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# Using remote sensing to characterize riparian vegetation: a review of available tools and perspectives for managers

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## **Research Highlights**

- Review shows diverse approaches and objectives for mapping riparian vegetation
- Scale of observation, remote sensing data and mapped features are strongly related
- Finer spatial and temporal resolution will renew large scale and diachronic analyses
- We discuss the challenges of conveying remote sensing tools to managers
- Open access tools and co-construction with managers foster technology transfer

## **Abstract**

1 Riparian vegetation is a central component of the hydrosystem. As such, it is often subject to  
2 management practices that aim to influence its ecological, hydraulic or hydrological functions.  
3 Remote sensing has the potential to improve knowledge and management of riparian vegetation by  
4 providing cost-effective and spatially continuous data over wide extents. The objectives of this  
5 review were twofold: to provide an overview of the use of remote sensing in riparian vegetation  
6 studies and to discuss the transferability of remote sensing tools from scientists to managers. We  
7 systematically reviewed the scientific literature (428 articles) to identify the objectives and remote  
8 sensing data used to characterize riparian vegetation. Overall, results highlight a strong relationship  
9 between the tools used, the features of riparian vegetation extracted and the mapping extent. Very  
10 high-resolution data are rarely used for rivers longer than than 100 km, especially when mapping  
11 species composition. Multi-temporality is central in remote sensing riparian studies, but authors use  
12 only aerial photographs and relatively coarse resolution satellite images for diachronic analyses.  
13 Some remote sensing approaches have reached an operational level and are now used for  
14 management purposes. Overall, new opportunities will arise with the increased availability of very  
15 high-resolution data in understudied or data-scarce regions, for large extents and as time series. To  
16 transfer remote sensing approaches to riparian managers, we suggest mutualizing achievements by  
17 producing open-access and robust tools. These tools will then have to be adapted to each specific  
18 project, in collaboration with managers.

## **Keywords**

20 Riparian forest, alluvial forest, floodplain vegetation, LiDAR, UAV, satellite

21

## 22        **1. Introduction**

23        At the interface between terrestrial and aquatic biota, riparian vegetation is a central element in the  
24        hydrosystem, where it plays many ecological roles and interacts with all hydrosystem components  
25        (Naiman et al., 2005). In a broad sense, riparian vegetation corresponds to all vegetation types that  
26        grow within the area influenced by a river network (Naiman and Décamps, 1997).

27        Despite covering a relatively small area, riparian vegetation provides many ecosystem services  
28        related to river flow (Dixon et al., 2016), sedimentary processes (Zaimes et al., 2004), biodiversity  
29        (Naiman and Décamps, 1997), water quality (Honey-Rosés et al., 2013, Brogna et al., 2018), cultural  
30        value (Décamps, 2001, Klein et al., 2015, Vollmer et al., 2015). However, riparian ecosystems  
31        experience multiple pressures (e.g. land use, water diversion, modified flood regime) (Stella and  
32        Bendix, 2019) and have been severely altered in many regions of the world, for example in Western  
33        Europe (Hughes et al., 2012), southwestern North America (Poff et al., 2011), in the Murray-Darling  
34        Basin in Australia (Mac Nally et al., 2011) or in South Africa (Holmes et al, 2005). Consequently,  
35        riparian vegetation is often the focus of management practices, including restoration or  
36        rehabilitation measures (Dufour and Piégay, 2009; González et al., 2015; Capon and Pettit, 2018),  
37        buffer implementation (Lee et al., 2004) or repeated maintenance operations such as wood removal  
38        (Piégay and Landon, 1997; Wohl et al., 2016).

39        In this context, management practices must be based on accurate and up-to-date information about  
40        the state of riparian vegetation (National Research Council, 2002). Regional or national programs  
41        have thus been established in many countries to monitor the health of riparian ecosystems.  
42        Examples include southern Belgium (Debruxelles et al, 2009), Spain and more generally the European  
43        Union in the frame of the Water Framework Directive (Munné et al., 2003, Willaarts et al., 2014),  
44        Australia with the South East Queensland Healthy Waterways Partnership (Bunn et al., 2010) or the  
45        monitoring of riparian condition in several National Parks in North America (Starkey, 2016). Dense  
46        sampling schemes can help target and implement management practices (Landon et al., 1998;

47 Beechie et al., 2008) or assess their effectiveness (González et al., 2015). However, due to the spatial  
48 arrangement, dynamism and inaccessibility of riparian ecosystems, data acquisition in the field can  
49 be labor-intensive, especially for large areas (i.e. more than 100 km of a river) (Johansen et al., 2007).  
50 It is thus difficult to sample densely in the field, and the density or the extent of observations must be  
51 reduced. This can be problematic, because river scientists argue that small scale or discontinuous  
52 observations are inadequate to understand spatially continuous processes that occur at large spatial  
53 scales (Fausch et al., 2002; Marcus and Fonstad, 2008; see also Tabacchi et al., 1998 or Palmquist et  
54 al., 2018 for examples related to riparian vegetation).

55 Remote sensing provides the ability to acquire continuous data over large extents. In the past few  
56 decades, the continued development of sensors, vectors and computational power has fueled the  
57 development of applications in environmental science (Anderson and Gaston, 2013; Wulder et al.,  
58 2012). The positive contribution of remote sensing to the management of natural resources is  
59 adressed by many articles related to river or riparian management (Carbonneau and Piégay, 2012,  
60 Dufour et al., 2012). This is not only a theoretical issue as is it regularly raised by riparian managers in  
61 the grey literature (Vivier et al., 2018, Fédération des Conservatoires d'espaces naturels, 2018).  
62 However, it is difficult for managers to know whether and which remote sensing methods are  
63 relevant to a particular situation (Dufour et al., 2012).

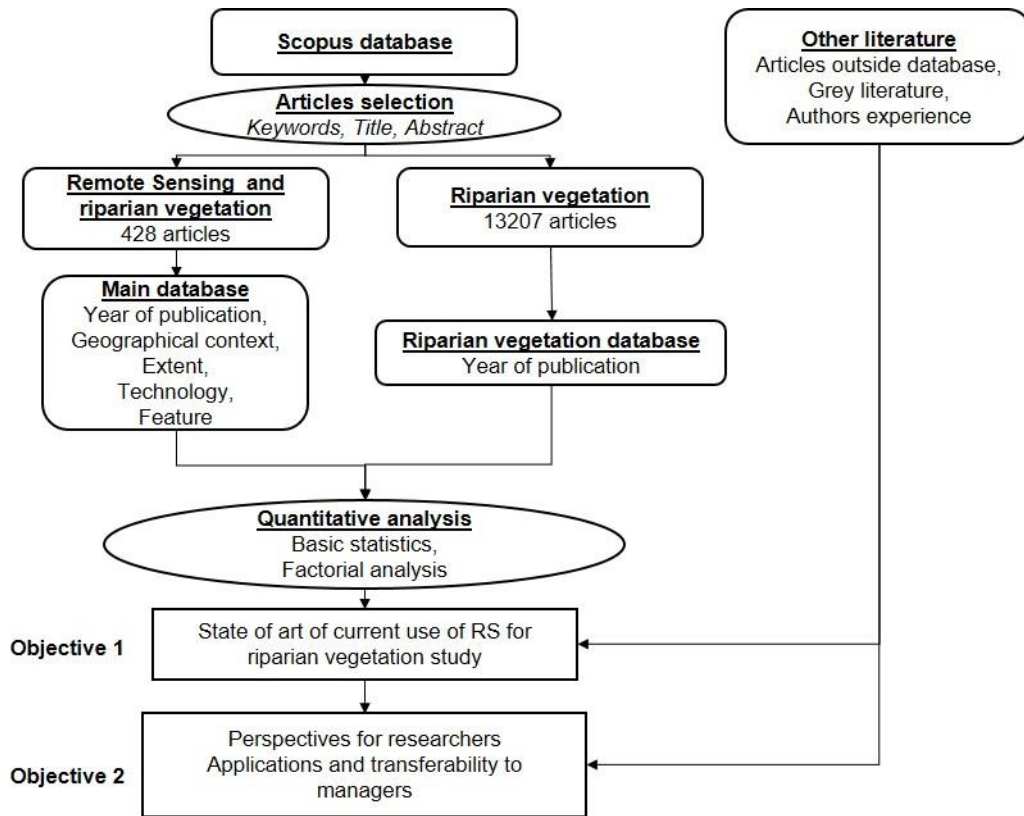
64 The use of remote sensing to study riparian vegetation raises specific challenges. These challenges  
65 are linked to the vegetation's relative structural complexity and spatial organization (Naiman and  
66 Décamps, 1997), or to the difficulty to extract specific features or processes related to riparian  
67 vegetation functions (e.g. surface roughness by Straatsma and Baptist (2008), shading of streams by  
68 Loicq et al., 2018). In a recent literature review, remote sensing emerged as a particularly dynamic  
69 subject in riparian studies (Dufour et al., 2019). Remote sensing of riparian vegetation was  
70 mentioned in several reviews addressing the remote sensing of rivers (Muller et al., 1993; Goetz,  
71 2006, Tomsett and Leyland, 2019, Piégay et al., 2020). Specific aspects were also reviewed such as

72 the mapping of roughness coefficients with remote sensing (Forzieri et al., 2012) or the use of  
73 satellite images to map riparian vegetation in New Zealand (Ashraf et al., 2010). Dufour et al. (2012)  
74 and Dufour et al. (2013) summarized and discussed several examples of remote sensing applications  
75 to map riparian vegetation. However, none of the aforementioned articles comprehensively  
76 reviewed the use of remote sensing to map riparian vegetation across regions, scales and  
77 researcher's interests. Indeed, the latter are fragmented among several fields of knowledge (e.g.  
78 ecology, geomorphology or hydraulics) (Dufour et al., 2019).

79 The aims of this article are 1) to provide a comprehensive overview of the relevance of remote  
80 sensing to support the study of riparian vegetation and 2) to discuss how remote sensing approaches  
81 can be valued as operational tools for managing riparian vegetation. To these ends, we first  
82 systematically review the different types of data used to study major features, functions and  
83 processes related to riparian vegetation across scales (section 3). The second part of the article  
84 (section 4) is based on expert judgment. We provide concrete examples where remote sensing is  
85 used in management contexts, in order to identify the challenges of conveying remote sensing tools  
86 from scientists to managers.

## 87 **2. Materials and methods**

88 Our approach was structured as following: we first selected relevant articles in the Scopus database.  
89 Second, relevant information was extracted for each article, and summarized into graphs. Our results  
90 were discussed in terms of trends and perspectives for research, and in terms of operability and  
91 transferability to riparian managers. The Figure 1 synthesizes our approach. Major steps are further  
92 detailed in the following sections.

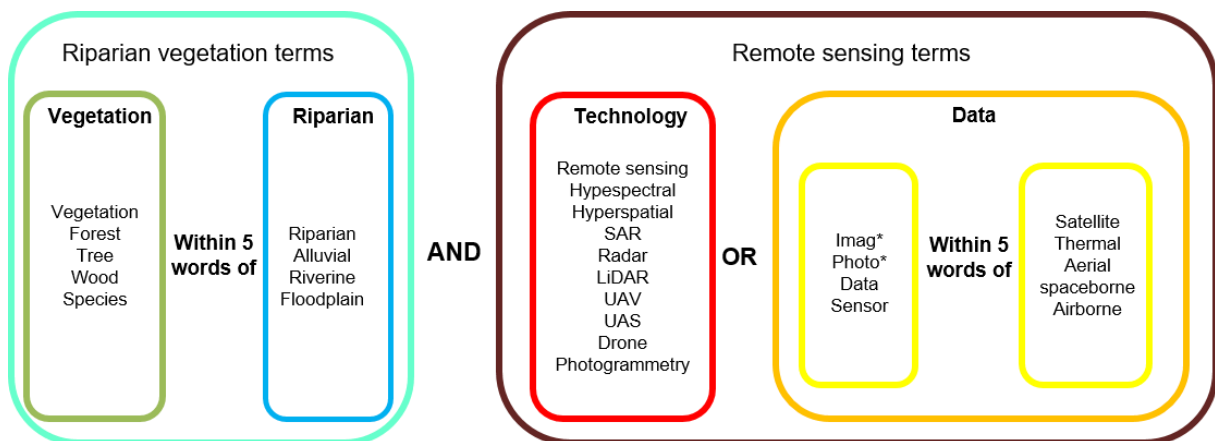


93

94 *Figure 1. General workflow for the reviewing process*

95 **2.1. Database collection**

96 Relevant articles were selected from the Scopus database (www.scopus.com) for the period 1980 -  
 97 April 2018, when the database was queried. We searched the title, abstract and the keywords for  
 98 words related both to riparian vegetation and to remote sensing technologies. More precisely, we  
 99 used the request described in the Figure 2.



100

101 *Figure 2. Keywords used for database collection*



102 Our choice of keywords excluded articles that mentioned riparian zones, but not specifically riparian  
103 vegetation. While some of these articles could have been relevant for this review, including keywords  
104 related to riparian zones would have resulted in unmanageable noise.

105 This request yielded 791 articles. We first filtered out irrelevant articles based on their title (672  
106 articles kept). Then, we sorted through the remaining articles based on their abstracts (428 articles  
107 kept). During these two filtering steps, we removed mainly articles in which riparian vegetation was  
108 not an essential part of the study. For example, we removed geomorphological articles in which  
109 riparian vegetation was mentioned in the abstract but was not actually studied. Articles that used GIS  
110 but no remote sensing data were also removed (e.g. those using cadastral archives).

111 We also built a second database using only keywords related to riparian vegetation, excluding those  
112 related to remote sensing. This second database was solely used to estimate the proportion of  
113 remote sensing studies among riparian vegetation studies, and was not analyzed using the analysis  
114 grid described in the following section.

## 115 **2.2. Analysis grid**

116 We searched for features that characterized the articles collected to perform quantitative analysis  
117 and statistics. We built our analysis grid (Table 1) around five groups of variables: “general  
118 information”, “remote sensing technology”, “study extent”, “type of indicator” and “multi-  
119 temporality”. In this paragraph, when not obvious, we highlight in bold the codes (used in figures)  
120 associated with the variables. “General information” included variables such as the publication year  
121 and location of study area. “Remote sensing technology” described the type of remote sensing data  
122 used. To simplify interpretation, we recorded this information as common combinations of sensors  
123 and vectors. We distinguished the following: airplane with a RGB/GS (red-green-blue or  
124 panchromatic), digital or analog sensor (**Plane\_RGB**); airplane with a multispectral or hyperspectral  
125 sensor (**Plane\_MSHS**); UAV with any sensor (**UAV**); any vector with a LiDAR sensor (**LiDAR**); any  
126 vector with a RADAR sensor (**RADAR**) and satellite with a multispectral or hyperspectral sensor. This

127 last variable was coded according to image resolution: medium ( $> 10$  m, **Satlow**) or high ( $\leq 10$  m,  
128 **Sathi**). "Study extent" described the extent of the study area as the **length** of studied river or **area** of  
129 the study area. These two variables were recorded in categories and then summarized into a single  
130 category to simplify interpretation: **study extent**. "Type of indicator" described the type of features  
131 extracted with remote sensing data to describe riparian vegetation. Delineation of riparian  
132 vegetation among other land cover types (**DLC**) is the first feature extracted for managing riparian  
133 vegetation. Species composition is a major feature of riparian plant formations. It is related to  
134 habitat provision, bank stabilization and flood regulation functions; for example, willow is a pioneer  
135 species that helps to stabilize banks (Hupp, 1992). We distinguished studies that differentiate groups  
136 of species (**Communities**) and studies that differentiate species (**SP**). We also distinguished studies in  
137 which the target species were invasive (**SP\_invasive**), since riparian zones are particularly prone to  
138 invasions (Richardson et al., 2007). We distinguished studies in which the target communities were  
139 **succession stages**, since riparian systems are pulsed systems in which succession is regularly  
140 reinitiated, leading to a mosaic of succession stages (Kalliola and Puhakka, 1988). The structure of  
141 riparian vegetation is related to many ecological functions. We recorded general descriptors of  
142 vegetation structure such as vegetation **height**, **density**, **biomass** and **landscape** structure. We also  
143 recorded studies interested in hydraulic properties of vegetation (**Roughness**), since riparian  
144 vegetation has tremendous effects on the hydraulic regime of rivers, especially by slowing river flow  
145 (Curran and Hession, 2013). Riparian **shade** (or overhang) influences fish habitats and is a major  
146 factor regulating stream temperature (Poole and Berman, 2001). Large woody debris (**LWD**) has  
147 many effects on provision of aquatic habitats, river morphology and flood risk prevention (Wohl,  
148 2017). Features related to physiological processes, including **phenology** and **health status** (e.g. tree  
149 dieback), are a major concern for managers (Cunningham et al., 2018). Riparian **evapotranspiration**  
150 has often been studied in arid or semi-arid systems because it has a major effect on providing water  
151 for human use (Dahm et al., 2002). "Multi-temporality" included only one variable (**Diachronic**),  
152 which corresponded to a special type of study – diachronic analysis – that uses a temporal series of

153 images to describe vegetation dynamics. We recorded all variables as presence/absence data to  
 154 capture the use of several types of data or the mapping of several indicators in the same article.

155 *Table 1. Analysis grid used for each article in the database*

Group of variables	Variable	Values	Description
<b>General information</b>	Year		Publication year
	X1		Longitude of the study area
	Y1		Latitude of the study area
	Biome		World Wildlife Fund Biome of the study area (extracted from the geographical coordinates of the study area)
<b>Type of remote sensing data</b>	Plane_RGB	0/1	Use of black and white or true-color aerial images (except images acquired from UAVs)
	Plane_MSHS	0/1	Use of aerial images with 4 or more spectral bands (except those from UAVs)
	Satlow	0/1	Use of satellite images with resolution > 10 m
	Sathi	0/1	Use of satellite images with resolution ≤ 10 m
	UAV	0/1	Use of images acquired from UAVs
	LiDAR	0/1	Use of LiDAR data
	RADAR	0/1	Use of RADAR data
<b>Extent of the study area</b>	Length	1 to 5	Length of the river studied (for studies at the scale of the minor bed or floodplain)
	Area	1 to 5	Area of the study area (for studies at the watershed scale)
	Study extent	1 to 5	Combination of Length and Area: <ul style="list-style-type: none"> <li>• Local: Length &lt; 10 km</li> </ul>

				<ul style="list-style-type: none"> <li>• River segment: Length 10-100 km OR Area &lt; 100 km<sup>2</sup></li> <li>• Subregional: Length 100-1000 km OR Area 100-1000 km<sup>2</sup></li> <li>• Regional: Length &gt; 10,000 km OR Area 1000-10,000 km<sup>2</sup></li> <li>• Very large scale: Area &gt; 10,000 km<sup>2</sup></li> </ul>
<b>Type of indicator</b>	Delimitation	DLC	0/1	Mapping of riparian vegetation (including land cover studies)
	Species composition	Communities	0/1	Mapping of several distinct riparian plant communities
		Succession stages	0/1	Mapping of several succession stages
		SP	0/1	Mapping of riparian vegetation at the species level
		SP_invasives	0/1	Mapping of invasive species
	Vegetation structure	Height	0/1	Mapping of vegetation height
		Landscape	0/1	Calculation of landscape metrics (e.g. continuity)
		Density	0/1	Mapping of vegetation density
		Shade	0/1	Mapping of shade cast by vegetation
		Biomass	0/1	Mapping of biomass
		LWD	0/1	Large woody debris (wood in rivers)
		Roughness	0/1	Mapping of vegetation hydraulic properties
	Physiological processes	Evapotranspiration	0/1	Estimate of vegetation evapotranspiration
		Health status	0/1	Mapping of vegetation health status (e.g. tree dieback, defoliation)
		Phenology	0/1	Mapping of vegetation phenology
<b>Multi-temporality</b>	Diachronic	0/1	Diachronic analysis	

### 156 **2.3. Statistical analysis**

157 We computed the annual number of published studies using remote sensing of riparian vegetation.  
158 We also computed for each year the proportion of studies that used remote sensing among all  
159 riparian vegetation studies. To do so, we compared the number of articles in the database related to  
160 remote sensing and riparian vegetation with the number of articles in the database related to  
161 riparian vegetation in general.

162 The data collected with the analysis grid were summarized and plotted. We computed the number of  
163 articles for each WWF biome, the use of different remote sensing technologies through time. We  
164 then compared the use of different technologies according to the scale of observation, the indicator  
165 extracted and the multi-temporal character of studies.

166 Finally, we performed a multiple correspondence analysis in order to highlight relationships between  
167 the type of data and the type of feature extracted. We used the package FactoMineR of R software.  
168 All variables were recorded as categorical variables. Variables related to study extent and multi-  
169 temporality were added as supplementary variables.

### 170 **2.4. Interpretation of results**

171 Results were discussed in two phases. First (section 3), we use our quantitative review of the  
172 literature to establish the state of the art and main perspectives in the use of remote sensing to map  
173 riparian vegetation. Second (section 4), we discuss how remote sensing can be used in real  
174 management contexts. We first discuss the added value of remote sensing in such contexts using  
175 concrete examples from the grey literature and personal experience. Then, we use these examples to  
176 discuss the challenges that must be overcome in order to promote the use of remote sensing by  
177 riparian managers. Therefore, while the section 3 of this article is based on a rigorous review of the  
178 scientific literature, the section 4 of this article is rather based on expert judgment.

179

### 3. Results and discussion of the systematic review

180

#### 3.1. Location of the studies

181

Most studies in the 428 selected lay in the Northern Hemisphere (79%), especially in North

182

America (40% of studies) and Europe (20% of studies) (Figure 3). South America, Oceania, Asia

183

(mostly Japan) and Africa represented respectively 9%, 9%, 11% and 5% of studies. Most represented

184

biomes (Figure 4) were hardwood and mixed temperate forests (28%), temperate coniferous forests

185

(14%), and deserts and xeric bushes (13%). Mediterranean biomes (10%) and temperate open

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biomes (8%) were also well represented. Well-represented biomes generally corresponded to those

187

in developed countries. Conversely, boreal forests and tundra were least represented (< 1% of

188

studies), though they cover a large area globally (> 10% of emerged land area). In addition, despite

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the large extent of tropical biomes (tropical and equatorial forests or open vegetation, ca. 30% of

190

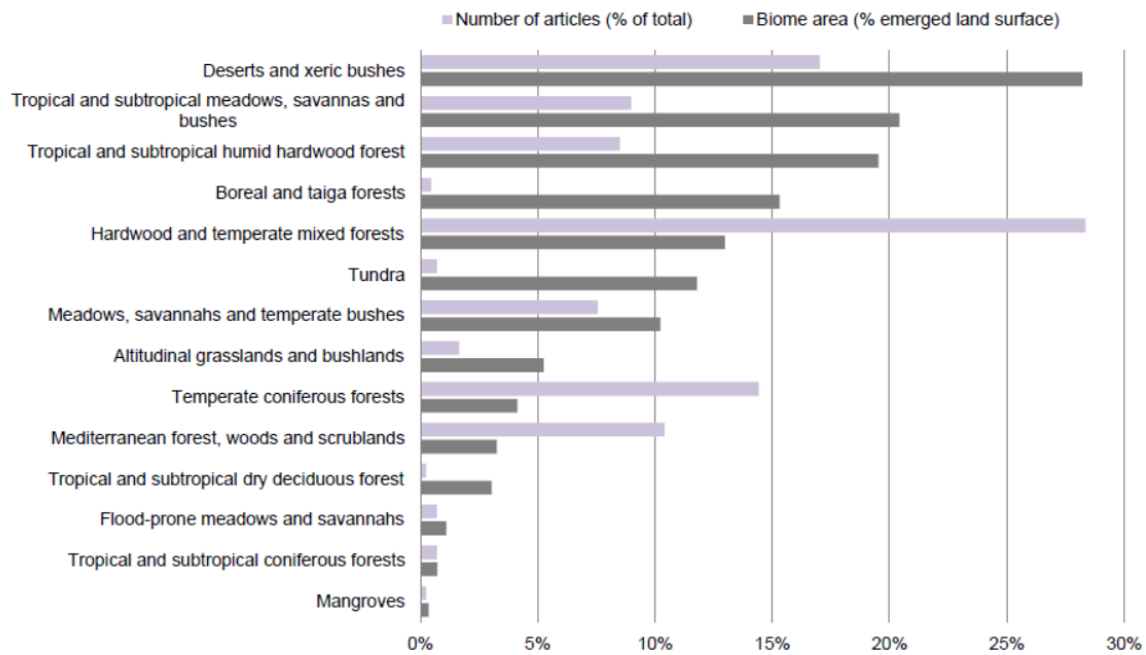
emerged land area), few studies focused on them.



191

192

*Figure 3: Locations of the study areas of the studies reviewed*



193

194 *Figure 4. Locations of studies reviewed, by World Wildlife Fund biome*

195 This result highlights the lack of knowledge and studies about tropical and boreal riparian forests,  
 196 perhaps due to the location of laboratories, which are often located in developed countries and  
 197 temperate climates. Our results are similar to those of Dufour et al. (2019) for all riparian vegetation  
 198 studies and those of Bendix and Stella (2013) for studies of vegetation/hydromorphology  
 199 relationships.

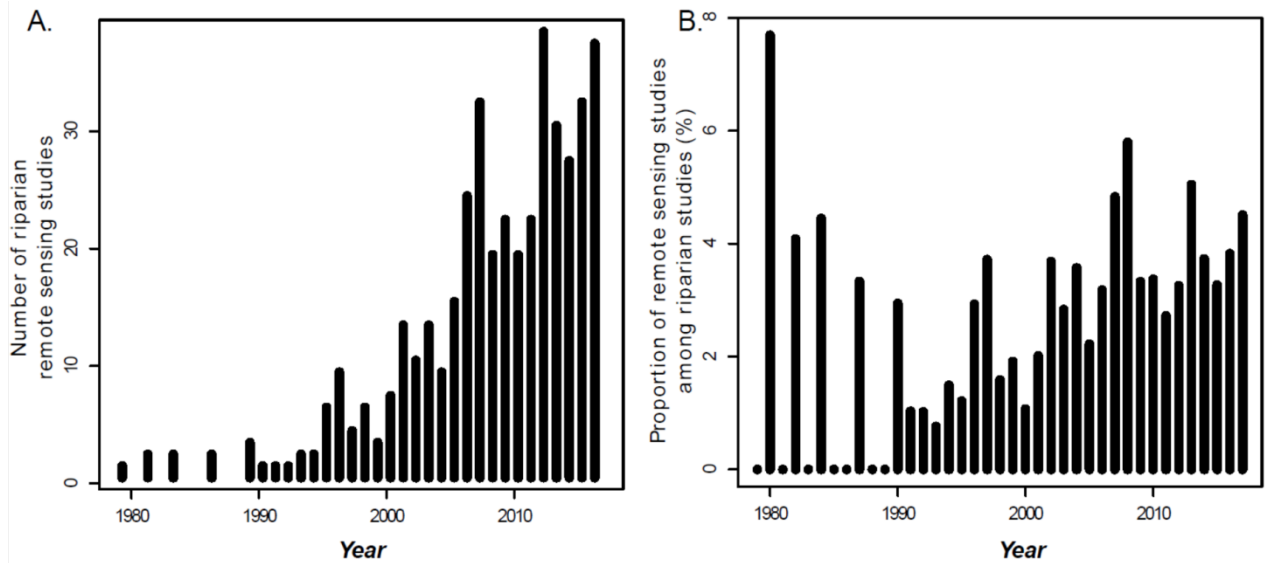
200 However, we suggest that the increasing quality of remote sensing data has great potential for  
 201 research in understudied areas and at the global scale. One condition is that these data must be  
 202 available to their potential users. Open or free remotely sensed data, such as Landsat, MODIS or,  
 203 more recently, Sentinel images, allow researchers to overcome the issue of the prohibitive cost of  
 204 data acquisition. This is particularly true for researchers in developing countries for data that are  
 205 produced in wealthier countries (Sá and Grieco, 2016). However, to broaden the user base, it is also  
 206 necessary to facilitate access to these data (Turner et al., 2015). Access can be facilitated by  
 207 providing higher-level (e.g. atmospherically corrected) or derived products, such as global land cover  
 208 maps (Gong et al., 2013), global floodplain models (Nardi et al., 2019) and maps of riparian zones

209 (Weissteiner et al., 2016, at the European scale). Access can also be made easier by developing an  
210 open, free or user-friendly environment to find, visualize and process data (Turner et al., 2015).

### 211 **3.2. Changes over time in the number of studies that used remote** 212 **sensing to study riparian vegetation**

213 Most of the 428 studies (89%) that used remote sensing to study riparian vegetation from 1980-2018  
214 were published after 2000 (Figure 5A), when the number of studies began to increase greatly. Before  
215 1990, few studies used remote sensing to study riparian vegetation. The percentage of studies using  
216 remote sensing among studies studying riparian vegetation increased in the 2000s (Figure 5B). Each  
217 year after 2000, 2-6% of all studies of riparian vegetation used remote sensing. Thus, even recently,  
218 relatively few studies use remote sensing data to study riparian vegetation, and field-based  
219 approaches dominate riparian vegetation studies despite the development of remote sensing and  
220 modeling approaches. This could be due to three main reasons. First, field-based approaches have  
221 traditionally been used and are straightforward. Some aspects of riparian vegetation, such as  
222 biogeochemical functioning and soil properties, cannot realistically be studied with remote sensing  
223 (Dufour et al., 2012). Second, the spatial structure of riparian vegetation makes it difficult to study  
224 using remote sensing. Its complexity (Naiman et al., 2005) and narrow shape is difficult to observe  
225 with low resolution satellite images (Johansen et al., 2010). Additionally, the linear shape of riparian  
226 corridors requires acquiring images over large areas (to cover sufficient corridor length), only to focus  
227 on small areas (near the river, rather than other land cover classes). For example, Weissteiner et al.  
228 (2016) estimated that Europe's riparian area represented ca. 1% of its total continental area. Third,  
229 we removed duplicate and irrelevant articles from our database, but did not do so when identifying  
230 all articles describing studies of riparian vegetation in general, which may have led us to  
231 underestimate the percentage of all riparian studies that used remote sensing.



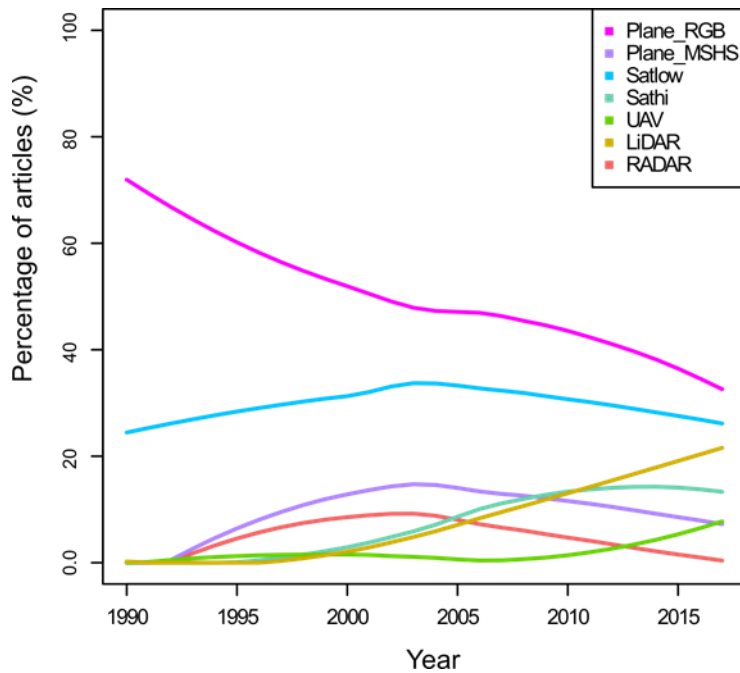


232

233 *Figure 5. A: Number of studies from 1980-2018 that used remote sensing to study riparian vegetation. B: Percentage of*  
 234 *studies from 1980-2018 that used remote sensing, out of all studies concerning riparian vegetation (see section 2.3).*

235 **3.3. Changes in remote sensing data over time**

236 The remote sensing data used most were aerial RGB/GS images (44% overall) and medium-resolution  
 237 satellite images (> 10 m resolution, and ≤ 50 m for most studies) (Figure 6). Aerial multispectral  
 238 images appeared in the 1990s and peaked during the 2000s. The use of high resolution satellite data  
 239 (≤ 10 m such as IKONOS, SPOT 5 and WorldView) started in the late 1990s and reached a plateau  
 240 around 2010. The use of LiDAR data consistently increased during the 2000s, accounting for 20% of  
 241 studies using remote sensing for riparian vegetation in 2017. The use of UAV images sharply  
 242 increased in the 2010s. As the use of these technologies increased, the percentage of studies using  
 243 RGB/GS aerial images and low resolution satellite images decreased slightly. Overall, less than 2% of  
 244 studies used RADAR data. Their use peaked in the early 2000s and then decreased.



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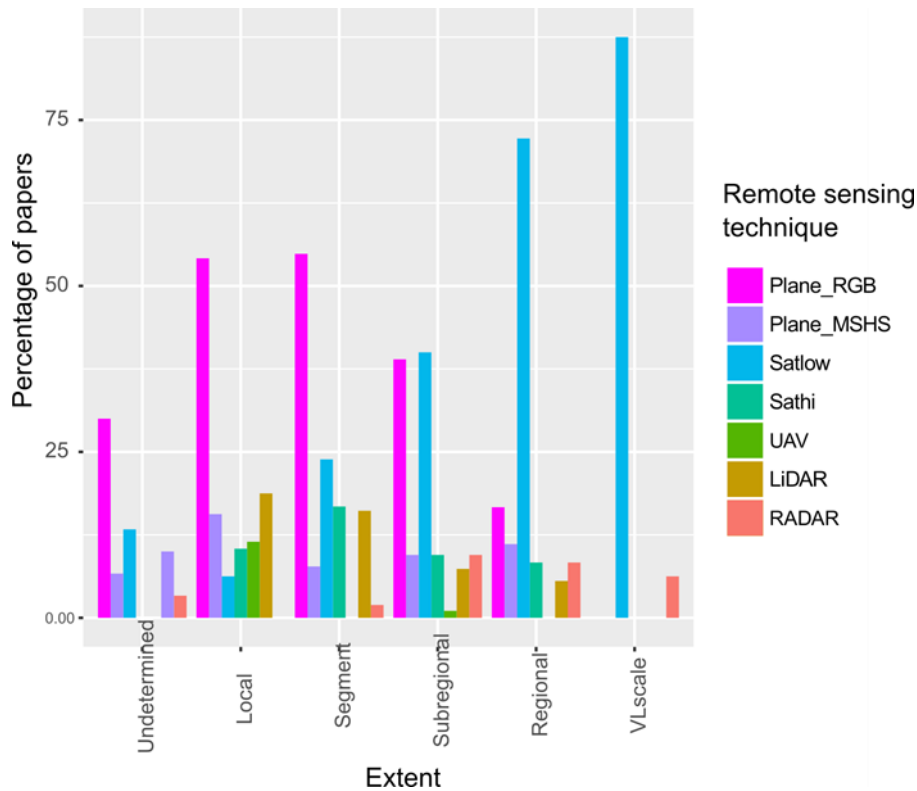
246 *Figure 6. Percentage of studies that used a given technology per year. The curve was smoothed using a loess regression.*

247 The popularity of RGB/GS aerial and low resolution satellite images can be explained by their low  
 248 cost and wide availability, including as time series. Other data have been used as they became  
 249 available (e.g. LiDAR and high resolution satellite images in the 2000s, UAVs in the 2010). The relative  
 250 decrease in the use of multispectral aerial images could be due to their replacement by high  
 251 resolution satellite images. Finally, the low percentage in the use of RADAR data could be due to the  
 252 relative difficulty of interpretation of such data, especially as water surfaces can modify RADAR  
 253 signals. Most studies in our database that used RADAR data focused on the interaction between  
 254 water and riparian vegetation, mapping flooding events or roughness coefficients (Townsend, 2002).  
 255 The early decrease in the use of RADAR data coincides with the increase in the use of LiDAR data,  
 256 which also provide structural information.

### 257 **3.4. Which technology for which study scale?**

258 There was a strong relationship between the scale of the study (local to very large scale) and the type  
 259 of remote sensing data used (Figure 7). In general, aerial images were used more at relatively local  
 260 scales (i.e. local and river segment), while medium-resolution satellite images were used more at  
 261 larger scales (i.e. regional or very large scale). There is often a tradeoff between resolution and

262 coverage: UAVs can produce images with centimetric resolution but struggle to cover large areas,  
 263 while satellites such as Landsat and MODIS provide images at a lower resolution (30 m for Landsat,  
 264 250 m for MODIS) but can cover large areas.



265  
 266 *Figure 7. Percentage of studies that used a given remote sensing technology, by spatial extent of the study*

### 267 3.4.1. Use of UAVs at the local scale

268 At the local scale (< 10 km long), 86% of studies were based on airborne remote sensing (of which  
 269 79% used airplanes and 11% used UAVs). This scale of study lies within the range of action of  
 270 relatively inexpensive UAVs that can carry RGB and multispectral cameras. While most UAVs were  
 271 used at the local scale, the low percentage of local scale studies that used UAVs was surprising. This  
 272 can be explained by the recent availability of these platforms: of studies published in the 2010s, 20%  
 273 of those at the local scale used UAVs. UAVs are considered more versatile than planes, and a growing  
 274 number of “ready-to-fly” platforms allow end-users to perform their own acquisitions (Anderson and  
 275 Gaston, 2013). Moreover, UAV imagery provides very high spatial resolution imagery (up to  
 276 centimetric), which is ideal for operator photointerpretation, which is frequently used at this scale.

277 However, most developed countries have established regulations that restrict the potential and  
278 spread of UAV technology (Stöcker et al., 2017).

#### 279 **3.4.2. Use of airplanes and satellites at the segment and subregional scales**

280 Both airborne and spaceborne sensors were used at the segment (10-100 km) and subregional scales  
281 (100-1000 km). RGB/GS aerial images were used in 55% and 39% of studies at respectively the river-  
282 segment and subregional scale (Figure 7). Most researchers photointerpret these images to describe  
283 riparian vegetation features. This method is long-standing, but remains a relevant and effective  
284 approach to map riparian vegetation over small watersheds or along dozens (more rarely hundreds)  
285 of km of rivers (Jansen and Backx, 1998; Matsuura and Suzuki, 2013; Carli and Bayley, 2015; González  
286 del Tánago et al., 2015; Solins et al., 2018). However, photointerpretation of hundreds of km of river  
287 can become tedious. In this case, one would use more automated approaches, such as object-based  
288 approaches, which can decrease the time required for photointerpretation (Belletti et al., 2015).

289 The effectiveness of automated techniques is strongly correlated with the homogeneity of spectral  
290 signatures within a single feature class (Cushnie, 1987). Homogeneity in spectral signatures requires  
291 homogeneous atmospheric and illumination conditions within the dataset. To this end, airplanes  
292 equipped with multispectral cameras can be used over long river segments in a short period to avoid  
293 variations in weather and illumination conditions (Forzieri et al., 2013; Bucha and Slávik, 2013).  
294 However, this approach remains challenging for large river networks, which decreases the possibility  
295 of automation at these scales (Dauwalter et al., 2015).

296 In this context, the wider swath of satellite imagery would be an advantage. High-resolution satellite  
297 images were often used to map vegetation automatically (16% and 9% of studies at respectively the  
298 river-segment and subregional scale) (Figure 7). For example, Strasser and Lang (2015), Riedler et al.  
299 (2015) and Doody et al. (2014) used WorldView-2 data to map riparian vegetation along a few dozen  
300 km. Tormos et al. (2011) and Macfarlane et al. (2017) used SPOT images and GeoEye-1 images to  
301 map vegetation along corridors respectively 60 and 90 km long. However, it may be difficult to

302 acquire high-quality datasets for larger areas, for which several high-resolution satellite images must  
303 be combined (Goetz, 2002; Johansen et al., 2010b; Zogaris et al., 2015).

304 The percentage of studies based on LiDAR surveys decreased with scale: 19%, 16%, 7% and 6% of  
305 studies at respectively the local, river-segment, subregional and regional scale (Figure 7). However,  
306 some authors were able to use LiDAR data to monitor narrow riparian corridors over large areas  
307 (Johansen et al., 2010; Michez et al., 2017). One advantage of tri-dimensional LiDAR data is that they  
308 are less subject to changing atmospheric and lightning conditions during the survey than spectral  
309 data. Moreover, LiDAR coverage is becoming more frequent at the regional/national scale (Parent et  
310 al., 2015; Wasser et al., 2015; Shendryk et al., 2016; Tompalski et al., 2017). When an initial  
311 nationwide LiDAR survey is performed, digital aerial photogrammetry (DAP) can be used to further  
312 update LiDAR canopy height models (CHMs). DAP CHMs can be produced from aerial images  
313 acquired on a regular basis by national or regional mapping agencies in several countries and can  
314 potentially provide vegetation height data at low additional cost (Michez et al., 2017).

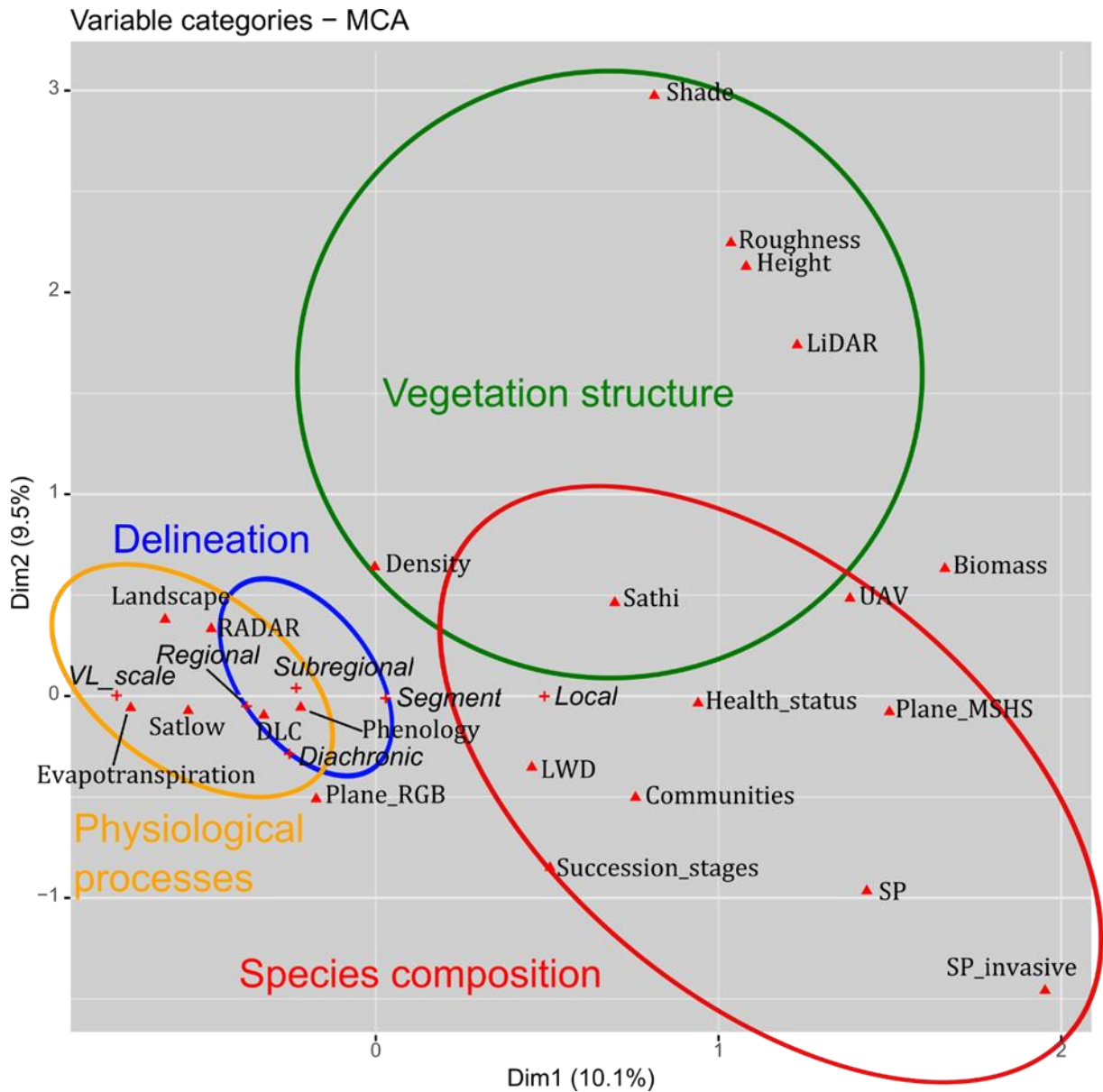
### 315 **3.4.3. Large scale: satellite images**

316 The use of satellite images with medium to coarse resolution (> 10 m) increased as the extent  
317 increased. For studies at the regional or very large scale, satellite images were used in respectively  
318 72% and 82% of cases (Figure 7). Coarse-resolution images (> 100 m) were not used to study riparian  
319 vegetation, which often appears as linear or fragmented features (Gergel et al., 2007). Medium-  
320 resolution images such as Landsat TM, ETM+ or OLI images are preferred. The use of these data to  
321 map riparian vegetation cover has yielded satisfying results in wide riparian corridors (Lattin et al.,  
322 2004, Yousefi et al., 2018). However, their resolution often becomes limiting in the case of narrow  
323 riparian corridors or small vegetation units that are a few Landsat pixels wide (Congalton et al., 2002,  
324 Henshaw et al., 2013). Although aerial images (multispectral, RGB and panchromatic) were used in  
325 25% of studies at the regional scale, they were always used with medium-resolution satellite images  
326 (Fullerton et al., 2006; Groeneveld and Watson, 2008; Claggett et al., 2010). High-resolution satellite

327 images, which were used in 8% of studies at the regional scale, were used mostly with pansharpener  
328 methods to enhance lower resolution satellite images (Seddon et al., 2007; Staben and Evans, 2008;  
329 Scott et al., 2009).

### 330 **3.5. Which technology for which riparian feature?**

331 The features of interest extracted from remote sensing data to describe riparian vegetation were  
332 strongly related to the type of remote sensing data (Figure 8). Four major trends emerged. First, the  
333 study of physiological processes (e.g. phenology, evapotranspiration and, to a lesser extent, health  
334 status) was strongly associated with the use of medium-resolution satellite images and large study  
335 extents. Second, the study of features or processes related to vegetation structure (shade,  
336 roughness, height) was strongly associated with the use of LiDAR data. Third, the study of features  
337 related to species composition was associated with the use of high-resolution multispectral images  
338 (acquired from satellites, planes or UAVs) or RGB/GS aerial images (especially for successional stages)  
339 and with small study extents. Fourth, the delineation of riparian vegetation was weakly associated  
340 with the use of RGB/GS aerial images or medium-resolution satellite images. These four trends are  
341 discussed in the following four sections.



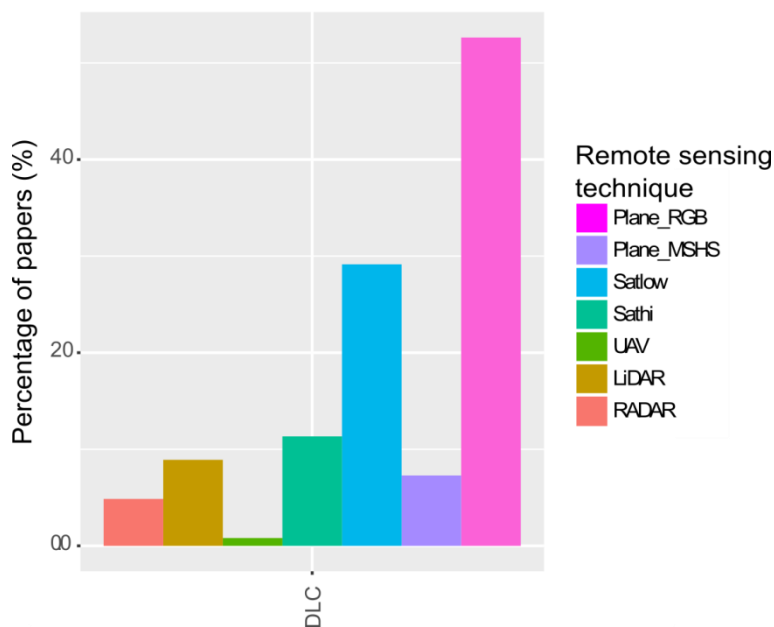
342

343 Figure 8. Results of the multiple correspondence analysis (see section 2.3. for the methods). Supplementary variables (i.e.  
 344 variables related to study extent and multi-temporality) are represented as crosses with text in italics. The first two axes  
 345 explain 19.6% of total variance. Ellipses were drawn arbitrarily to simplify interpretation. See Table 1 for code definitions.

### 346 3.5.1. Delineation of riparian vegetation

347 How riparian vegetation is delineated depends on how it is defined (Verry et al., 2004). In general,  
 348 riparian vegetation is defined based on its specific characteristics (e.g. spectral signature, texture)  
 349 and on contextual information (e.g. topographic position, proximity to a river) (Weissteiner et al.,  
 350 2016). Photointerpretation of RGB/GS aerial images is a traditional approach in which the operator  
 351 uses both types of information (Morgan et al., 2010). It was used in 53% of studies that delineated

352 riparian vegetation (Figure 9). Multispectral images (airborne or spaceborne, accounting for 45% of  
 353 studies) are often used to delineate riparian vegetation in an automated way (Alaibakhsh et al., 2017;  
 354 Johansen et al., 2010b; Bertoldi et al., 2011). Contextual information can be provided by ancillary  
 355 data (e.g. hydrographic network, as in Claggett et al. (2010) or Yang (2007)), a LiDAR digital terrain  
 356 model (DTM) (Arroyo et al., 2010; Wagner-Lücker et al., 2013), or a Shuttle RADAR Topography  
 357 Mission DTM (Maillard and Alencar-Silva, 2013; Weissteiner et al., 2016). Congalton et al. (2002)  
 358 indicate that medium-resolution satellite data (used in 29% of studies) are not adapted for  
 359 delineating narrow riparian corridors because the corridors do not contain enough pixels (see section  
 360 3.4.3).



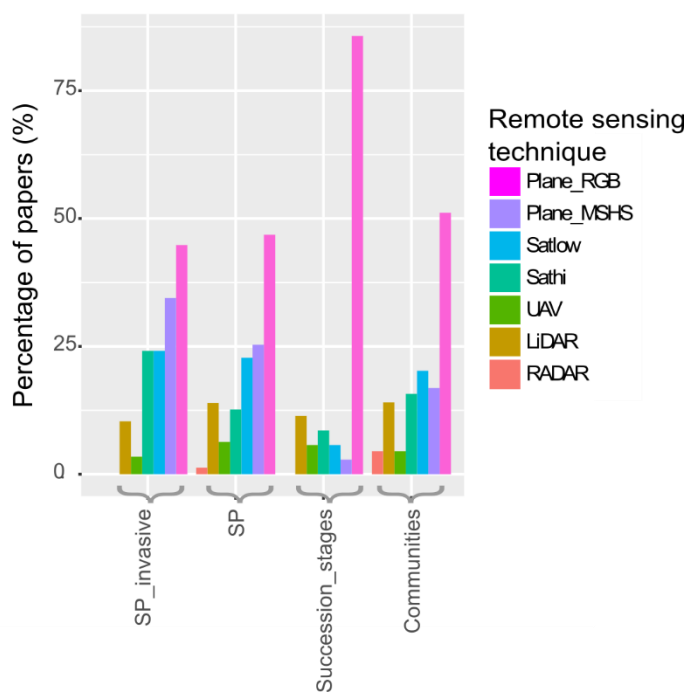
361  
 362 *Figure 9. Percentage of studies that used given remote sensing data to delineate riparian vegetation (i.e. distinguish riparian*  
 363 *vegetation from other land-cover types)*

### 364 3.5.2. Species composition

365 Species composition is a recurrent subject that was studied in 42% of studies. Photointerpretation of  
 366 RGB/GS aerial images concerned 51%, 47% and 45% of studies that differentiated respectively  
 367 communities, species, and invasive species (Figure 7). This approach is widely used to describe  
 368 successional stages or changes in their distribution (86% of such studies). Indeed, RGB/GS aerial  
 369 images have been available since before the 1950s (González et al., 2010; Rood et al., 2010; Varga et



370 al., 2013; Wan et al., 2015). However, manual interpretation of images is time-consuming, and the  
 371 discriminating power of RGB/GS aerial images is limited by their low spectral range (Narumalani et  
 372 al., 2009; Fernandes et al., 2014). Medium-resolution satellite images were used in 21% of studies  
 373 that differentiated communities. These images were used mainly when vegetation patches were  
 374 larger than the image resolution (Vande Kamp et al., 2013; Hamandawana and Chanda, 2013; Sridhar  
 375 et al., 2010; Groeneveld and Watson, 2008; Townsend and Walsh, 2001), although spectral unmixing  
 376 can, to some extent, resolve this issue (Gong et al., 2015; Wang et al., 2013).



377  
 378 *Figure 10. Percentage of studies that used given remote sensing data to map indicators related to species composition.*

379 The most promising approaches to address this issue are based on high-resolution, aerial or  
 380 spaceborne, multispectral or hyperspectral images. These images were used in 30%, 33% and 45% of  
 381 studies that differentiated respectively communities, species and invasive species (Figure 10). The  
 382 accuracy of a particular project depends on the context, objectives, available data and methods used  
 383 to evaluate it. Therefore, we present recent studies that mapped species in the Table 2. In general, a  
 384 large number of narrow spectral bands increases the ability to distinguish species. However, in  
 385 mature, species-rich floodplain forests, it remains challenging to obtain classification accuracy that is

386 satisfactory for operational use, even when using hyperspectral imagery (Richter et al., 2016). The  
387 use of multi-temporal images, which reveal the succession of phenological stages, can sometimes  
388 replace the spectral range. For example, Rapinel et al. (2019) used Sentinel-2 time series to classify  
389 grassland plant communities in a temperate floodplain using the relationship between inundation,  
390 grassland management and vegetation composition. Similarly, Michez et al. (2016b) used UAV time  
391 series to distinguish riparian tree species using images acquired during several phenological stages  
392 (from spring to fall). It is also possible to acquire images at a single but appropriate date to take  
393 advantage of the singular aspect of one species at a particular phenological stage. This approach is  
394 especially effective when a single species has to be mapped, such as the invasive species *Arundo*  
395 *donax* (Fernandes et al., 2013b) or *Heracleum mantegazzianum* (Michez et al., 2016a). The spatial  
396 resolution of images must be sufficiently high to limit the occurrence of mixed pixels that hinder the  
397 performance of automated classifications (Belluco et al., 2006; Narumalani et al., 2009). However,  
398 small mixture of species remains a source of difficulty, even with a cm resolution (Michez et al.,  
399 2016a). LiDAR data, also used to classify species, can supplement multispectral data with vegetation  
400 height data (Forzieri et al., 2013). They can also be used to segment trees before classifying them  
401 (Dutta et al., 2017). They have also been used as the sole source of data by relating species identity  
402 to the structure of the point cloud (Laslier et al., 2019).

<u>Reference</u>	<u>Data</u>	<u>Classes</u>	<u>Accuracy</u>	<u>Comment</u>
<b>Mature riparian forests</b>				
Fernandes et al. (2013a)	RGB-NIR aerial imagery (0.5 m resolution)	3 types of mature, temperate/Mediterranean riparian forests	61 (small) - 78% (large river)	
Dunford et al. (2009)	RGB imagery acquired with UAV (0.13 m resolution)	4 tree species ( <i>Populus</i> , <i>Salix</i> and 2 <i>Pinus</i> ) in a riparian Mediterranean forest	91% (for an image) - 71% (for a mosaic)	
Michez et al. (2016b)	RGB-NIR imagery acquired with UAV (0.1 m resolution)	5 tree species in a temperate, riparian forested/agricultural landscape	84 (forested) - 80% (agricultural)	Multi-temporal dataset
Richter et al. (2016)	Hyperspectral aerial imagery (367 bands, 2 m resolution)	10 tree species in a mature temperate floodplain forest	74% (single-date survey) - 78% (two-date survey)	
Dutta et al. (2017)	Hyperspectral aerial imagery (48 bands, 1 m resolution)	4 groups of tree species in a mature, temperate riparian forest	86%	LiDAR is used to segment the trees
Laslier et al. (2019)	High density (> 45 points/m <sup>2</sup> ) LiDAR point cloud	8 tree species in a temperate riparian agricultural/forested landscape	67%	
<b>Pioneer/species-poor riparian settings</b>				
Macfarlane et al. (2017)	Pansharpened GeoEye-1 imagery (RGB-NIR, 0.5 m resolution)	Pioneer ( <i>Salix</i> , <i>Populus</i> ) and invasive ( <i>Tamarix</i> ) species in an arid context	80%	
Forzieri et al. (2013)	RGB-NIR aerial imagery (0.2 m resolution); hyperspectral aerial imagery (102 bands, 3 m resolution) and LiDAR data (DSM/DTM with 1 m resolution)	Pioneer ( <i>Salix</i> , <i>Populus</i> ) and invasive ( <i>Arundo donax</i> ) species in a temperate context	93%	

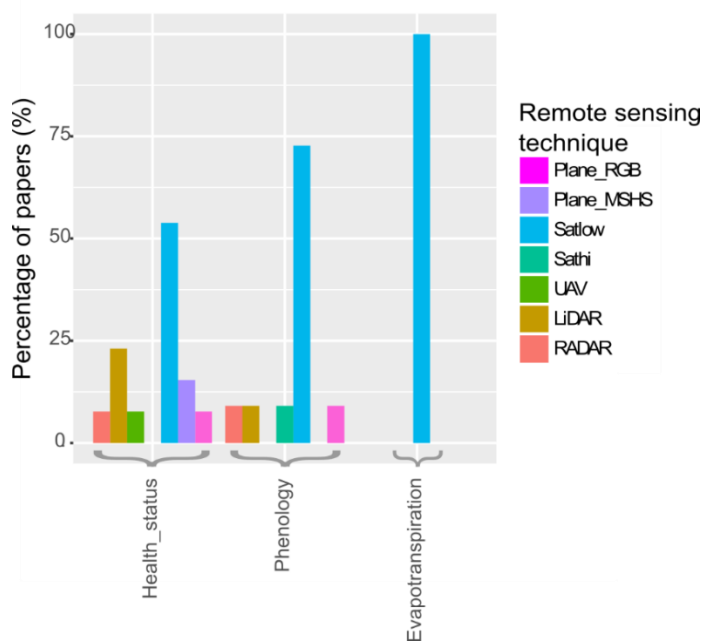
Invasive species				
Narumalani et al. (2009)	Hyperspectral aerial imagery (62 bands, 1.5 m resolution)	<i>Tamarix, Elaeagnus angustifolia, Cirsium arvense, Carduus nutans</i> and mixed classes	74%	Mixed classes are not well classified and decrease overall accuracy
Fernandes et al. (2014)	RGB-NIR aerial imagery (0.5 m resolution)	<i>Arundo donax</i>	97%	Choice of the best date for aerial survey
	WorldView 2 imagery (8 bands, 2 m resolution)	<i>Arundo donax</i>	95%	
Michez et al. (2016a)	RGB-NIR imagery acquired with UAV (0.05-0.1 m resolution)	<i>Impatiens glandulifera</i>	72%	Mixture with native species hinders accurate classification
		<i>Heracleum mantegazzianum</i>	97%	
		<i>Fallopia japonica</i>	68%	
Peerbhay et al (2016)	WorldView 2 imagery (8 bands, 2 m resolution)	<i>Solanum mauritanum</i>	68%	
Miao et al. (2011)	Hyperspectral aerial imagery (227 bands, 1 m resolution)	<i>Prosopis glandulosa</i> and <i>Tamarix</i>	92%	
Doody et al. (2014)	WorldView 2 imagery (8 bands, 2 m resolution)	<i>Salix</i>	93%	

404 These approaches based on high resolution data, although powerful, are mainly used at the local  
405 scale. We showed in the section 3.4.2 that upscaling such data was challenging beyond a few dozen  
406 km of river. However, at this scale, remote sensing would be a particularly useful alternative to field  
407 campaigns or photointerpretation. Species classification methods that are more robust to upscaling  
408 still need to be developed, as indicated by Fassnacht et al. (2016) in a review of forest tree species  
409 classification.

### 410 3.5.3. Physiological processes

411 Medium-resolution satellite images (> 10 m resolution and ≤ 50 m for most studies) were the most  
412 popular type of data used to assess physiological processes of riparian vegetation (100%, 73% and

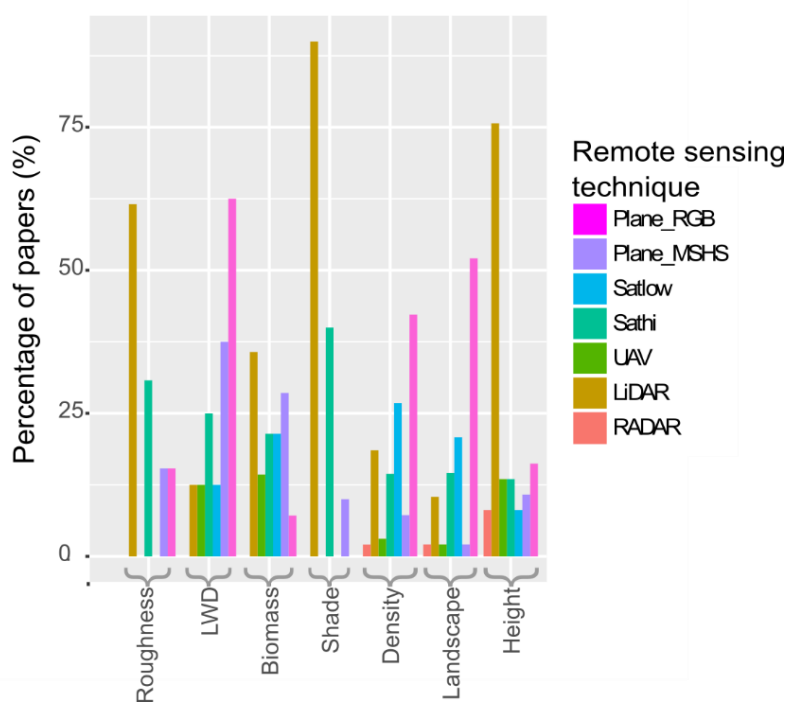
413 54% of studies concerning respectively evapotranspiration, phenology and health status) (Figure 11).  
 414 One advantage of using these images in this context is that they are often available as dense series,  
 415 which is useful for studying cyclic processes. For example, Wallace et al. (2013) used AVHRR images  
 416 (return period < 1 day) to detect variations in the timing of greening up/scenesing of vegetation.  
 417 Nagler et al. (2012) used MODIS (return period 1-2 days) to study phases of the life cycle of the  
 418 tamarix leaf beetle (*Diorhabda carinulata*) throughout the year. Cadol and Wine (2017) and Nagler et  
 419 al. (2016) used long-term records (several years) of satellite images along with flow data to  
 420 investigate relationships between hydrology and physiological processes in riparian vegetation.  
 421 Zaimes et al. (2019) used a 27-year time series of Landsat images to study the impact of dam  
 422 construction on vegetation health status. Sims and Colloff (2012) used MODIS images over several  
 423 years to assess responses of riparian vegetation during and after flooding events. However, the low  
 424 resolution often means that pixels in the image aggregate greater heterogeneity in ground features.  
 425 Accuracy thus decreases, making it more complicated to study different types of vegetation  
 426 separately (Tillack et al., 2014; Cunningham et al., 2018). The health status of vegetation is often  
 427 studied with higher resolution data, occasionally with a single image (Tillack et al., 2014; Michez et  
 428 al., 2016b; Bucha and Slávik, 2013; Shendryk et al., 2016; Sankey et al., 2016).



429  
 430 Figure 11. Percentage of studies that used given remote sensing data to describe physiological indicators.

431 **3.5.4. Vegetation structure**

432 LiDAR appears to be the most used technology for describing vegetation structure features, except  
 433 for Large Woody Debris, landscape metrics and vegetation cover (Figure 12). LiDAR appears  
 434 therefore to be the most promising technology for describing vegetation structure and related  
 435 functions such as shading or surface roughness. The LiDAR signal can penetrate the canopy and the  
 436 water surface, and provides information about topography under dense canopies, the internal  
 437 structure of canopies and bathymetry.



438  
 439 *Figure 12. Percentage of studies that used given remote sensing data to map structural features of riparian vegetation.*

440 Retrieving simple structural attributes of vegetation (e.g. height, continuity, overhanging character) is  
 441 straightforward, since they can be extracted from DTMs, DSMs or CHMs delivered by LiDAR data  
 442 producers. These applications have reached an operational level. However, further methodological  
 443 developments for processing the 3D point cloud and new generations of full-waveform LiDAR data  
 444 must be explored before they can be transferred to management operations. For example, full-  
 445 waveform LiDAR data have shown promising results in forestry applications (e.g. Koenig and Höfle,  
 446 2016), but there are few examples for riparian vegetation (Shendryk et al., 2016).

447 LiDAR data have been used in 90% of studies (Figure 12) to map riparian shade, which is a major  
448 parameter that influences stream water temperature (Poole and Berman, 2001). Temperature  
449 regulates the habitat of aquatic species such as the brown trout (*Salmo trutta fario* L.) (Caissie, 2006;  
450 Georges et al., 2019), and the effect of riparian shade on stream water temperature is strong enough  
451 to affect aquatic communities significantly (Bowler et al., 2012). Field methods used to measure  
452 stream shade are expensive and time-consuming (Rutherford et al., 2018). LiDAR data appears to be  
453 the most promising alternative because they can describe shade at a fine scale (Richardson et al.,  
454 2019). Several methods for using LiDAR data to measure riparian shade have been described in the  
455 literature. Richardson et al. (2009) calculated light penetration index raster products as a predictor of  
456 light conditions. LiDAR data can describe shadowing properties using a simple CHM derived from  
457 point clouds (Michez et al., 2017; Loicq et al., 2018; Wawrzyniak et al., 2017). Other studies have  
458 used 3D point clouds to retrieve the finest-scale information about vegetation structure. For  
459 example, Akasaka et al. (2010) used a LiDAR point cloud to estimate biomass overhanging the river,  
460 while Tompalski et al. (2017) used one to model solar shading on a given summer day. Recently,  
461 Shendryk et al. (2016) used full-waveform LiDAR data to estimate the dieback of individual riparian  
462 trees, which was related to their shadowing properties.

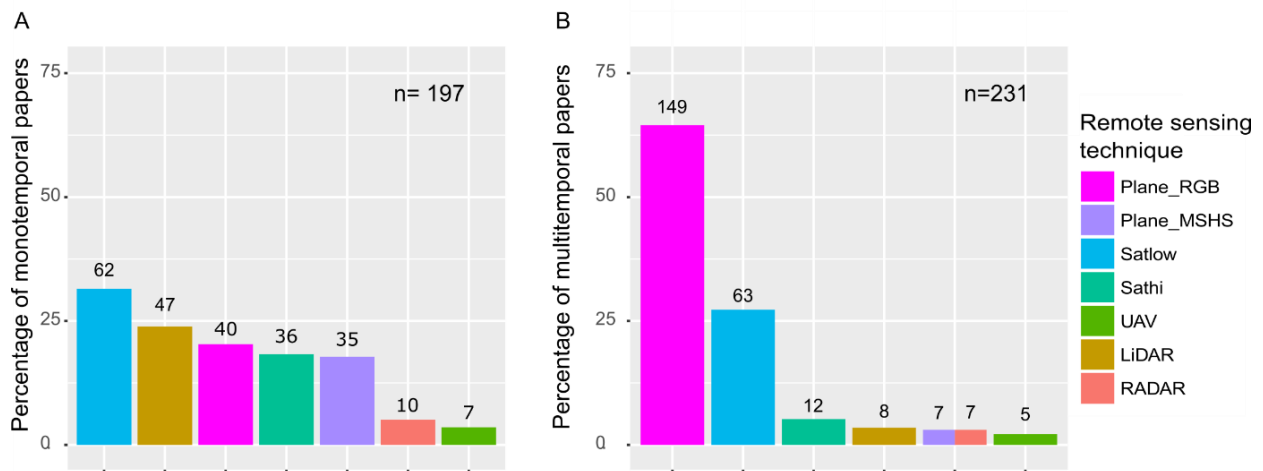
463 LiDAR data have also been used in 61% of studies to map floodplain roughness in a spatially  
464 continuous manner (Figure 12). Forzieri et al. (2012) distinguished two main approaches for mapping  
465 floodplain roughness using remote sensing: classification-derived mapping and hydrodynamic  
466 modeling. In the former, thematic maps of land cover or vegetation classes are produced with  
467 remote sensing data. A roughness coefficient (often Manning's coefficient) is then assigned to each  
468 class using a lookup table. In the latter, hydrodynamic properties of vegetation are estimated using  
469 an indicator of vegetation structure (e.g. leaf area index, stem or crown diameter, vegetation height).  
470 LiDAR technology has several advantages in this case: it measures structural attributes directly and  
471 can account for complex, multilayered structures (Manners et al., 2013; Jalonen et al., 2015).  
472 Hydrodynamic modeling is often combined with classification-derived mapping, with separate

473 modeling of hydrodynamic properties of each vegetation class (Straatsma and Baptist, 2008; Zahidi  
474 et al., 2018). Development of restoration and multi-objective management practices (to promote  
475 ecosystem health while protecting people and goods) has increased demand for models that  
476 represent effects of vegetation on flow more accurately (Rubol et al., 2018). However, research on  
477 hydrodynamic properties of vegetation and how to measure them in the field is ongoing (Shields et  
478 al., 2017).

### 479 **3.6. Multi-temporality of remote sensing riparian studies**

480 Overall, 54% of studies in the database were multi-temporal (i.e. studies where data acquired at  
481 several dates are used to understand the dynamics of riparian vegetation). RGB/GS aerial images  
482 were used in more than 60% of the multi-temporal studies (Figure 13A), such as those of Dufour et  
483 al. (2015) or Lallias-Tacon et al. (2017). Such studies usually focus on decadal time scales. It can be  
484 explained by the fact that this type of images is simple to use and has been available over a large  
485 extent since the 1950s (Dufour et al., 2012). In most of the countries previously highlighted as active  
486 in riparian research, public administrations have performed long-term and systematic national aerial  
487 surveys for general purposes (e.g. urban planning) that researchers can use at low cost. Most multi-  
488 temporal studies that included aerial photographs used photointerpretation to describe riparian  
489 vegetation features. Medium resolution satellite images were often used in multi-temporal studies,  
490 notably for the study of physiological processes (see section 3.5.3).





491  
 492 *Figure 13. Use of remote sensing data in (A) multi-temporal and (B) mono-temporal studies (respectively 54% and 46% of*  
 493 *the studies).*

494 Conversely, more recent technologies (e.g. high-resolution satellite images, LiDAR data) were far  
 495 more common in studies that focused on one period than in multi-temporal studies (Figure 13B). For  
 496 example, LiDAR and high-resolution satellite data were used in respectively 24% and 18% of mono-  
 497 temporal studies against 4% and 5% of multi-temporal studies. In mono-temporal studies, the  
 498 methods developed to map riparian forest attributes were more complex and mostly automated,  
 499 such as supervised classifications (Michez et al., 2016b; Antonarakis et al., 2008) and calculation of  
 500 metrics (Riedler et al., 2015).

501 We predict that diachronic analyses will be renewed by the increasing quality and availability of  
 502 remote sensing data. Indeed, data acquired from new sensors, such as LiDAR and hyperspectral  
 503 sensors, become more and more available as time series. For example, a LiDAR survey covers the  
 504 entire region of Wallonia (southern Belgium) every six years. In France, in the framework of the  
 505 Litto3D program, ca. 45,000 km<sup>2</sup> of coast (bathymetry included) will be regularly covered with a  
 506 dense LiDAR survey, in order to monitor sediment dynamics and erosion processes. These new data  
 507 provide the opportunity to monitor changes in specific features of riparian vegetation, such as  
 508 canopy height, species composition or fine scale physiological processes. In addition, acquisition

509 frequency has increased. For example, UAVs can acquire dense time series easily. High-resolution  
510 satellite images such as Sentinel-1 and Sentinel-2 (four bands at 10 m resolution) provide images of  
511 the Earth's entire surface every few days. More recently, CubeSat constellations provide higher  
512 resolution and higher frequency. For example, the Dove constellation (Planet Labs, Inc., San  
513 Francisco, CA, USA) provides resolution up to 3 m and daily coverage. This increased frequency of  
514 image acquisition provides new opportunities to study rapid riparian vegetation processes, including  
515 intra-annual ones such as phenology and impacts of flood events.

#### 516 **4. Perspectives for riparian vegetation management**

517 The second objective of this review was to discuss how remote sensing approaches developed by  
518 scientists can be used by riparian managers. Research in remote sensing of riparian vegetation often  
519 has an applied perspective, and 38% of the abstracts in our database contained the words  
520 "management", "restoration" or their derivatives. However, scientific articles usually do not describe  
521 how remote sensing developments are made available to managers, and how they can be  
522 implemented in management situations.

523 Therefore, we completed our systematic review of the literature with an approach based on expert  
524 judgment, focusing on how remote sensing developments can be valued as operational tools  
525 available to managers. In section 4.1, we selected five examples of applications for riparian  
526 management. For each example, we highlight how remote sensing approaches can be embedded in  
527 operational tools, and how scientific developments (previously discussed in section 3) can contribute  
528 to these tools. In section 4.2, we further discuss the challenges of knowledge transfer from scientists  
529 to managers, illustrated by the five selected examples.

##### 530 **4.1. Examples of near-operational applications**

531 We chose three contrasting fields of applications that we considered as particularly relevant for the  
532 riparian context: eradication of invasive plant species, monitoring ecological integrity at the regional  
533 scale and maintenance of hydraulic conveyance.

534 **4.1.1. Example 1: Managing invasive plant species at the local scale**

535 Riparian managers often conduct programs to eradicate invasive plant species. These programs  
536 require identifying and locating individuals prior to eradication measures and subsequent monitoring  
537 of invasive cover (i.e. to ensure that practices were effective and that the species do not re-emerge)  
538 (Vaz et al., 2018). These actions can be performed with UAVs that combine high spatial resolution  
539 (useful for detecting invasive plant species at an early stage, before they form large clumps) and high  
540 temporal resolution (invasive plant species are often more distinct from the background during a  
541 particular phenological phase, according to Manfreda et al. (2018)). Many studies have shown that  
542 detecting invasive plant species using a UAV could outperform ground surveys in terms of cost,  
543 effectiveness and risk mitigation for operators (Martin et al., 2018; Michez et al., 2016a). The  
544 detection of invasive plants can be performed using photo-interpretation (most simple method) or a  
545 supervised classification (most scalable method) of orthoimages (Hill et al., 2017). In the future, real-  
546 time or onboard processing (i.e. analysis of streamed imagery) will enable detection and eradication  
547 steps to be performed at the same time (Hill and Babbar-Sebens, 2019).

548 In order to implement this approach, river managers must have access to skilled staff who are able to  
549 pilot the UAV and process the images based on the needs of riparian managers. The staff can be  
550 recruited and trained within the organization, or work for an exterior contracting organization. For  
551 invasive species, work is often concentrated in time, and skilled staff must be available at that time.

552 **4.1.2. Examples 2 and 3: Monitoring ecological integrity at the regional scale**

553 Managers of riparian vegetation at the regional or national scale sometimes need information about  
554 the entire river network to assess effects of policies or define management strategies (e.g. to  
555 prioritize which zones should be restored). For example, all EU member states must monitor the  
556 state of riparian ecosystems to comply with the Water Framework Directive (WFD), which promotes  
557 a good health status of European rivers. These assessments have historically been performed during  
558 field visits to sites sampled throughout each river network (Hering et al., 2010; Munné et al., 2003).

559 They can include remote sensing techniques in different ways. We briefly present two contrasting  
560 approaches to include remote sensing in ecological assessments: a sampling- and  
561 photointerpretation-based approach using aerial images, or the use of regional LiDAR data to map  
562 riparian structural attributes automatically.

563 In the first approach (hereinafter referred to as example 2), aerial images can be integrated with  
564 minor adaptations into a traditional field-based, sampling approach. Aerial images are used to target  
565 sampling sites (e.g. where riparian vegetation is present) and to perform certain aspects of the  
566 assessment, especially those that require less specific information at a larger scale. For example, the  
567 Riparian Quality Index, initially developed for Iberian rivers, includes measurements of width,  
568 continuity, strata, composition, regeneration, bank condition, lateral connectivity and substratum  
569 (González del Tánago and García de Jalón, 2011). Width, continuity and strata can be described using  
570 aerial imagery, while other attributes are assessed in the field.

571 In the second approach (hereinafter referred to as example 3), regional LiDAR data can be used to  
572 assess riparian features in a spatially continuous manner. In this case, the strength of LiDAR data is  
573 that the 3D component is homogenous at the regional scale unlike spectral data (see section 3.4.2).  
574 Moreover, it can extract attributes of the channel even when it is hidden by vegetation. Riparian  
575 attributes are calculated with a high level of automation and can be updated at the same frequency  
576 as the actualization frequency of the LiDAR cover. For example, in Wallonia (southern Belgium),  
577 Michez et al. (2017) used LiDAR and photogrammetric point clouds to map riparian buffer attributes  
578 along 12,000 km of rivers (vegetation continuity, height and overhang; channel width and sinuosity;  
579 and lateral connectivity, indicated by emerged channel depth). The results are meant to be used as  
580 decision making tools by river managers. They are made available on an online platform, where river  
581 managers must plan their management practices for a six year period.

582 **4.1.3. Examples 4 and 5: Improving flood modeling with better estimates of**  
583 **floodplain roughness**

584 Many regions of the world must address significant and increasing threats of flooding, as well as the  
585 need to conserve riparian ecosystems (Straatsma et al., 2019). Floodplain vegetation can influence  
586 flood risk by increasing hydraulic roughness (Curran and Hession, 2013). In the Netherlands, where  
587 these challenges are particularly acute, several remote sensing applications integrate riparian  
588 vegetation management more into flood mitigation strategies.

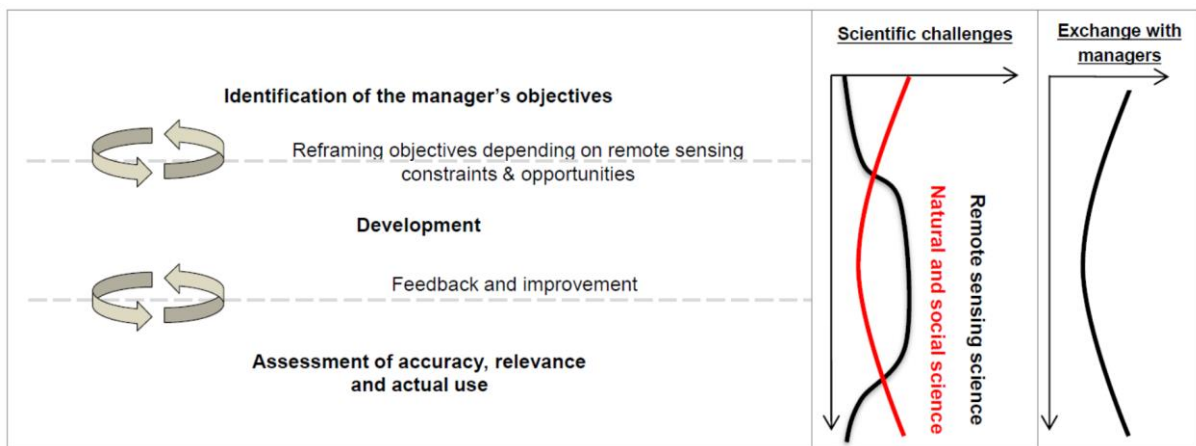
589 One example (hereinafter referred to as example 4) includes a legal map produced to describe the  
590 maximum roughness of vegetation cover allowed within the floodplains of major Dutch rivers. The  
591 legal map uses a historical situation as a target reference (Rijkswaterstaat, 2014). To support use of  
592 this legal map, Deltares (an independent applied research institute) and the Rijkswaterstaat (the  
593 administration responsible for river management) developed an online vegetation-mapping tool  
594 based on free multispectral, high-resolution satellite images. In the Google Earth Engine  
595 environment, users can easily classify the vegetation cover observed on recent Sentinel-2 images to  
596 ensure that it complies with the legal standard. The tool is available on smartphones and can be used  
597 in the field. Actual vegetation can be compared to the map before each winter, when most floods  
598 occur. The tool provides information about the areas on which management practices should focus,  
599 following a dialogue with the landowners concerned (Penning, 2018).

600 Modeling approaches are also useful to support decisions. To prevent flood damage in Dutch deltas,  
601 multiple practices, such as raising dikes or removing riparian vegetation, must be implemented in a  
602 coordinated manner. Straatsma and Kleinhans (2018) developed the RiverScape toolbox. This tool  
603 models the effects of riparian cutting on flow using hydrological and spatial data (including a DTM, a  
604 vegetation map and its associated roughness coefficients). The RiverScape toolbox (hereinafter  
605 referred to as example 5) can optimize the location of cutting operations to reduce water levels  
606 during floods.

## 607 **4.2. Challenges of conveying tools to managers**

608 The five examples given in the previous section illustrate that remote sensing approaches can be  
 609 embedded in operational tools for riparian managers. In this section, we discuss more generally how  
 610 scientists and managers can collaborate to produce and implement such tools for the management  
 611 of riparian vegetation.

612 We distinguish three main steps in this process (Figure 14). First, managers and remote sensing  
 613 experts must work together to define clear **objectives**. Second, the **development** step implies a  
 614 technological phase. Third, thorough **assessment** must be performed for accuracy, reliability and  
 615 relevance for managers. **Critical thinking** is required throughout this process because the choice of a  
 616 remote sensing approach is not neutral and has implications for how riparian vegetation is managed.



617  
 618 *Figure 14. Conceptual framework of the transfer of remote sensing tools from scientists to managers. On the graphics to the*  
 619 *right, the horizontal axes represent scientific challenge and exchange degree to be planned between managers and*  
 620 *researchers (from low to high), while the vertical axes represent their dynamics from start to finish.*

#### 621 4.2.1. Identifying the issues/needs of riparian vegetation managers

622 The first step in implementing a remotely sensed application is to define the needs and objectives of  
 623 riparian vegetation managers. Key issues must be addressed, such as the features to be mapped, the  
 624 scale of observation, the time required to obtain usable information and the frequency of updating.  
 625 Objectives can be refined during the development step, depending on the tradeoffs between costs  
 626 and image quality. Nevertheless, thoroughly defining the objectives beforehand is clearly a factor of

627 success (Kennedy et al., 2009). In the example 1 (use of UAVs to help eradicate invasive species,  
628 section 4.1.1), it is often easier to detect plants at a particular phenological phase. For instance, *H.*  
629 *Mantegazzianum* is easier to detect while flowering, thanks to its characteristic white umbels  
630 (Michez et al, 2016a). While this detection period might be appropriate for scientific purposes, it  
631 does not fully satisfy eradication requirements, since individuals must be removed before they form  
632 fruit, which leaves little time for eradicators to remove them. One must consider that kind of details  
633 when developing operational tools for management.

634 The thorough definition of objectives is not straightforward. To translate monitoring objectives into a  
635 remote sensing approach requires an explicit space for collaboration between remote sensing  
636 specialists and managers (Kennedy et al., 2009). Managers are often unsure about the operational  
637 potential of remote sensing approaches (Vanden Borre et al., 2011). This is increasingly true, since  
638 new technologies (e.g. satellites, UAVs) seem to be developed very quickly, and even faster than the  
639 applications for using them. Therefore, realistic monitoring objectives must be defined along with  
640 remote sensing specialists. Moreover, field and remote sensing approaches often are not perfectly  
641 interchangeable (Dufour et al., 2012). Challenging the work routine of managers might be required to  
642 fully benefit from remote sensing approaches. The collaborative process should thus be open enough  
643 to consider adapting work routines. Similarly, when relevant, managers and scientists from different  
644 fields must be involved. It is important to combine a variety of scientific perspectives (e.g. geomatic,  
645 landscape planning, riparian ecology) to avoid too narrow or inappropriate solutions.

646 In many cases at this stage, riparian vegetation is not the center of management operations. Many  
647 studies and management operations focus on the river channel and its hydrological and  
648 geomorphological components. In the example 5 (modeling the impact of management practices on  
649 flood hazard, section 4.1.3), the RiverScape toolbox does not only consider riparian cuttings but also  
650 raising dykes or lowering floodplain level.

#### 651 **4.2.2. Developing applications that use remote sensing data**

652 Once the objectives have been clearly identified, the next step is to develop the solution to use  
653 remote sensing data to pursue the manager's objectives. Several stakeholders are involved in this  
654 process. We artificially distinguish "data producers" from the "developers".

655 We consider "data producers" the stakeholders who provide rough datasets, such as raw satellite  
656 images or raw ancillary data (e.g. national space agencies such as NASA and CNES, UAV constructors).  
657 While they do not interact closely with riparian vegetation managers, their role is important in the  
658 long run since they set the agenda for the main future developments of new remote sensing  
659 technologies. More directly, they can promote the use of remote sensing data for natural resource  
660 managers by making the data affordable and easier to use, as mentioned in section 3.1. In the  
661 example 4 (floodplain roughness monitoring with Google Earth Engine, section 4.1.3), the  
662 classification of vegetation in the floodplain is made possible by the availability of free temporal  
663 series of Sentinel-2 images.

664 We consider "developers" the stakeholders who develop tools that use raw remote sensing data.  
665 They may interact more closely with riparian vegetation managers and provide solutions that are  
666 tailored to the latter's needs through the previously mentioned space for collaboration. The main  
667 stakeholders in this category are academic and research institutes, as well as commercial or non-  
668 academic organizations, which use remote sensing data. In theory, the needs identified define the  
669 type of stakeholders involved. For example, if the manager's issue has scientific relevance (e.g.  
670 understanding the spread of an invasive species not studied before), academics would logically be  
671 involved. If no scientific issue is identified, however, then commercial or non-academic organizations  
672 are more appropriate.

673 Simple remote sensing approaches can be sometimes be deployed with only minor investment, such  
674 as the monitoring of riparian quality attributes with aerial images described in the example 2 (section  
675 4.1.2). However, the fixed costs of implementing a remote sensing approach are often relatively high  
676 and can be prohibitive for many local managers, even though free solutions increasingly appear on



677 the market. These costs include designing the method, deploying the platform or acquiring the  
678 minimum number of satellite images and possibly training personnel. Moreover, performing certain  
679 analyses requires technical skills (e.g. object-based image analysis, machine learning approaches,  
680 LiDAR full waveform analysis). Therefore, remote sensing could have greater relevance when the  
681 area to be mapped is large and/or the operation must be repeated several times (Johansen et al.,  
682 2007). The approach deployed in the example 3 (monitoring river networks with LiDAR data) is  
683 efficient because it concerns 12.000 km of rivers and it is to be repeated every 6 years. However,  
684 many stakeholders with different objectives are generally involved, since riparian vegetation covers  
685 large geographical areas. This can reduce the potential for economies of scale, whether for river  
686 managers trying to develop their own expertise or for businesses offering their services. This narrow  
687 market provides relatively limited opportunities for companies to develop specific tools adapted for  
688 this vegetation type. Indeed, we do not expect specific UAV applications to become as developed for  
689 managing invasive species in riparian areas (see example 1 in section 4.1.1) as they are for precision  
690 agriculture.

691 To address the challenge of attaining “critical mass” for riparian vegetation, we suggest a more  
692 collaborative approach, as described by Steiniger and Hay (2009). Processing routines developed by  
693 remote sensing scientists could be embedded into OpenAccess toolboxes. To benefit a large  
694 audience, these tools must be robust by having little sensitivity to situations that differ slightly from  
695 those for which they were created. For managers to use them, they need to be flexible and integrate  
696 easily with other processing routines or platforms (e.g. GIS platforms) (Vanden Borre et al., 2011).  
697 Finally, they should be based on widely available data: the tool presented in the example 4  
698 (floodplain roughness monitoring using Sentinel images in the Netherlands, section 4.1.3) could  
699 potentially be replicated in many regions since Sentinel-2 images are available worldwide.  
700 OpenAccess tools for river or ecosystem management could be collected in community repositories  
701 along with other tools for river or ecosystem management, along with freely available datasets, as

702 suggested by Tomsett and Leyland (2019) or Piégay et al (2020). These tools could form a foundation  
703 that commercial companies, researchers and managers could adapt to specific projects.

#### 704 **4.2.3. Assessment and feedback**

705 The final step in conveying remote sensing tools to riparian managers involves accurate and effective  
706 assessment of the maps produced and the potential for future monitoring. Accuracy involves the  
707 statistical validity of the product, which is the conformity of the map to reference data (e.g. thematic  
708 accuracy, in the case of classification). This step is crucial because it indicates the extent to which the  
709 map can be trusted. Remote sensing specialists usually consider it a central element, although  
710 controversy remains on the reliability of popular accuracy assessment methods (Pontius and  
711 Millones, 2011). Moreover, users must be cautious when reproducing the method at another site,  
712 since accuracy is often assessed for small test sites, and robustness is often not assessed sufficiently  
713 (Fassnacht et al., 2016).

714 However, the relevance of a remote sensing approach cannot be reduced to its accuracy. The  
715 relevance of the information for management purposes must consider the costs and benefits of  
716 obtaining such information (Kennedy et al., 2009). We argue that temporality should be considered  
717 when addressing this aspect. The true effectiveness of a tool is often observed long after it is first  
718 produced. Moreover, the issue of using remote sensing data in future monitoring (or not) must be  
719 considered. For example, after a restoration action, vegetation must be monitored in the short term  
720 (i.e. after one year) and the long term (i.e. after 5-10 years). Consequently, it is important to define  
721 which stakeholders are involved in this future monitoring (the initial producer of the map, the  
722 managers themselves or an external stakeholder) and which methods will be used. If managers are in  
723 charge of future monitoring, training should be provided. The example 2 (monitoring of riparian  
724 quality attributes with aerial images, see section 4.1.2) only requires basic training in GIS and photo-  
725 interpretation. However, for the example 3 (monitoring river networks with LiDAR data), training

726 courses that include programming must be provided to river managers, in order to enable them to  
727 update riparian indicators based on future regional LiDAR coverage.

728 The ease of use of the tools developed and their integration into existing workflows are also central  
729 aspects determining whether a manager will adopt remote sensing tools (Vanden Borre et al., 2011).  
730 We argue that it is crucial to obtain feedback from managers about the real use of the maps and  
731 features produced using remote sensing data. This feedback would help to develop tools that are  
732 more adapted to the managers' needs.

#### 733 **4.2.4. Issues beyond the remote sensing discipline**

734 The development and use of remote sensing tools to manage riparian vegetation is not only a  
735 technical issue. It raises at least two particular issues that must be addressed in an interdisciplinary  
736 or even transdisciplinary manner. First, the information must be scientifically relevant from a  
737 thematic perspective. In the example 3 (section 4.1.2), LiDAR data make it possible to measure  
738 vegetation height or continuity. However, whether this information is sufficient or relevant to assess  
739 a particular function of riparian vegetation must be discussed with experts from different disciplines  
740 (e.g. ecologists, hydrologists). Second, critical feedback about the use of remote sensing tools is also  
741 needed afterwards. Using these tools to assess environmental patterns and processes or to map  
742 natural resources is clearly not neutral. In some cases, these methods exclude certain stakeholders  
743 who do not have access to the technology, limit the understanding of certain complex phenomena  
744 and generate controversial data (e.g. Fairhead and Leach, 1998; Harwell, 2000; Turner and Taylor,  
745 2003; Rajão, 2013). In the example 5 (section 4.1.3), the RiverScape tool helps managers finding the  
746 best location for practices that aim to reduce flood hazard. However, the tool is not meant to be  
747 used alone to make decisions. Within a larger governance system, it can help stakeholders find a  
748 common ground through providing a large scale perspective, and through highlighting tradeoffs  
749 between stakes and stakeholders (Straatsma et al, 2019). More generally, sociological and cultural  
750 effects must be understood, and adverse effects of using remote sensing for natural resource

751 management should be properly handled. Social scientists should be involved throughout the  
752 process to address these issues.

## 753 **5. Conclusion**

754 We found a substantial body of literature in which remote sensing was used to study riparian  
755 vegetation. Remote sensing became considerably popular at the turn of the millennium, but its  
756 relative use in riparian vegetation studies remains limited (ca. 4%), and mostly in developed  
757 countries. In order to increase the user base, scientists can develop approaches that are robust to  
758 slight context changes and that take advantage of widely available data. These approaches can be  
759 embedded in Open Access or easy-to-use tools. The production, dissemination and use of large or  
760 global datasets concerning rivers, floodplains or land cover should also be promoted.

761 Development of new sensors and platforms has improved remote sensing approaches. However,  
762 most studies that use newer sensors and platforms focus on the local-to-river segment scale. Large-  
763 scale studies are based on medium-resolution satellite images. Algorithms are needed to process  
764 high-resolution data that is robust to upscaling. Spectral heterogeneity makes upscaling the study of  
765 species composition using spectral data more challenging than upscaling the study of vegetation  
766 structure using 3D data.

767 Riparian vegetation is highly dynamic, and the multi-temporal nature of riparian remote sensing  
768 studies is central (54 % of studies are multi-temporal). To date, diachronic analyses have relied  
769 essentially on aerial photographs, and it is clear that these data will remain popular given their  
770 availability and simplicity of use. However, other data time series become increasingly available.  
771 Scientists should test using these data to study complex and subtle phenomena, beyond changes in  
772 the extent of riparian forests or plant succession. For example, temporal series of LiDAR data should  
773 be tested to map subtle changes in vegetation structure such as growth, regeneration or senescence.  
774 Higher resolution or more frequent satellite images could help understand physiological or

775 community responses of riparian vegetation to environmental stress over large extents, yet at a finer  
776 spatial or temporal scale than before.

777 It is often suggested that remote sensing approaches can contribute to management of riparian  
778 vegetation by providing objective, continuous and up-to-date data for a large area. This contribution  
779 was difficult to determine via a review of the scientific literature, and an extensive review of the gray  
780 literature could provide further insight into this subject. However, there are many examples of  
781 operational or near-operational applications, not only with aerial images but also with more recent  
782 data (LiDAR, UAVs and satellite images). We suggest that a collaborative effort is required to make  
783 remote sensing approaches more robust and available, both in terms of cost and ease of use.  
784 However, implementing a remote sensing approach in actual management context still requires a  
785 tailored approach. It must include managers and scientists (thematicians and remote sensing  
786 scientists), be structured around well-defined objectives and include sufficient feedback.

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