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# Automated quantification of floating wood pieces in rivers from video monitoring: a new software tool and validation.

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## Abstract

Wood is an essential component of rivers and plays a significant role in ecology and morphology. It can be also considered as a risk factor in rivers due to its influence on erosion and flooding. Quantifying and characterizing wood fluxes in rivers during floods would improve our understanding of the key processes but is hindered by technical challenges. Among various techniques for monitoring wood in rivers, streamside videography is a powerful approach to quantify different characteristics of wood in rivers, but past research has employed a manual approach that has many limitations. In this work, we introduce new software for the automatic detection of wood pieces in rivers. We apply different image analysis techniques such as static and dynamic masks, object tracking, and object characterization to minimize false positive and missed detections. To assess the software performance, results are compared with manual detections of wood from the same videos, which was a time-consuming process. Key parameters that affect detection are assessed including surface reflections, lighting conditions, flow discharge, wood position relative to the camera, and the length of wood pieces. Preliminary results had a 36% rate of false positive detection, primarily due to light reflection and water waves, but post-processing reduced this rate to 15%. The missed detection rate was 71% of piece numbers in the preliminary result, but post processing reduced this error to only 6.5% of piece numbers, and 13.5% of volume. The high precision of the software shows that it can be used to massively increase the quantity of wood flux data in rivers around the world, potentially in real time. The significant impact of post-processing indicates that it is necessary to train the software in various situations (location, timespan, weather conditions) to ensure reliable results. Manual wood detections and annotations for this work took more than one human-month of labor. In comparison, the presented software coupled with an appropriate post processing step performed the same task in real time (55 hr) on a standard desktop computer.

30           Keywords: River monitoring, Wood flux, Wood discharge, Large wood, Ground video imagery, Auto-  
31           matic detection

## 32   **1. Introduction**

33           Floating wood has a significant impact on river morphology (Gurnell et al., 2002; Gregory et al., 2003;  
34           Wohl, 2013; Wohl and Scott, 2017). It is both a component of stream ecosystems and a source of risk for  
35           human activities (Comiti et al., 2006; Badoux et al., 2014; Lucía et al., 2015). The deposition of wood at  
36           given locations can cause a reduction of the cross-sectional area, which can both increase upstream water  
37           levels (and the risk for neighboring communities), and laterally concentrate the flow downstream, which can  
38           lead to damaged infrastructure (Lyn et al., 2003; Lagasse, 2010; Mao and Comiti, 2010; Badoux et al., 2014;  
39           Ruiz-Villanueva et al., 2014; De Cicco et al., 2018; Mazzorana et al., 2018). Therefore, understanding and  
40           monitoring the dynamics of wood within a river is fundamental to assess and mitigate risk. An important  
41           body of work on this topic has grown over the last two decades, which has led to the development of many  
42           monitoring techniques (Marcus et al., 2002; MacVicar et al., 2009a; MacVicar and Piégay, 2012; Benacchio  
43           et al., 2015; Ravazzolo et al., 2015; Ruiz-Villanueva et al., 2018; Ghaffarian et al., 2020; Zhang et al., 2020)  
44           and conceptual and quantitative models (Braudrick and Grant, 2000; Martin and Benda, 2001; Abbe and  
45           Montgomery, 2003; Gregory et al., 2003; Seo and Nakamura, 2009; Seo et al., 2010). A recent review by  
46           Ruiz-Villanueva et al. (2016), however, argues that the area remains in relative infancy compared to other  
47           river processes such as the characterization of channel hydraulics and sediment transport. Many questions  
48           remain open areas of inquiry including wood hydraulics, which is needed to understand wood recruitment,  
49           movement and trapping, and wood budgeting, where better parametrization is needed to understand and  
50           model the transfer of wood in watersheds at different scales.

51           In this domain, the quantification of wood mobility and wood fluxes in real rivers is a fundamental  
52           limitation that constrains model development. Most early works were based on repeated field surveys (Keller  
53           and Swanson, 1979; Lienkaemper and Swanson, 1987), with more recent efforts taking advantage of aerial  
54           photos or satellite images (Marcus et al., 2003; Lejot et al., 2007; Lassetre et al., 2008; Senter and Pasternack,  
55           2011; Boivin et al., 2017) to estimate wood delivery at larger time scales of 1 year up to several decades.  
56           Others have monitored wood mobility once introduced by tracking wood movement in floods (Jacobson et  
57           al., 1999; Haga et al., 2002; Warren and Kraft, 2008). Tracking technologies such as active and passive Radio  
58           Frequency Identification transponders (MacVicar et al., 2009a; Schenk et al., 2014) or GPS emitters and

59 receivers (Ravazzolo et al., 2015) can improve the precision of this strategy. To better understand wood flux,  
60 specific trapping structures such as reservoirs or hydropower dams can be used to sample the flux over time  
61 interval windows (Moulin and Piégay, 2004; Seo et al., 2008; Turowski et al., 2013). Accumulations up-  
62 stream of a retention structure can also be monitored where they trap most or all of the transported wood, as  
63 was observed by Boivin *et al.* (2015), to quantify wood flux at the flood event or annual scale. All these  
64 approaches allow the assessment of wood budget and the in-channel wood exchange between geographical  
65 compartments within a given river reach and over a given period (Schenk et al., 2014; Boivin et al., 2015,  
66 2017).

67 For finer scale information on the transport of wood during flood events, video recording of the water  
68 surface is suitable for estimating instantaneous fluxes and size distributions of floating wood in transport  
69 (Ghaffarian et al., 2020). Classic monitoring cameras installed on the river bank are cheap and relatively easy  
70 to acquire, setup and maintain. As is seen in Table 1, a wide range of sampling rates and spatial/temporal  
71 scales have been used to assess wood budgets in rivers. MacVicar and Piégay (2012) and Zhang et al., (2020)  
72 (in review), for instance, monitored wood fluxes at 5 frames per second (fps) and a resolution of  $640 \times 480$   
73 up to  $800 \times 600$  pixels. Boivin et al. (2017) used a similar camera and frame rate as MacVicar and Piégay  
74 (2012) to compare periods of wood transport with and without the presence of ice. Senter et al. (2017) ana-  
75 lyzed the complete daytime record of 39 days of videos recorded at 4 fps and a resolution of  $2048 \times 1536$   
76 pixels. Conceptually similar to the video technique, time-lapse imagery can be substituted when large rivers  
77 where surface velocities are low enough and the field of view is large. Kramer and Wohl (2014); Kramer et  
78 al. (2017) applied this technique in the Slave River (Canada) and recorded one image every 1 and 10 minutes.  
79 Where possible, wood pieces within the field of view are then visually detected and measured using simple  
80 software to measure the length and diameter of the wood to estimate wood flux (piece/s) or wood volume  
81 ( $m^3/s$ ) (MacVicar and Piégay, 2012; Senter et al., 2017). Critically for this approach, the time it takes for  
82 the researchers to extract information about wood fluxes has limited the fraction of the time that can be  
83 reasonably analyzed. Given the outdoor location for the camera, the image properties depend heavily on  
84 lighting conditions (e.g. surface light reflections, low light, ice, poor resolution or surface waves) which may  
85 also limit the accuracy of frequency and size information (Muste et al., 2008; MacVicar et al., 2009a). In  
86 such situations, simpler metrics such as a count of wood pieces, a classification of wood transport intensity,  
87 or even just a binary presence/absence may be used to characterize the wood flux (Boivin et al., 2017; Kramer  
88 et al., 2017).

**Table 1**

89           A fully automatic wood detection and characterization algorithm can greatly improve our ability to  
90 exploit the vast amounts of data on wood transport that can be collected from streamside video cameras.  
91 From a computer science perspective, however, automatic detection and characterization remain challenging  
92 issues. In computer vision, detecting objects within videos typically consists of separating the foreground  
93 (the object of interest) from the background (Roussillon et al., 2009; Cerutti et al., 2011, 2013). The basic  
94 hypothesis is that the background is relatively static and covers a large part of the image, allowing it to be  
95 matched between successive images. In the riverine environments, however, such an assumption is unrealistic  
96 because the background shows a flowing river, which can have rapidly fluctuating properties (Ali and  
97 Tougne, 2009). Floating objects are also partially submerged in water that has high suspended material con-  
98 centrations during floods, making them only partially visible (*e.g.* a single piece of wood may be perceived  
99 as multiple objects) (MacVicar et al., 2009b). Detecting such an object in motion within a dynamic back-  
100 ground is an area of active research (Ali et al., 2012, 2014; Lemaire et al., 2014; Piégay et al., 2014; Be-  
101 nacchio et al., 2017). Accurate object detection typically relies on the assumption that objects of a single  
102 class (*e.g.* faces, bicycles, animals, etc.) have a distinctive aspect or set of features that can be used to distin-  
103 guish between types of objects. With the help of a representative dataset, machine learning algorithms aim  
104 at defining the most salient visual characteristics of the class of interest (Lemaire et al., 2014; Viola and  
105 Jones, 2006). When the objects have a wide intra-class aspect range, a large amount of data can compensate  
106 by allowing the application of deep learning algorithms (Gordo et al., 2016; Liu et al., 2020). To our  
107 knowledge, such a database is not available in the case of floating wood.

108           The camera installed on the Ain River in France has been operating more or less continuously for over  
109 10 years and vast improvements in data storage mean that this data can be saved indefinitely (Zhang et al.,  
110 2020). The ability to process this image database to extract the wood fluxes allows us to integrate this infor-  
111 mation over floods, seasons and years, which would allow us to significantly advance our understanding of  
112 the variability within and between floods over a long time period. An unsupervised method to identify float-  
113 ing wood in these videos by applying intensity, gradient and temporal masks was developed by Ali and  
114 Tougne (2009) and Ali *et al.* (2011). In this model, the objects were tracked through the frame to ensure that  
115 they followed the direction of flow. An analysis of about 35 minutes of the video showed that approximately  
116 90% of the wood pieces was detected (*i.e.* about 10% of detection were missed), which confirmed the poten-  
117 tial utility of this approach. An additional set of false detection related to surface wave conditions amounted  
118 to approximately 15% of the total detection. However, the developed algorithm was not always stable and

119 was found to perform poorly when applied to a larger data set.

120 The objectives of the presented work are to describe and validate a new algorithm and computer inter-  
121 face for quantifying floating wood pieces in rivers. First, the algorithm procedure is introduced to show how  
122 wood pieces are detected and characterized. Second, the computer interface is presented to show how manual  
123 annotation is integrated with the algorithm to train the detection procedure. Third, the procedure is validated  
124 using data from the Ain River. The validation period occurred over six days in January and December 2012  
125 where flow conditions ranged from  $\sim 400 \text{ m}^3/\text{s}$ , which is below bankfull discharge but above the wood  
126 transport threshold, to more than  $800 \text{ m}^3/\text{s}$ . The developed algorithm can be used to characterize wood  
127 pieces for a large image database at the study site. Future applications of this approach at a wide range of  
128 sites should lead to new insights on the variability of wood pieces at the reach and watershed scales in world  
129 rivers.

## 130 **2. Methodological procedure for automatic detection of wood**

131 The algorithm for wood detection comprises a number of steps that seek to locate objects moving  
132 through the field of view in a series of images and then identify the objects most likely to be wood. The  
133 algorithm used in this work modifies the approach described by Ali *et al.*, (2011). The steps work from a  
134 pixel to image to video scale, with the context from the larger scale helping to assess whether the information  
135 at the smaller scale indicates the presence of floating wood or not. In a still image, a single pixel is charac-  
136 terized by its location within the image, its color and its intensity. Looking at its surrounding pixels, on an  
137 image scale, allows that information to be spatially contextualized. Meanwhile, the video data adds temporal  
138 context, so that previous and future states of a given pixel can be used to assess its likeliness of representing  
139 floating wood. Since an image is only a discrete 2D representation of the real 3D world, details about the  
140 camera parameters such as optical image deformations, geographic situation, perspective deformations or  
141 behavior regarding luminosity can be used to infer what wood should look like and where it should occur.  
142 On a video scale, the method can embed expectations about how wood pieces should move through frames,  
143 how big they should be, and how lighting and weather conditions can evolve to change the expectations of  
144 wood appearance, location, and movement. The specific steps followed by the algorithm are shown in a  
145 simple flow chart (Fig 1.a). An example image with a wood piece in the middle of the frame is also shown  
146 for reference (Fig 1.b).

**Fig 1**

147 **2.1. Wood probability masks**

148 In the first step, each pixel was analyzed individually and independently. The static probability mask  
149 answers the question “is one pixel likely to belong to a wood-block, given its color and intensity?”. The  
150 algorithm assumes that the wood pixels can be identified by pixel light intensity ( $x$ ) following a Gaussian  
151 distribution (Fig 2.a). To set the algorithm parameters, manual annotations of wood are used to obtain a  
152 representative sample of wood pixels, from which both the mean ( $\mu$ ) and standard deviation ( $\sigma$ ) are calcu-  
153 lated. This procedure produces a static probability mask (Fig 2.b). From this figure, it is possible to identify  
154 the sectors where wood presence is likely, which includes the floating wood piece seen in Fig 1.b, but also  
155 includes standing vegetation in the lower part of the image and a shadowed area in the upper left. The ad-  
156 vantage of this approach is that it is computationally very fast. However, misclassification is possible, par-  
157 ticularly when light condition changes.

**Fig 2**

158 The second mask, called the dynamic probability mask, outlines each pixel’s recent history. The corre-  
159 sponding question is: “is this pixel likely to represent wood now, given its past and present characteristics?”.  
160 Again, this step is based on what is most common in our database: it is assumed that a wood pixel is darker  
161 than a water pixel. Depending on lighting conditions like shadows cast on water or waves, this is not always  
162 true, i.e. water pixels can be as dark as wood pixels. However, pixels displaying successively water then  
163 wood tend to become immediately and significantly darker, while pixels displaying wood then water tend to  
164 become significantly lighter. Meanwhile, pixels that keep on displaying wood tend to be rather stable. Thus,  
165 we assign wood pixel probability according to an updated version of the function proposed by Ali et al.  
166 (2011) (Fig 3.a) that takes 4 parameters. This function  $H$  is an updating function, which produces a temporal  
167 probability mask from the inter-frame pixel value. On a probability map, a pixel value ranges from -1 (likely  
168 not wood) to 1 (likely wood). The temporal mask value for a pixel at location  $(x, y)$  and at time  $t$  is  
169  $P_T(x, y, t) = H(\Delta_t, I) + P_T(x, y, t - 1)$ . We apply a threshold to the output of  $P_T(x, y, t)$  so that it always  
170 stays within the interval  $[0, 1]$ . The idea is that a pixel that becomes suddenly and significantly darker is  
171 assumed to be likely wood.  $H(\Delta_t, I)$  is such that under those conditions, it increases the pixel probability map  
172 value (parameters  $\tau$  and  $\beta$ ). A pixel that becomes lighter over time is unlikely to correspond to wood (pa-  
173 rameter  $\alpha$ ). A pixel which intensity is stable and that was previously assumed to be wood shall still corre-  
174 spond to wood, while a pixel which intensity is stable and which probability to be wood was low is unlikely  
175 to represent wood now. A small decay factor ( $\delta$ ) was introduced in order to prevent divergence (in particular,

176 it prevents noisy areas from being activated too frequently).

### Fig 3

177 The final wood probability mask is created using a combination of both the static and dynamic proba-  
178 bility masks. Wood objects thus had to have a combination of the correct pixel color and the expected tem-  
179 poral behavior of water-wood-water color. The masks were combined assuming that both probabilities are  
180 independent, which allowed us to use the Bayesian probability rule in which the probability masks are simply  
181 multiplied, pixel by pixel, to obtain the final probability value for each pixel of every frame.

## 182 2.2. Wood object identification and characterization

183 From the probability mask it is necessary to group pixels with high wood probabilities into objects and  
184 then to separate these objects from the background to track them through the image frame. For this purpose,  
185 pixels were classified as high-or low-probability based on a threshold applied to the combined probability  
186 mask. Then, the high-probability pixels were grouped into connected components (that is, small, contiguous  
187 regions on the image) to define the objects. At this stage, a pixel size threshold was applied on the detected  
188 objects so that only the bigger objects were considered to represent woody objects on the water surface (Fig  
189 4.a the big white region at the middle). A number of smaller components were often related to non-wood  
190 objects, for example waves, reflections, or noise from the camera sensor or data compression.

191 After the size thresholding step, movement direction and velocity were used as filters to distinguish real  
192 objects from false detections. The question here is, “is this object moving through the image frame the way  
193 we would expect floating wood to move?”. To do this, the spatial and temporal behavior of components were  
194 analyzed. First, to deal with partly immersed objects, we agglomerated multiple objects within frames as  
195 components of a single object if the distance separating them was less than a set threshold. Second, we asso-  
196 ciated wood objects in successive frames together to determine if the motion of a given object was compatible  
197 with what is expected from driftwood. This can be achieved according to the dimensionless parameter  
198 “ $PT/\Delta T$ ”, which provides a general guideline for the distance an object pass between two consecutive frames  
199 (Zhang et al., 2020). Here  $PT$  (passing time) is the time that one piece of wood passes through the camera  
200 field of view and  $\Delta T$  is the time between two consecutive frames and practically it is recommended to use  
201 videos with  $PT/\Delta T > 5$  in this software. In our case, tracking wood is rather difficult for classical object  
202 tracking approaches in computer vision: the background is very noisy, the acquisition frequency is low and  
203 the objects appearance can be highly variable due to temporarily submerged parts and highly variable 3D



204 structures. Given these considerations it was necessary to use very basic rules for this step. The rules are  
205 therefore based on loose expectations, in terms of pixel intervals, on the motions of the objects, depending  
206 on the camera location and the river properties. How many pixels is the object likely to move between image  
207 frames from left to right? How many pixels from top to bottom? How many appearances are required? How  
208 many frames can we miss because of temporary immersions? Using these rules, computational costs re-  
209 mained low and the analysis could be run in real-time while also providing good performance.

#### Fig 4

210 The final step was to characterize each object, which at this point in the process are considered wood  
211 objects. Each appears several times in different frames and a procedure is needed to either pick a single  
212 representative occurrence or use a statistic tool to analyse multiple occurrences to estimate characterization  
213 data. Here we assumed that the biggest occurrence, in terms of pixels number, was the most representative  
214 state. This assumption is based on the principle that a bigger number of pixels corresponds to a better or a  
215 fuller view (the object is less immersed than on other occurrences, for instance). This approach also matched  
216 the manual annotation procedure where we tended to pick the view where the object covers the largest area  
217 to make measurements. For the current paper, every object was characterized from the raw image based on its  
218 size and its location (in pixels).

### 219 2.3. Image rectification

220 Warping images according to a perspective transform results in an important loss of quality. On warped  
221 images, areas of the image farther to the camera provide little detail and are overall very blurry and non-  
222 informative. Therefore, given the topology of our images, image rectification was necessary to calculate  
223 wood length, velocity, volume and other characteristics from the saved pixel-based characterization of each  
224 object. To do so, the fisheye lens distortion was first corrected. A fisheye lens distortion is a characteristic  
225 of the lens that produces visual distortion intended to create a wide panoramic or hemispherical image. This  
226 effect was corrected by a standard Matlab process using the ComputerVisionToolbox<sup>TM</sup>.

227 Ground-based cameras have also an oblique angle of view, which means that pixel to meter correspond-  
228 ence is variable and images need to be orthorectified to obtain estimates of object size and velocity in real  
229 terms (Muste et al., 2008). Orthorectification refers to the process by which image distortion is removed and  
230 the image scale is adjusted to match the actual scale of the water surface. Translating from pixels to cartesian  
231 coordinates required us to assume that our camera follows the pinhole camera model and that the river can

232 be assimilated to a plane of constant altitude. Under such conditions, it is possible to translate from pixel  
233 coordinates to a metric 2D space thanks to a perspective transform assuming a virtual pinhole camera on the  
234 image and estimating the position of the camera and its principal point (center of the view). An example of  
235 orthorectification on a detected wood piece in a set of continuous frames and pixel coordinates (Fig 5.b) is  
236 presented in Fig 5.c in metrics coordinates. The transform matrix is obtained with the help of at least 4 non-  
237 colinear points (Fig 5.a blue GCPs (Ground Control Points) acquired with DGPS) from which we know both  
238 the relative 2D metric coordinates for a given water level (Fig 5.c blue points), and their corresponding lo-  
239 calization within the image(Fig 5.b blue points). To achieve better accuracy, it is advised to acquire additional  
240 points and to solve the subsequent over-determined system with the help of a Least Square Regression (LSR).  
241 Robust estimators such as RANSAC can provide useful to prevent acquisition noise. After identifying the  
242 virtual camera position, the perspective transform matrix then becomes parameterized with the water level.  
243 Handling the variable water level was performed for each piece of wood, by measuring the relative height  
244 between the camera and the water level at the time of detection based on information recorded at the gauging  
245 station to which the camera was attached.

**Fig 5**

### 246 **3. User interface**

247 The software was developed to provide a single environment for the analysis of wood pieces on the  
248 surface of the water from streamside videos. It consists of four distinct modules: Detection, Annotation,  
249 Learning, and Performance. The home screen (Fig 6) allows the operator to select any of these modules.  
250 From within a module, a menu bar on the left side of the interface allows operators to switch from one module  
251 to another. In the following sections, the operation of each of these modules are described.

**Fig 6**

#### 252 **3.1. Detection**

253 The detection module is the heart of the software. This module allows, from learned or manually spec-  
254 ified parameters, the detecting of floating objects without human intervention (see Fig 7). This module con-  
255 tains two main parts: (i) Detection tab, which allows operator to open, analyze and export the results from  
256 one video or a set of videos, and (ii) Configuration tab, which allows operator to load and save the software  
257 configuration by defining the parameters of wood detection (as described in Sect 2), saving and extracting  
258 the results, and displaying the interface.

259 The detection process is intended to work as a video file player. The idea is to load a video file (or a  
260 stream url), and to let the software read the video until the end. When required, the reader generates a visual  
261 output, showing how the masks behave by adding color and information to the video content (see Figure 7).  
262 A small textual display area shows the frequency of past detections. Meanwhile, the software generates a  
263 series of files summarizing the positive outputs of the detection. They consist in YAML and CSV files, as  
264 well as image files to show the output of different masks, the original frames, etc. A configuration tab is  
265 available, and provides many parameters organized by various categories. The main configuration tab is  
266 divided in seven parts. The first part is dedicated to general configurations such as frame skipped between  
267 each computation and defining the areas within the frame where wood is not expected (e.g. bridge pier or  
268 river bank). In the second and third parts, the parameters of the intensity and temporal masks are listed (see  
269 Sect 2.1). The default values are  $\mu = 0.2$  and  $\sigma = 0.08$  for the intensity mask, and  $\tau = 0.25$  and  $\beta = 0.45$   
270 for the temporal mask. In the fourth and fifth parts, object tracking and characterization parameters are de-  
271 fined respectively as described in Sect 2.2. Detection time is defined in the sixth part using an optical char-  
272 acter recognition technique. Finally, the parameters of the orthorectification (see Sect 2.3) are defined in the  
273 seventh part. The detection software can be used to process videos in batch (“script” tab), without generating  
274 a visual output to save computing resources.

**Fig 7**

### 275 **3.2. Annotation**

276 As mentioned in Sec. 2, the detection procedure requires the classification of pixels and objects into  
277 wood and non-wood categories. To train and validate the automatic detection process, a ground-truth or set  
278 of videos with manually annotations are required. Such annotations can be performed using different tech-  
279 niques. For example, objects can be identified with the help of a bounding box or selection of endpoints, as  
280 in MacVicar and Piégay(2012); Ghaffarian et al., (2020) and Zhang et al., (2020). It is also possible to sample  
281 wood pixels without specifying instances or objects, or to sample pixels within annotated objects. Finally,  
282 objects and/or pixels can be annotated multiple times in a video sequence to increase the amount and detail  
283 of information in such an annotation database. However, this annotation process is time-consuming, so a  
284 trade-off must be made between training and accuracy for different lighting conditions, camera parameters,  
285 wood properties, and river hydraulics.

286 Given that the tool is meant to be as flexible as possible, the annotation tool was developed to allow  
287 operator to perform as fine annotation as they wish. As it is shown in Fig 8, this module contains three main

288 parts: (i) The column on the far left allows operator to switch to another module (detection, learning or per-  
289 formance), (ii) the central part consists of a video player with a configuration tab for extracting the data, and  
290 (iii) the right part where the tools to generate, create, visualize and save annotations are located. The tools  
291 allow rather quick coarse annotation, similar to what was done by MacVicar and Piégay (2012) and Boivin  
292 *et al.*, (2015), while still allowing the possibility of finer pixel-scale annotation.

### Fig 8

293 The principle of this module is to associate annotations with the frames of a given video. Annotating a  
294 piece of wood is like drawing its shape, directly on a frame of the video, using the drawing tools provided by  
295 the module. It is possible to add a text description to each annotation. Each annotation is linked to a single  
296 frame of the video; however, a frame can contain several annotations. An annotated video, therefore, consists  
297 of a video file, as well as a collection of drawings, possibly with textual descriptions, associated with frames.  
298 It is possible to link annotations from one frame to another to signify that they belong to the same piece of  
299 wood. These data can be used to learn the movement of pieces of wood in the frame.

### 300 3.3. Performance

301 The performance module allows the operator to set rules to compare automatic and manual wood de-  
302 tection results. This section also allows the operator to use a bare, pixel-based annotation or specify an or-  
303 thorectification matrix to extract wood-size metrics directly from the output of an automatic detection.

304 For this module an automatic detection file is first loaded and then the result of this detection is com-  
305 pared with a manual annotation for that video, if the latter is available. Comparison results are then saved in  
306 the form of a summary file (\*.csv format), allowing the operator to perform statistical analysis of the results  
307 or the performance of the detection algorithm. A manual annotation file can only be loaded if it is associated  
308 with an automatic detection result.

309 The performance of the detected algorithm can be realized on several levels:

- 310 • Object. The idea is to annotate one (or more) occurrences of a single object, and to operate the  
311 comparison at bounding box scale. A detected object may comprehend a whole sequence of occur-  
312 rences, on several frames. It is validated when only a single occurrence happens to be related to an  
313 annotation. This is the minimum possible effort required to have an extensive overview of the  
314 object frequency on such an annotations database. This approach can however lead us to misjudge

- 315 overall wrongly detected sequences as True Positives (see below), or vice-versa.
- 316 • Occurrence. The idea is to annotate, even roughly, every occurrence of every woody object, so that  
317 the comparison can happen between bounding boxes rather than at pixel level. Every occurrence  
318 of any detected object can be validated individually. This option requires substantially more anno-  
319 tation work than the object annotation.
- 320 • Pixel. This case implies that every pixel of every occurrence of every object is annotated as wood.  
321 It is very powerful in the event of evaluating the algorithm performances, and eventually refining  
322 its parameters with the help of some machine learning technique. However, it requires an extensive  
323 annotation work.

#### 324 **4. Performance assessment**

325 To assess the performance of the automatic detection algorithm, we used a set of videos from the Ain  
326 River in France that were both comprehensively manually annotated and automatically analyzed. According  
327 to the data annotated by the observer, the performance of the software can be affected by different conditions:  
328 (i) wood piece length, (ii) distance from the camera, (iii, iv) wood X, Y position, (v) flow discharge, (vi)  
329 daylight, and (vii, viii) light and darkness of the frame (see Table 2). If for example software detects a 1 cm  
330 piece at a distance of 100 m from the camera, there is a high probability that this is a false positive detection.  
331 Therefore, knowing the performance of the software in different conditions, it is possible to develop some  
332 rules to enhance the quality of data. The advantage of this approach is that all eight parameters introduced  
333 here are accessible easily in the detection process. In this section the monitoring details and annotation meth-  
334 ods are introduced before the performance of the software is evaluated by comparing the manual annotations  
335 with the automatic detections.

**Table 2**

#### 336 **4.1. Material and methods**

##### 337 **4.1.1. Monitoring site and annotation**

338 The Ain River is a piedmont river with a drainage area of  $3630 \text{ km}^2$  at the gauging station of Chazey-  
339 sur-Ain, with a mean flow width of 65 m, a mean slope of 0.15%, and a mean annual discharge of  $120 \text{ m}^3/\text{s}$ .  
340 The lower Ain River is characterized by an active channel shifting within a forested floodplain (Lassetre et  
341 al., 2008). An AXIS221 Day/Night<sup>TM</sup> camera with a resolution of  $768 \times 576$  pixels was installed at this station

342 to continuously record the water surface of the river at a maximum frequency of 5 fps (Fig 9). This camera  
343 replaced a lower resolution camera at the same location used by MacVicar and Piégay (2012). The specific  
344 location of the camera is on the outer bank of a meander, on the side closest to the thalweg, at a height of 9.8  
345 m above the base flow elevation. The meander and a bridge pier upstream help to steer most of the floating  
346 wood so that it passes relatively close to the camera where it can be readily detected with a manual procedure  
347 (MacVicar and Piégay, 2012). The transformation matrix at the base flow elevation with the camera as the  
348 origin is shown in Fig 10. Straight lines near the edges of the image appear curved because the fisheye  
349 distortion has been corrected on this image (see Sect 2.3); conversely, a straight line, in reality, is presented  
350 without any curvature in the image.

**Fig 9**

**Fig 10**

351 The survey period examined on this river was during 2012 from which two flood events, (January 1-7  
352 and December 15) were selected for annotation. A range of discharges from  $400\text{m}^3/\text{s}$  to  $800\text{m}^3/\text{s}$  occurred  
353 during these periods (Fig 11), which is above a previously observed wood transport threshold of  $\sim 300\text{m}^3/\text{s}$   
354 (MacVicar and Piégay, 2012). The flow discharge is available from the website ([www.hydro.eaufrance.fr](http://www.hydro.eaufrance.fr)).  
355 On January 3<sup>rd</sup> and 5<sup>th</sup>, a spider was active in front of the camera, which prevented a good video recording  
356 and these days were therefore removed from the database. Detection was only possible during the daylight.  
357 A summary of automated and manual detections for the six days is shown in Table 3.

**Fig 11**

#### 358 **4.1.2. Assessment Methodology**

359 Ghaffarian et al. (2020), Zhang et al. (2020) show that the wood discharge can be measured from flux  
360 or frequency of wood objects. An object level detection was thus sufficient for the larger goals of this re-  
361 search at the Ain River, which is to get a complete budget of transported wood volume.

362 A comparison of annotated with automatic object detections gives rise to three options:

- 363 1- True Positive (*TP*): an object is correctly detected and is recorded in both the automatic and annotated  
364 database
- 365 2- False Positive (*FP*): an object is incorrectly detected and is recorded only in the automatic database.
- 366 3- False Negative (*FN*): an object is not detected automatically and is only recorded in the annotated

367 database.

368 Despite overlapping occurrences of wood objects in the two databases, the objects could vary in position  
369 and size between them. For the current study we set the TP threshold as the case where either at least 50%  
370 of the automatic and annotated bounding box areas were common or at least 90% of an automatic bounding  
371 box area was part of its annotated counterpart.

372 In addition to the raw counts of *TPs*, *FPS*, and *FNS*, we defined two measures of the performances of  
373 the application, where:

- 374 • Recall Rate (*RR*) is the fraction of wood objects that are automatically detected ( $TP/(TP + FN)$ ); and  
375 • Precision Rate (*PR*) is the fraction of detected objects that are wood ( $TP/(TP + FP)$ ).

376 The higher the *PR* and the *RR* are, the more accurate our application is. However, both rates tend to  
377 interact. For example, it is possible to design an application that displays a very high *RR* (which means that  
378 it doesn't miss many objects), but suffers from a very low *PR* (it outputs a high amount of inaccurate data),  
379 and vice-versa. Thus, we have to find a balance that is appropriate to each application.

### 380 **4.1.3. Factors used to understand variation in performance**

381 It was well known from previous manual efforts to characterize wood pieces and develop automated  
382 detection tools that it is easier to detect certain wood objects than others. In general, the ability to detect the  
383 wood objects in the dynamic background of a river in flood was found to vary with the size of the wood  
384 object, its position in the image frame, the flow discharge, the amount and variability of the light, interference  
385 from other moving objects such as spiders, and other weather conditions such as wind and rain. In this section,  
386 we describe and define the metrics that were used to understand the variability of the detection algorithm  
387 performance.

388 In general, more light results in better detection. The light condition can be varied by variation of a set  
389 of factors such as weather conditions or amount of sediment which is carried by the river. In any case, the  
390 daylight is a factor that can change the light condition systematically, *i.e.* low light early in the morning (Fig  
391 12.a), bright light at midday with potential for direct light and shadows (Fig 12.b), and low light again in the  
392 evening, though different from the morning because the hue is more bluish (Fig 12.c). This effect of the time  
393 of day was quantified simply by noting the time of the image, which was marked on the top of each frame of

394 the recorded videos.

### Fig 12

395 Detection is also strongly affected by the frame ‘roughness’, defined here as the variation in light over  
396 small distances in the frame. The change in light is important for the recognition of wood objects, but light  
397 roughness can also occur when there is a region with relatively light pixels due to something such as reflection  
398 of the surface of the water, and dark roughness can occur when there is a region with relatively dark pixels  
399 due to something such as shadows from the surface water waves. Detecting wood is typically more difficult  
400 around light roughness, which results in false negatives, while the color-map of a darker surface is often close  
401 to that of wood, which results in false positives. Both of these conditions can be seen in Fig 12 which is  
402 highlighted in Fig 12.a. In general, the frame roughness increases in windy days or when there is an obstacle  
403 in the flow, such as downstream of the bridge pier in the current case. The light roughness was calculated for  
404 the current study by defining a light intensity threshold and calculating the ratio of pixels of higher value  
405 among the frame. The dark roughness is calculated in the same way, but in this case the pixels less than the  
406 threshold were counted. In this work thresholds equal to 0.9 and 0.4 were used for light and dark roughness,  
407 respectively.

408 The oblique view of the camera means that the distance of the wood piece from the camera is another  
409 important factor in detection (Fig 13). The effect of distance on detection interacts with wood length, *i.e.*  
410 shorter pieces of wood that are not detectable near the camera may not be detectable toward the far bank due  
411 to the pixel size variation (Ghaffarian et al., 2020). Moreover, if a piece of wood passes through a region  
412 with high roughness (Fig 13) or amongst bushes or trees (Fig 13 right hand side) it is more likely that the  
413 software is unable to detect it. In our case, one day of video record could not be analyzed due to the presence  
414 of a spider that moved around in front of the camera.

### Fig 13

415 Flow discharge is another key variable in wood detection. Increasing flow discharge generally means  
416 that water levels are higher, which brings wood close to the near bank of the river closer to the camera. This  
417 change can make small pieces of wood more visible, but it also reduces the angle between the camera position  
418 and pixels, which makes wood farther from the camera harder to see. High flows also tend to increase surface  
419 waves and velocity, which can increase the roughness of the frame and lead to the wood being intermittently  
420 submerged or obscured. More suspended sediment is carried during high flows which can change water



421 surface color and increase the opacity of the water.

## 422 4.2. Detection performance

423 Automatic detection software performance was evaluated based on the event based  $TP$ ,  $FP$ , and  $FN$   
424 raw numbers and the precision (PR) and recall rates (RR) using the default parameters in the software. On  
425 average, manual annotation resulted in the detection of approximately twice as many wood pieces as the  
426 detection software (Table 3). Measured over all the events,  $RR = 29\%$ , which indicates that many wood  
427 objects were not detected by the software, while among detected objects about 36% were false detections  
428 ( $PR = 64\%$ ).

**Table 3**

429 To better understand model performance, we first tested the correlation between the factors identified  
430 in the previous section (Table 4). As shown, the pairs of dark/light roughness, length/distance and dis-  
431 charge/time were highly correlated ( $Corr. = 0.59, 0.46, 0.37$  respectively). For this reason, they were con-  
432 sidered together to evaluate the performance of the algorithm within a given parameter space. The X/Y po-  
433 sitions were also considered as a pair despite a relatively low correlation (0.15) because they represent the  
434 position of an object. As a note, the correlation between time and dark roughness is higher than discharge  
435 and time, but we used the discharge/time pair because discharge has a good correlation only with time. As  
436 recommended by MacVicar and Piégay (2012), wood lengths were determined on a log base 2 transformation  
437 to better compare different classes of floating wood, similar to what is done for sediment sizes.

**Table 4**

**Fig 14**

438 The presentation of model performance by pairs of correlated parameters clarifies certain strengths and  
439 weaknesses of the software (Figure 14). As expected, the results of Fig 14.b indicate that first, the software  
440 is not so precise for small pieces of wood (less than the order of 1 m), and second there is an obvious link  
441 between wood length and the distance from the camera so that by increasing the distance from the camera,  
442 the software is precise only for larger pieces of wood. Based on Fig 14.e, the software precision is usually  
443 better on the right side of the frame than the left side. It would be reasonable, as the software requires to  
444 detect a patch at least in 5 continuous frames to recognize it as a piece of wood (see Sect 2.2 and Fig 4 for  
445 more information). Therefore, most of the true positives are on the right side of the frame, where 5 continuous  
446 frames have already established. Also, the presence of the bridge pier (at  $X \cong -30$  to  $-40$  m based on Fig 10)

447 in the upstream, produces lots of waves that decreases the precision of the software. Also, Fig 14.h shows  
448 that the software is much more precise during the morning when there is enough light rather than evening  
449 when the sunshine decreases. However, at low flow ( $Q < 550 \text{ m}^3/\text{s}$ ) the software precision decreases sig-  
450 nificantly. Finally, based on Fig 14.k, the software does not work well in two roughness conditions: (i) in a  
451 dark smooth flow (light roughness  $\cong 0$ ) when there are some dark patches (shadows ) on the surface (dark  
452 roughness  $\cong 0.3$ ), and (ii) when both roughness increases and there are many noises in a frame.

453 To estimate the fraction of wood pieces that the software did not detect, the recall rate  $RR$  is calculated  
454 in different conditions and a linear interpolation was applied on  $RR$  as it is presented in Fig 14, third column.  
455 According to Fig 14.c,  $RR$  is fully dependent on piece length so that for the lengths at the order of 10 m ( $L =$   
456  $O(10)$ )  $RR$  is very good. By contrast when  $L = O(0.1\sim 1)$  the  $RR$  is too small. There is a transient region  
457 when  $L = O(1)$  which is slightly depends on the distance from the camera. One can say, the wood length is  
458 the most crucial parameter that affects the recall rate independent of the operator annotation. Based on Fig  
459 14.f, the  $RR$  is much better on the left side of the frame than on the right side. It can be because the operator's  
460 eye needs some time to detect a piece of wood, so most of the annotations are on the right side of the frame.  
461 Having a small number of detections on the left side of the frame results in the small value of  $FN$  which  
462 followed by high values of  $RR$  in this region ( $RR = TP/(TP + FN)$ ). Therefore, while the position of detec-  
463 tion plays a significant role in the recall rate, it is completely dependent on the operator bias. By contrast,  
464 frame roughness, daytime, and flow discharge do not play a significant role in the recall rate (Fig 14. i, l).

### 465 4.3. Post-processing

466 This section is separated into two main parts. First, we show how to improve the precision of the soft-  
467 ware by a posteriori distinction between  $TP$  and  $FP$ . After removing  $FPS$  from the detected pieces, in the  
468 second part, we test a process to predict the annotated data that the software missed *i.e.* false negatives.

#### 469 4.3.1. Precision improvement

470 To improve the precision of the automatic wood detection we first ran the software to detect pieces and  
471 extracted the eight key parameters for each piece as described in Sect 4.1.3. We then estimated the total  
472 precision of each object, as the average of four precisions from each sub-figure of Fig 14. In the current study  
473 the detected piece was considered to be a true positive if the total precision exceeded 50%. To check the  
474 validity of this process, we used cross-validation by leaving one day out, calculating the precision matrices  
475 based on five other days, and applying the calculated  $PR$  matrices on the day that was left out. As is seen in

476 Table 5, this post-processing step increases the precision of the software to 85%, an enhancement of 21%.  
477 The degree to which the precision is improved is dependent on the day left out for cross-validation. If, for  
478 example, the day left out had similar conditions to the mean, the *PR* matrices were well trained and were able  
479 to distinguish between *TP* and *FP* (e.g. 2<sup>nd</sup> Jan with 42% enhancement). On the other hand, if we have an  
480 event with new characteristics (e.g. very dark and cloudy weather or at discharges different from what we  
481 have in our database), the *PR* matrices were relatively blind and offered little improvement (e.g. 15<sup>th</sup> Dec  
482 with 10% enhancement).

#### Table 5

483 One difficulty with the post-processing reclassification of wood piece is that this new step can also  
484 introduce error by classifying real objects as false positives (making them a false negative) or vice-versa.  
485 Using the training data, we were able to quantify this error and categorized them as post-processed false  
486 negatives ( $FN_{pp}$ ) with an associated recall rate ( $RR_{pp}$ ). As shown in Table 5, the precision enhancement  
487 process lost only around 14% of *TPs* ( $RR_{pp}=86\%$ ).

488 Instead of using all eight key parameters (four *PR* matrices) to calculate the overall precision, it is also  
489 possible to use other configurations by combining different matrices as it is shown in Fig 15. In this figure,  
490 the precision matrices 1 to 4 are the same as the matrices presented in Fig 14 and different colors show  
491 different combinations of these matrices. As it is seen, some configurations (e.g. (2,4) or (1,3,4)) result in  
492 better precision and some cases (e.g. (1,2) or (1,3)) there is almost no difference between post-processed *PR*  
493 and the raw data. The reason that configurations like (2,4) or (1,3,4) with a better precision rate were not used  
494 here was that in these cases the post-processed recall rate  $RR_{pp}$  was low (around 60%) meaning that by using  
495 these configurations many of true positives was removed. Therefore, to have the best precision enhancement  
496 with maximum post-processed recall rate all 4 different precision matrices are used (Fig 15, dark red scatters).

#### Fig 15

#### 497 4.3.2. Modeling missed wood pieces based on the recall rate

498 The automated software detected 29% of the number of manually annotated wood pieces (Table 5). In  
499 the previous section, it was described how to enhance the precision of the software to ensure that these auto-  
500 matically detected pieces are *TPs*. The larger question, however, is how to model the missing pieces. Based  
501 on Fig 14, the software work well for very large objects in most areas of the image and in most lighting  
502 conditions. However, the smaller pieces were found to be harder to detect, making the wood length the most

503 important factor governing the recall rate. Based on this idea, the final step in the post processing is to apply  
504 a model to account for the smaller wood pieces.

505 The model is based on the concept of a threshold piece length. Above the threshold, wood pieces are  
506 likely to be accurately counting using the automatic software. Below the threshold, on the other hand, the  
507 automatic detection software is likely to deviate from the manual counts. The actual length distribution was  
508 first determined based on the manual annotations ( $TP + FN$ ) (Fig 16.a). Also shown are the raw results of  
509 the automatic detection software ( $TP + FP$ ) and the raw results with the false positives removed ( $TP$ ). At  
510 this stage, the difference between the  $TP$  and the  $TP + FN$  lines are the false negatives ( $FN$ ) that the software  
511 has missed. Comparison between the two lines shows that they tend to deviate between 2-3 m. The correla-  
512 tion coefficient between them was calculated for thresholds varying from 1 cm to 15 m length and 2.5 m  
513 length was defined as the optimum threshold length for recall modeling (Fig 16.b).

514 In the next step we wanted to estimate the pieces less than 2.5 m that the software missed. During the  
515 automatic detection process, when the software detects a piece of wood, according to Fig 14 (third column),  
516 the  $RR$  can be calculated for this piece (same protocol as precision enhancement in Sect 4.3.1). Therefore, if  
517 for example the average recall rate for a piece of wood is 50%, there is likely to be another piece in the same  
518 condition (defined by the eight different parameters described in Table 2) that the software could not detect.  
519 To correct for these missed pieces, additional virtual pieces were added to the database. Fig 16.a, shows the  
520 length distribution after adding these virtual pieces to the database (blue line, total of 5841 pieces). The result  
521 shows a good agreement between this and the operator annotations (green line, total of 6249 pieces), which  
522 results in a relative error of only 6.5% in the total number of wood pieces.

#### Fig 16

523 On the Ain River by separating videos to 15 min segments, MacVicar and Piégay, (2012) and Zhang et  
524 al., (2020) proposed the following equation for calculating wood discharge from the wood flux:

$$525 \quad Q_w = 0.0086F^{1.24} \quad (1)$$

526 where,  $Q_w$  is the wood discharge ( $m^3/15min$ ) and  $F$  is the wood flux (piece number/15 min). Using  
527 this equation, the total volume of wood was calculated based on three different conditions: (i) operator anno-  
528 tation ( $TP + FN$ ), (ii) raw data of the detection software ( $TP + FP$ ) and (iii) post-processed data of the de-  
529 tection software ( $TP_{modeled}$ ). Fig 17 shows a comparison of the total volume of wood from the manual

530 annotations in comparison with the raw and post-processed annotations from the detection software. As  
531 shown, the raw detection results underestimate wood volume by almost one order of magnitude. After pro-  
532 cessing, the results show some scatter but are distributed around the 1:1 slope, which indicates that they  
533 follow the manual annotation results. There is a slight difference for days with lower fluxes (Jan 4 and 7),  
534 where the post-processing tends to over-estimate wood volumes, but in terms of an overall wood balance the  
535 volume of wood on these days are negligible. In total,  $125 \text{ m}^3$  wood was annotated by the operator and the  
536 software automatically detected only  $46 \text{ m}^3$ , some of which represent false positives. After post-processing,  
537  $142 \text{ m}^3$  wood was estimated to have passed in the analyzed videos for a total error of 13.5%.

**Fig 17**

## 538 **5. Conclusion**

539 Here, we present new software for the automatic detection of wood pieces on the river surface. After  
540 presenting the corresponding algorithm and the user interface, an example of automatic detection was pre-  
541 sented. We annotated 6 days of flood events that were used to first check the performance of the software  
542 and then develop post-processing steps to both remove possibly erroneous data and model data that were  
543 possibly missed by the software.

544 To evaluate the performance of the software, we used precision and recall rates. The automatic detection  
545 software detects around one third of all annotated wood pieces with 64% precision rate. Then using the op-  
546 erator annotations as the ultimate goal, the post-processing part was applied to extrapolate data extracted  
547 from detection results, aiming to come as close as possible to the annotations. It is shown that using four pair  
548 of key factors: (i) light and dark roughness of the frame, (ii) daytime and flow discharge, (iii) X, Y coordinates  
549 of detection position, and (iv) distance of detection as a function of piece length, it is possible to detect false  
550 positives and increase the software precision to 86%. Using the concept of a threshold piece length for de-  
551 tection it is shown that it is then possible to model the missed wood pieces (false negatives). In the presented  
552 results, the final recall rate results in a relative error of only 6.5% for piece number and 13.5% for wood  
553 volume.

554 This work shows the feasibility of the detection software to detect wood pieces automatically. Auto-  
555 mation will significantly reduce the time and expertise required for manual annotation, making video moni-  
556 toring a powerful tool for researchers and river managers to quantify the amount of wood in rivers. The

557 software should be applied in other rivers to test it in different contexts and enhance its accuracy.

558 **6. Code/Data/Sample availability**

559 Not available.

560 **7. Author contribution**

561 Hossein Ghaffarian: Application of statistical, and computational techniques to analyses study data. Creation  
562 and presentation of the published work.

563 Hervé Piégay, Bruce MacVicar, Hossein Ghaffarian: Development and design of methodology; creation of  
564 models.

565 Laure Tougne, Pierre Lemaire: Programming and software development.

566 Pierre Lemaire, Zhang Zhi: Performing the surveys, and data collection.

567 Hervé Piégay, Bruce MacVicar, Pierre Lemaire, Hossein Ghaffarian: Critical review, commentary, and revi-  
568 sion.

569 Hervé Piégay: Oversight and leadership responsibility for the research activity planning and execution, in-  
570 cluding mentorship external to the core team.

571 **8. Competing interests**

572 The authors declare that they have no conflict of interest.

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722

**Table 1 Characteristics of streamside video monitoring techniques in different studies.**

Article	Sampling	Temporal scales	Camera resolution	Study site
MacVicar & Piégay (2012)	15 min segments	3 floods/18 hr/5 fps	640 × 480	Ain, France
Kramer & Wohl (2014)	Total duration	32 days/12761 frames/0.017 fps	n/a	Slave, Canada
Boivin et al. (2017)	Total duration	3 floods/150 hr/25 fps	640 × 480	St Jean, Canada
Kramer et al. (2017)	Total duration	11 months/0.0017 fps	1268 × 760	Slave, Canada
Senter et al. (2017)	15 min segments	39 days/180 hr/4 fps	2048 × 1536	North Yuba, USA
Ghaffarian et al. (2020)	Total duration	2 floods/80 hr/1 fps	600 × 800	Isère, France
Zhang et al. (2020)	Total duration	7 floods & 1 windy period /183 hr/5 fps	from 640 × 480 up to 800 × 600	Ain, France

**Table 2 Parameters used to assess the performance of the software**

Parameter	Rational	Metric
Piece length	Larger objects are easier to detect.	
Distance	Objects closer to the camera are easier to detect.	Detecting an object in pixel coordinates.
X position	Some particular areas of turbulent flow in the field of view	Transferring coordinates to metric.
Y position	affect detection (e.g. presence of a bridge pier).	Calculating length, position, and distance.
Discharge	Flow discharge affects water color, turbulence and the amount of wood.	Recorded water elevation data and calibrated rating curve at hydrologic station.
Time	Luminosity of the frames varies with time of day.	Time of day as indicated on top of each frame.
Dark roughness	Small spots with sharp contrast (either lighter or darker) affect detection.	% of pixels below an intensity threshold
Light roughness		% of pixels above an intensity threshold

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**Table 3 Summary of automated and manual detections**

Date	discharge ( $m^3/s$ )		Water level ( $m$ )		Detection time ( $hr$ )	Number		Precision rate%	Recall rate%
	$Q_{max}$	$Q_{min}$	$h_{max}$	$h_{min}$		annot.	det.		
1/1/2012	718	633	-7.4	-7.8	7 to 17	2282	972	77	33
2/1/2012	772	674	-7.2	-7.6	7 to 17	802	380	52	24
4/1/2012	475	423	-8.4	-8.6	7 to 17	140	158	20	22
6/1/2012	786	763	-7.2	-7.2	7 to 17	712	384	54	29
7/1/2012	462	430	-8.5	-8.6	7 to 17	117	73	40	25
15/12/2012	707	533	-7.5	-8.2	9 to 14	1296	503	72	28
Total	786	423	-7.2	-8.6	55 $hr$	5349	2470	64	29

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**Table 4 Correlation between parameters**

	Dark roughness	Light roughness	Length	Distance	X position	Y position	Discharge	Time
Dark roughness		0.59	-0.02	-0.04	0.04	0.1	0	0.57
Light roughness	0.59		-0.03	-0.03	0.03	0.09	-0.04	0.29
Length	-0.02	-0.03		0.46	-0.45	-0.35	-0.02	-0.01
Distance	-0.04	-0.03	0.46		-1	-0.16	0.14	-0.05
X position	0.04	0.03	-0.45	-1		0.15	-0.15	0.05
Y position	0.1	0.09	-0.35	-0.16	0.15		0	0.07
Discharge	0	-0.04	-0.02	0.14	-0.15	0		0.37
Time	0.57	0.29	-0.01	-0.05	0.05	0.07	0.37	

**Table 5 Precision rate (PR) before and after post-processing**

	1 Jan	2 Jan	4 Jan	6 Jan	7 Jan	15 Dec	Total	
Raw data	<i>TP</i>	745	196	31	206	29	363	1570
	<i>FP</i>	227	184	127	178	44	140	900
	<i>FN</i>	1537	606	109	506	88	933	3779
	<i>PR%</i>	77	52	20	54	40	72	64
	<i>RR%</i>	33	24	22	29	25	28	29
Post-proc.	<i>TP</i>	658	150	30	178	22	315	1353
	<i>FP</i>	64	10	60	39	11	68	252
	<i>FN<sub>pp</sub><sup>1</sup></i>	87	46	1	28	7	48	217
	<i>PR%</i>	91	94	33	82	67	82	85
	<i>RR<sub>pp</sub><sup>2%</sup></i>	88	77	97	86	76	87	86
<i>PR improvement</i>	14	42	13	28	27	10	21	

725 <sup>1</sup>  $FN_{pp}$  denotes the false estimations of the precision matrices which results in missing some  $TP$ .

726 <sup>2</sup>  $RR_{pp}$  denotes the recall rate of post processing which corresponds to  $FN_{pp}$ .

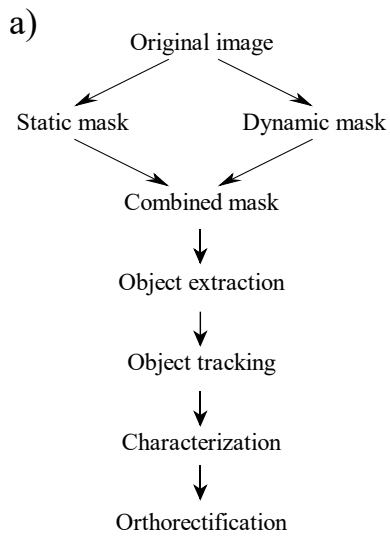
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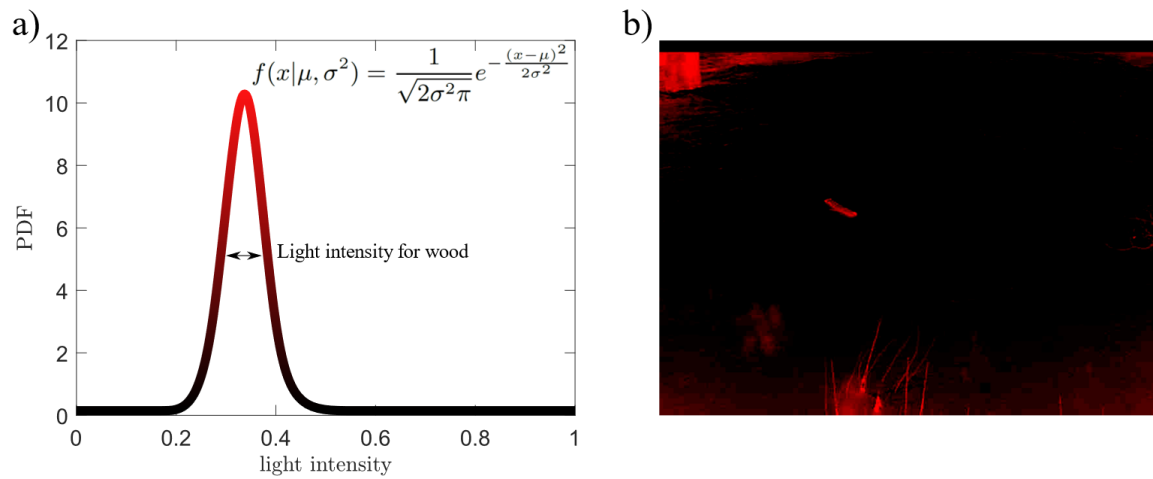
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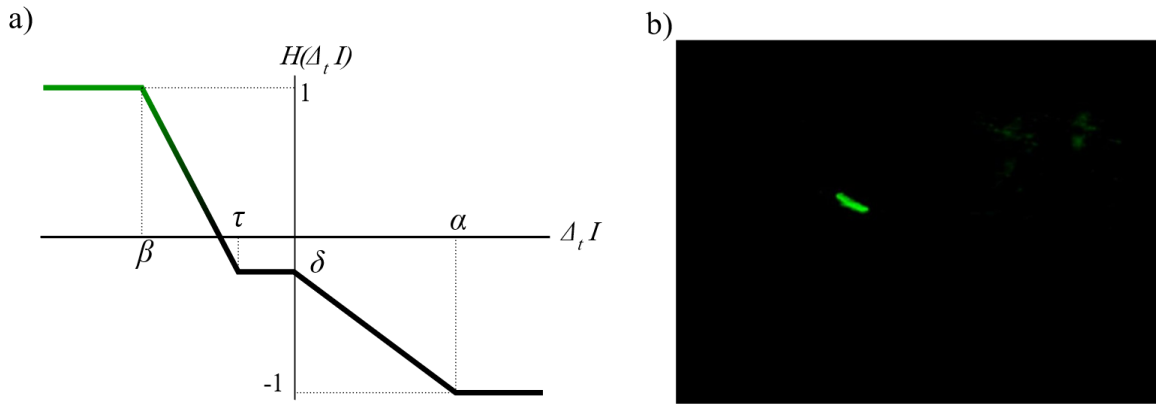
732

**Fig 1 a) Flowchart of the detection software and b) an example of frame on which these different flowchart steps are applied.**



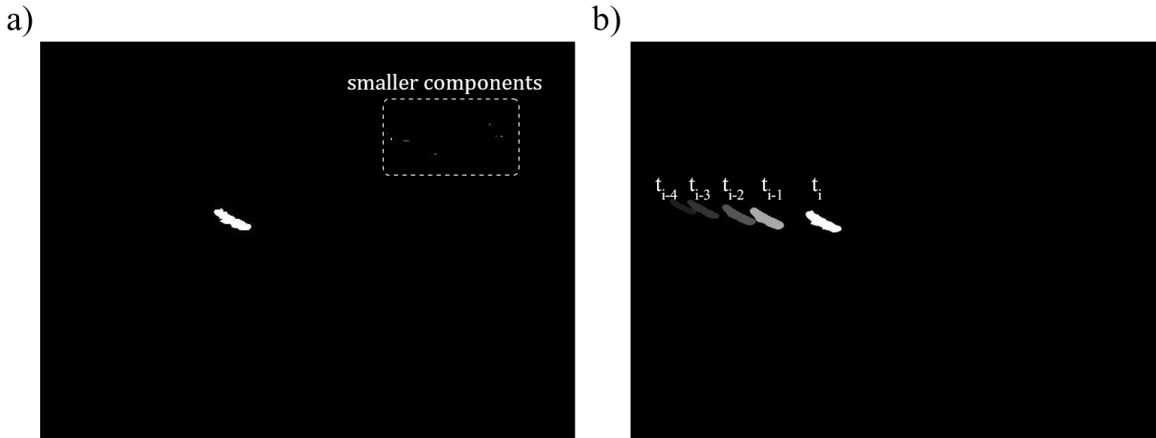
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**Fig 2 Static probability mask, a) Gaussian distribution of light intensity range for a piece of wood, b) employment of probability mask on the sample frame.**



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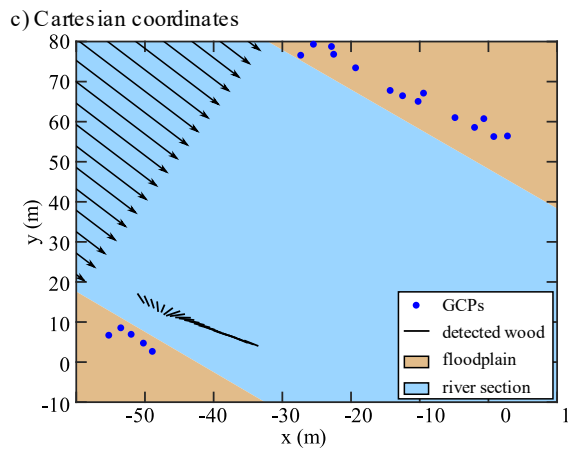
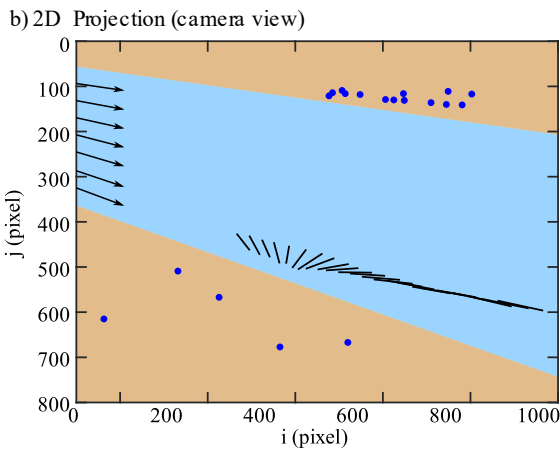
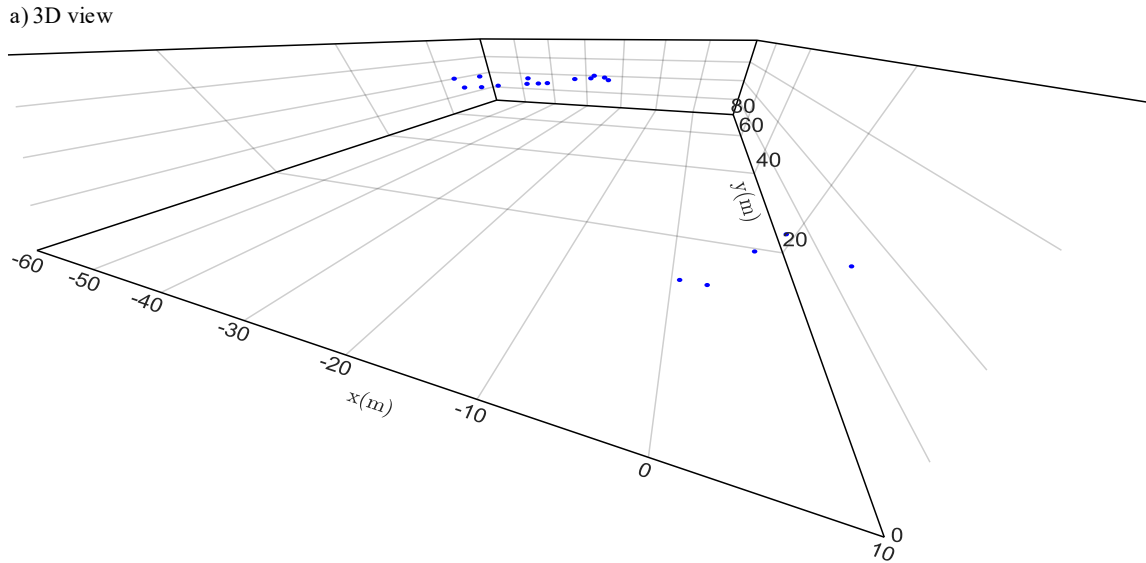
Fig 3 Dynamic probability mask, a) updating function  $H(\Delta_t, I)$  adapted from Ali et al. (2011) and b) employment of probability mask on the sample frame.



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Fig 4 a) Object extraction by (i) combining static and dynamic masks and (ii) applying a threshold to retain only high-probability pixels. b) Object tracking as a filter to deal with partly immersed objects and to distinguish between moving objects from static waves.





**Fig 5 Image rectification, process. 3D view of non-collinear GCPs in metric coordinates (a), their corresponding localization within the image (b), and the relative 2D metric coordinates for a given water level (c). (b,c) A practical example of the transformation of the coordinates is presented. The different solid lines represent the successive detection in a set of consecutive frames.**

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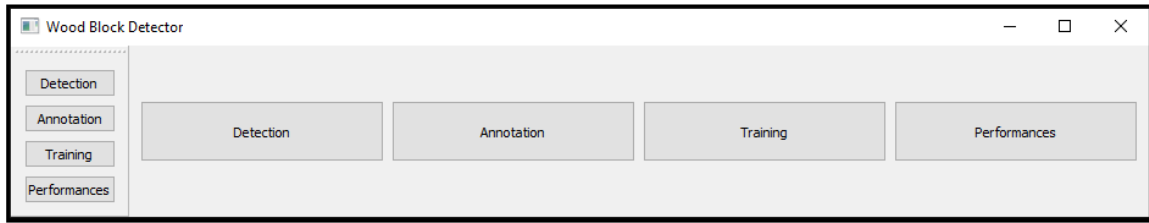


Fig 6 User interface of the detection software.

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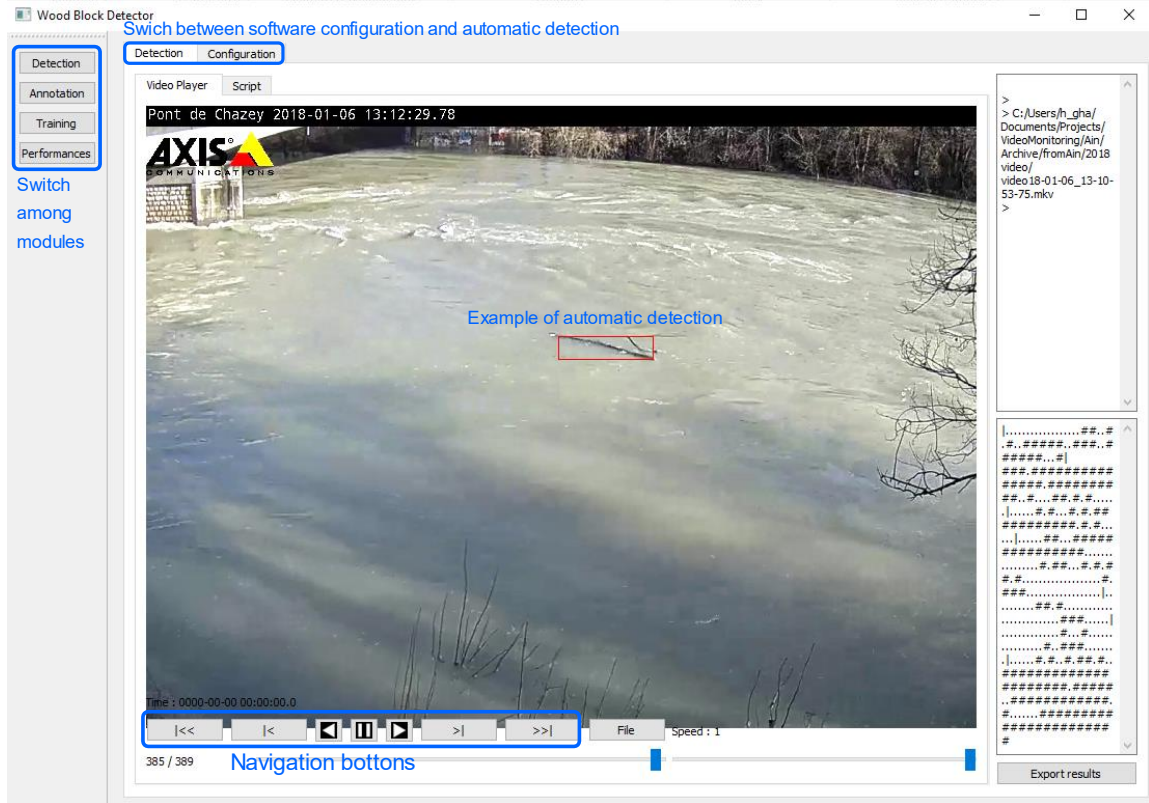
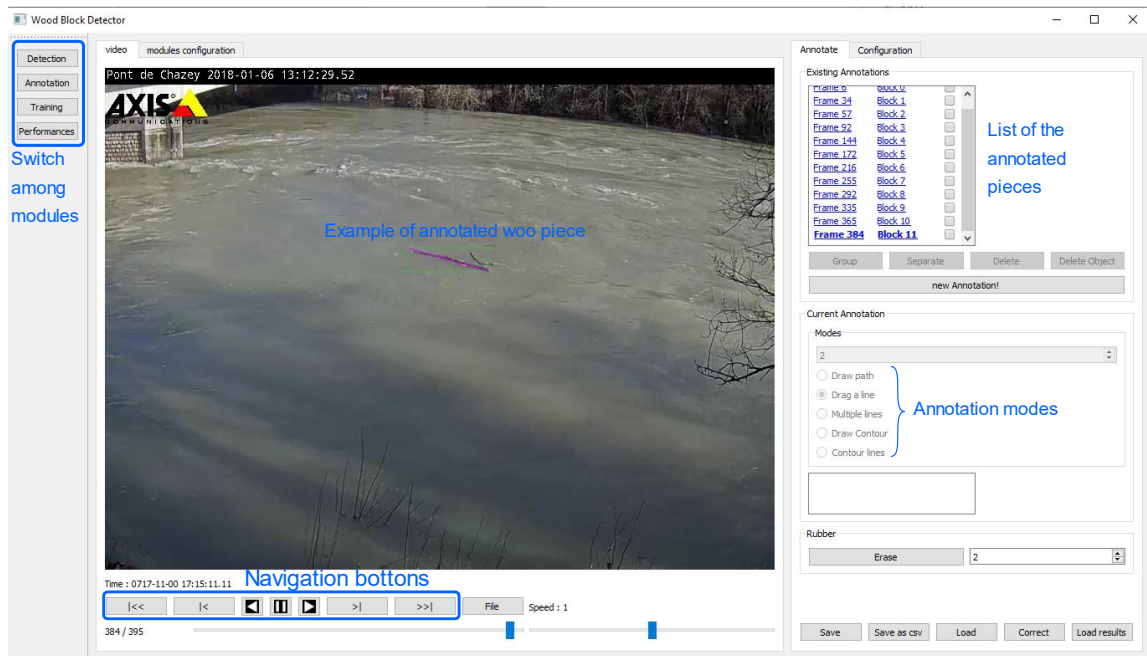
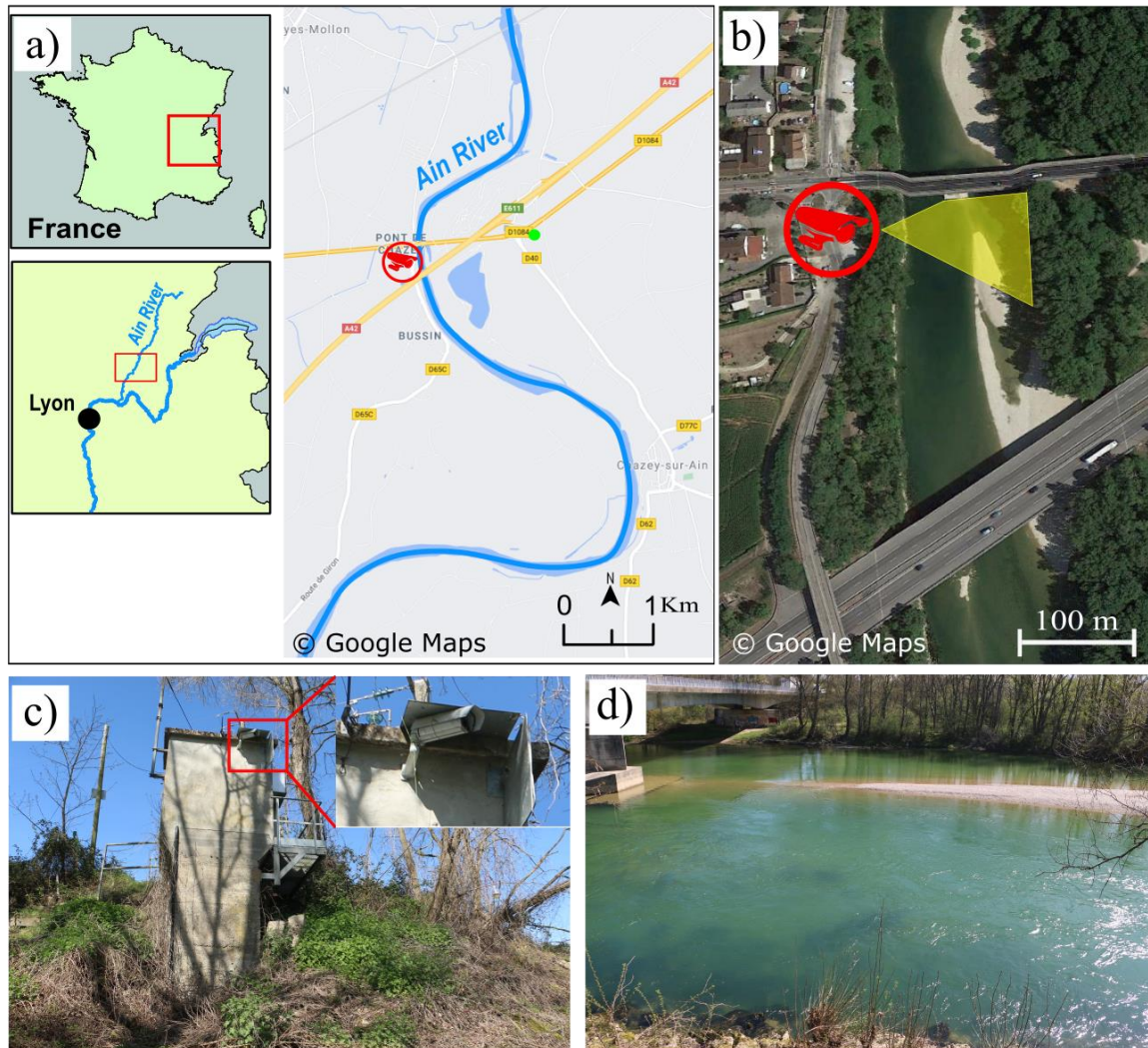


Fig 7 User interface of the detection module of automatic detection software.



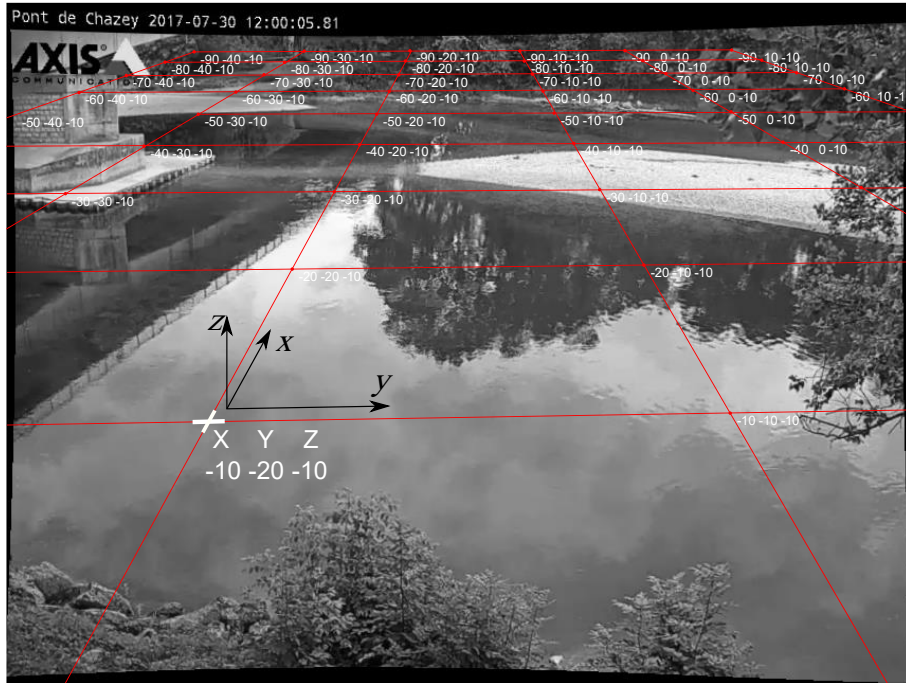
740

**Fig 8** User interface of the annotation module of automatic detection software.



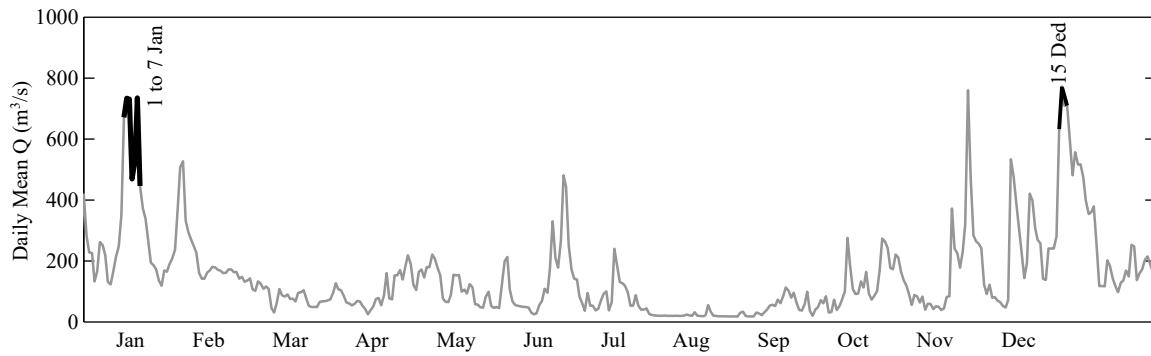
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**Fig 9** Study site at Pont de Chazey: a) Location of the Ain River catchment in France and location of the gauging and meteorological stations, b) camera position and its view angle in yellow, c) overview of the gauging station with the camera installation point.



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**Fig 10 Rectifying transformation matrix at low flow level with camera at (0,0,0).**



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**Fig 11 Daily mean discharge series for monitoring period from 1st to 7th January and in 15th December.**



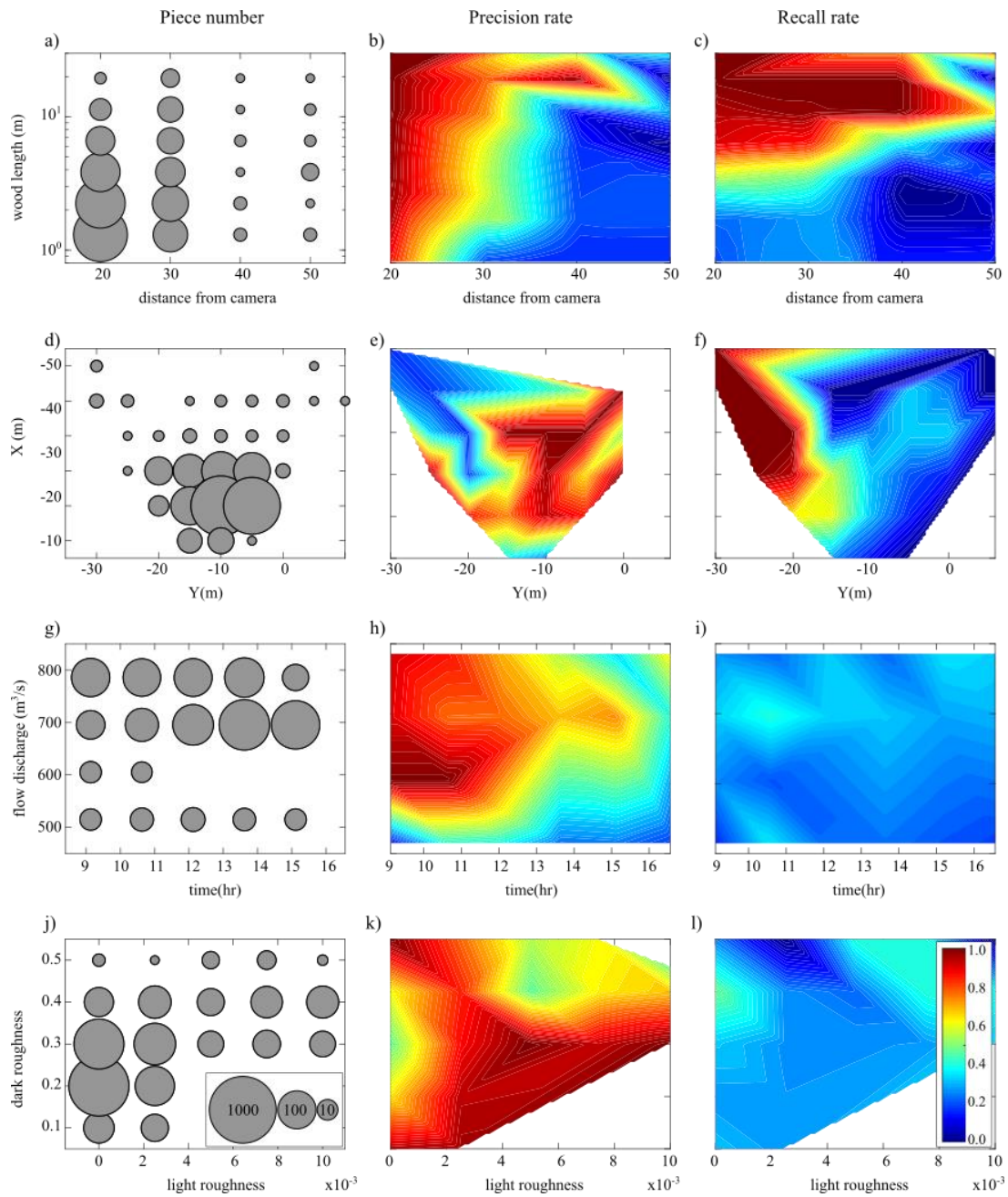
744

**Fig 12** Different light conditions during (a) morning, (b) noon and (c) late afternoon, results in different frame roughness's and different detection performances.



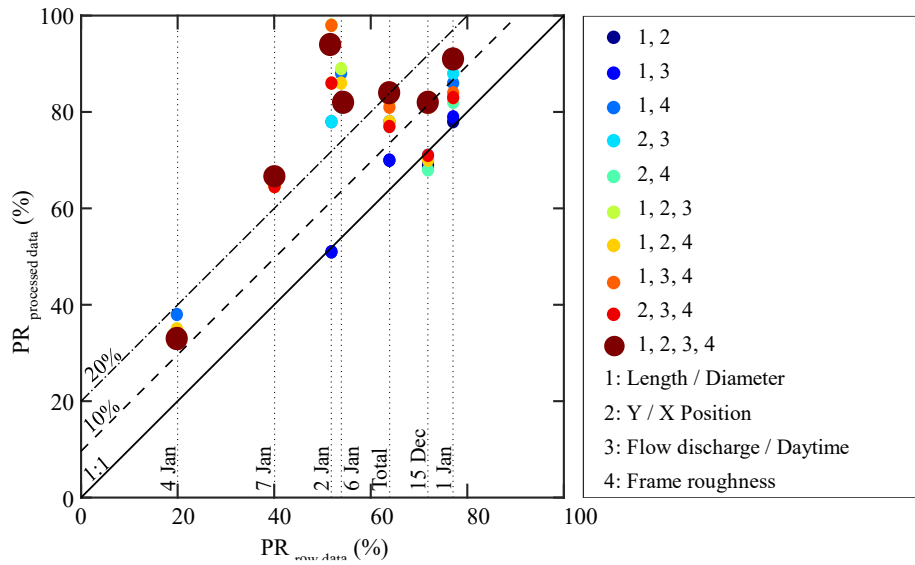
745

**Fig 13** Wood position can highly affect the quality of detection. Pieces that are passing in front of the camera are detected much better than the pieces far from the camera.



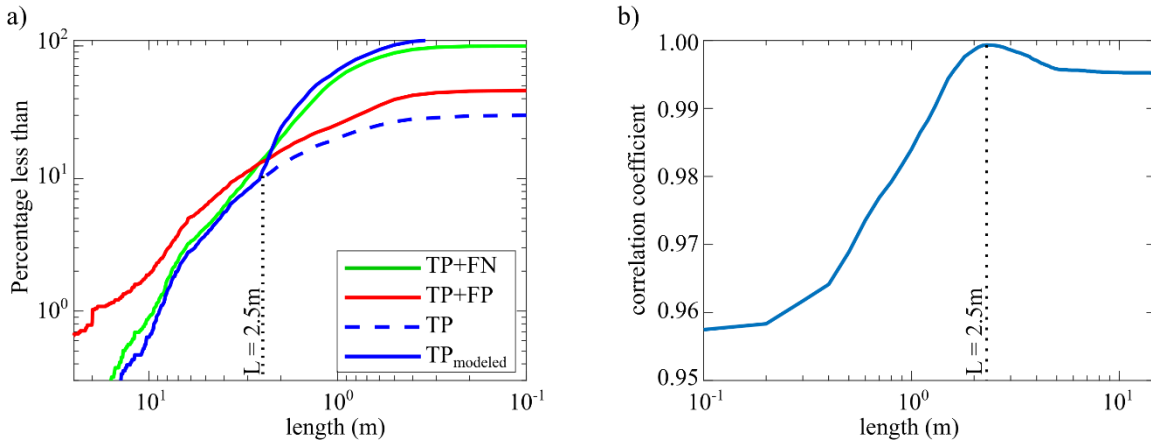
746

**Fig 14 Correction matrices: a, b, c) wood lengths as a function of the distance from the camera, d, e, f) detection position, g, h, i) flow discharges during the daytime, and j, k, l) light and dark roughness's. The first column shows number of all annotated pieces. Second and third columns show Precision and Recall rates of the software respectively.**



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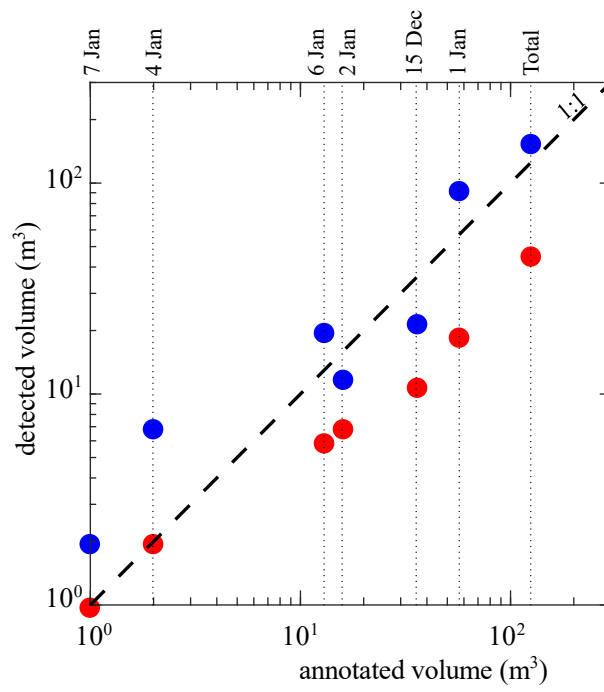
**Fig 15** Effect of using different combinations of *PR* matrices on precision improvement compared with 1:1 line (no improvement), 10% and 20% improvement lines.



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**Fig 16 a)** Steps to post-process software automatic detections: (i) raw detections (*TP + FP* red line), (ii) Only true positives using the *PR* improvement process (*TP* blue dashed line), and (iii) modeling false negatives (blue line). Operator annotation (green line is used as a benchmark). **b)** The correlation coefficient between operator annotation and modeled *TP* to find an optimum threshold length for *RR* improvement.





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**Fig 17 Comparison of the total volume of wood between operator annotation as the benchmark and raw data (red scatters) and post-processed data (blue scatters), compared with a 1:1 line.**