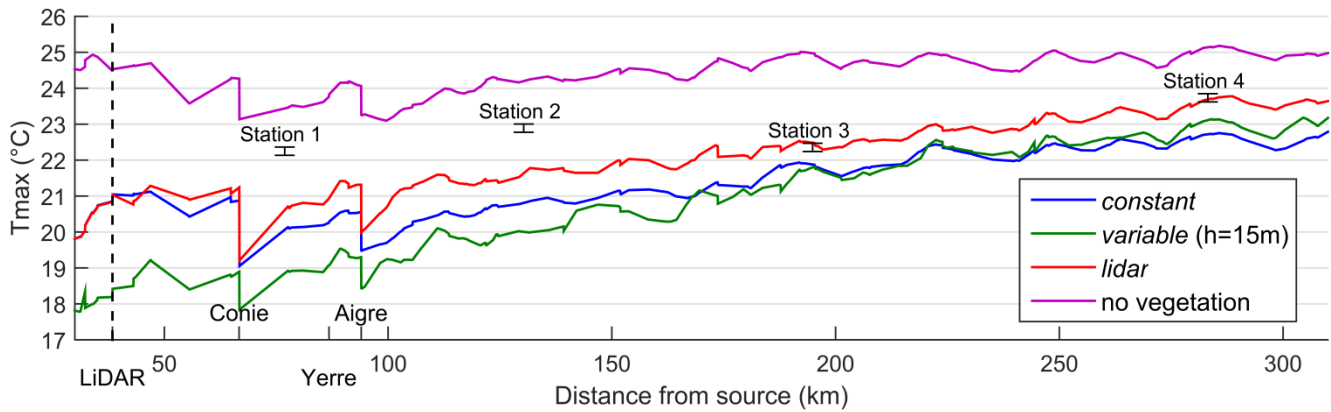
Averaged annual cycles of SDE show little difference between methods and always stay above 1 °C (Figure 9). That means that simulated  $T_{max}$  is substantially more variable than observed data, whatever the method used.

### 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 13<sup>th</sup> and the 31<sup>st</sup> 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 13<sup>th</sup> and 31<sup>st</sup> 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



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



415  
 416  
 417  
 418  
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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.

## 420 4. Discussion

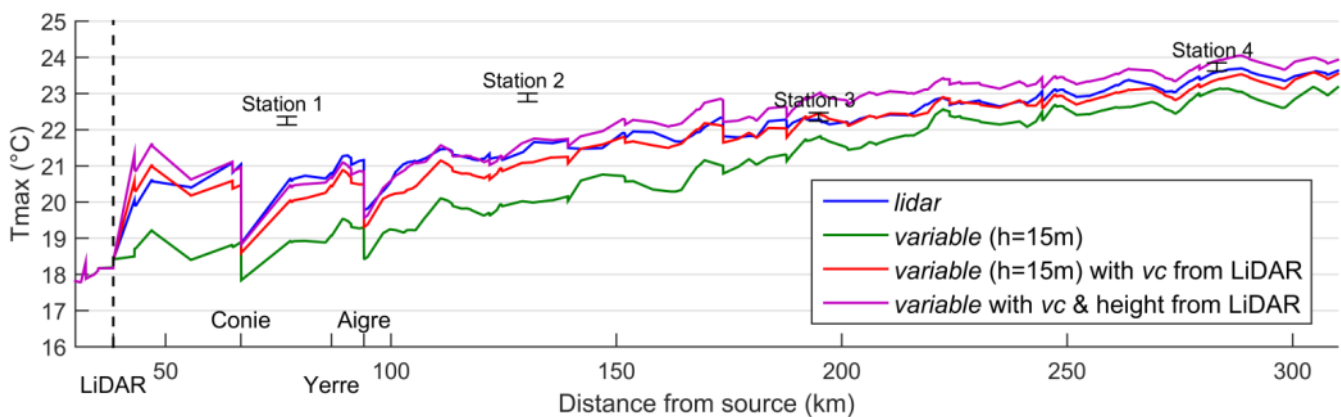
### 421 4.1. Discrepancies in computed SF and TVF

422 The global overestimation of SF and TVF provided by the *variable* method compared to the *lidar* method can be  
 423 explained by four key factors. First, the BD TOPO database that weights the results of the *variable* method  
 424 clearly overestimates vegetation cover in relation to the LiDAR-derived values (discussed in section 3.1). Second,  
 425 comparison of the wetted widths used in the *variable* method with LiDAR-derived river widths shows that the  
 426 former are underestimated, especially upstream of ~150 km and downstream of ~250 km from the source.  
 427 These width uncertainties drive an increase in SF (TVF) of 6% (4%) when averaged over the entire modelling  
 428 period and 14% (9%) between 13<sup>th</sup> and 31<sup>st</sup> August 2009. Third, discrepancies may also arise from the fact that  
 429 the *variable* method uses averaged stream azimuths while the *lidar* method intrinsically considers the position  
 430 of vegetation in regard to the water surface. Indeed, reach azimuth impacts the timing of minimum SF (Li et al.  
 431 2012), the hourly amount of direct solar radiation and hence the maximum daily temperature (Garner et al.,  
 432 2017). In order to quantify these discrepancies, we cut the Loir river GIS line in 50 m parts and compared  
 433 azimuths of these small reaches with the original T-NET reaches azimuths. The mean absolute difference is 26°  
 434 and R<sup>2</sup> is 0.66. Finally, the characterisation of vegetation cover and height at high resolution with the LiDAR data  
 435 may not be reproducible in the *variable* method by taking an average of these data at the reach scale. Indeed,  
 436 Greenberg et al. (2012) report that 28% of the change in insolation caused by removal of riparian vegetation  
 437 characterised with LiDAR data could not be explained by considering averages at the reach scale. In our case, a  
 438 multiple linear regression between LiDAR-derived TVF and LiDAR-derived tree height, vegetation cover and river  
 439 width averaged at the reach scale provides R<sup>2</sup>=0.83. Hence, 17% of the TVF variance cannot be explained by  
 440 these three variables when averaged at the reach scale.

441  
 442

### 442 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. Hilldale 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

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

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

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

565

## 566 **Acknowledgements**

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

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576 **References**

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