



HAL
open science

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

Léo Huylenbroeck, Marianne Laslier, Simon Dufour, Blandine Georges, Philippe Lejeune, Adrien Michez

► To cite this version:

Léo Huylenbroeck, Marianne Laslier, Simon Dufour, Blandine Georges, Philippe Lejeune, et al.. Using remote sensing to characterize riparian vegetation: A review of available tools and perspectives for managers. *Journal of Environmental Management*, 2020, 267, pp.110652. 10.1016/j.jenvman.2020.110652 . hal-02566402

HAL Id: hal-02566402

<https://hal.science/hal-02566402>

Submitted on 3 Nov 2022

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

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

Leo Huylenbroeck^{1*+}, Marianne Laslier^{2*}, Simon Dufour³, Blandine Georges¹, Philippe Lejeune¹,
Adrien Michez¹

*Contributed equally

+Corresponding author (leo.huylenbroeck@uliege.be)

¹ ULiège, Gembloux Agro-Bio Tech, TERRA Teaching and Research Centre (Forest is Life). 2, Passage des Déportés, 5030 Gembloux, Belgium

² INRAE centre de Lyon Grenoble Auvergne Rhône-Alpes. 5 Rue de la Doua, 69100 Villeurbanne, France

³ Université Rennes 2 LETG Rennes, Place du Recteur Henri Le Moal 35043 Rennes cedex, France

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 addressed 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).

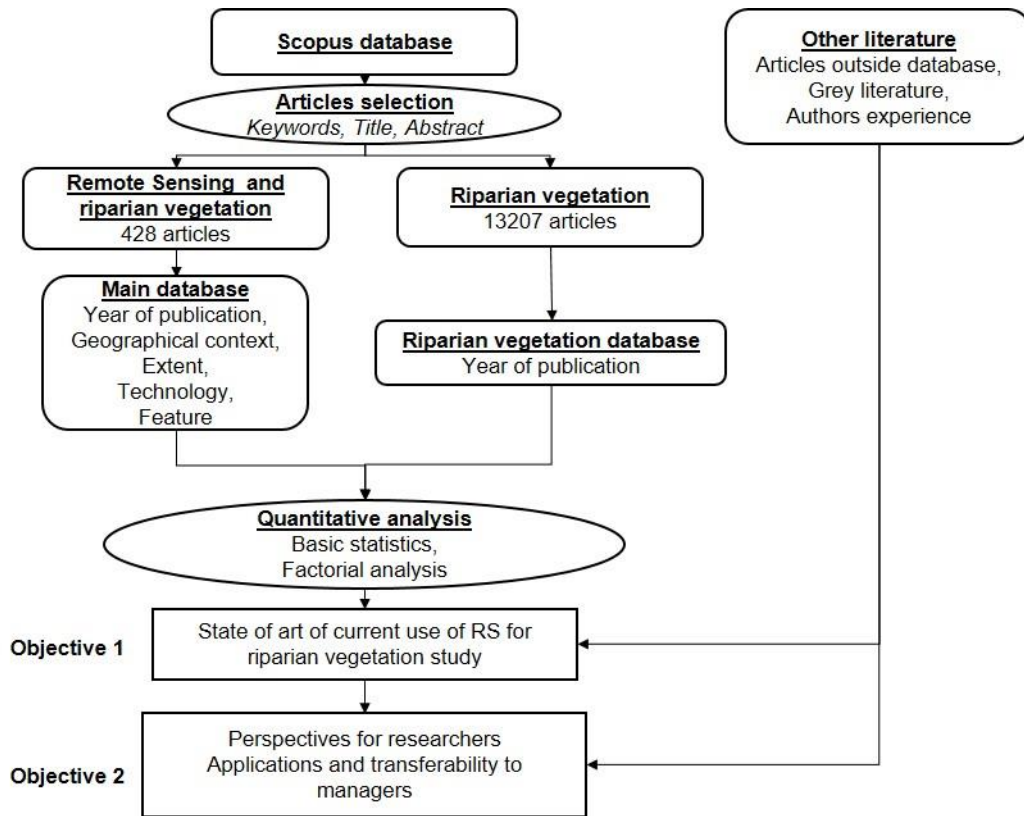
64 The use of remote sensing to study riparian vegetation raises specific challenges. These challenges
65 are linked to the vegetation's relative structural complexity and spatial organization (Naiman and
66 Décamps, 1997), or to the difficulty to extract specific features or processes related to riparian
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.

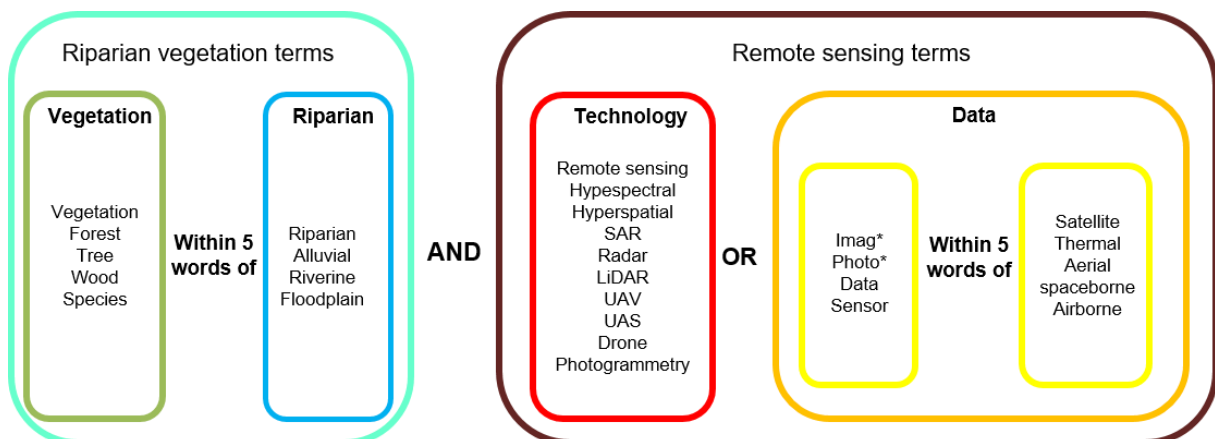


93

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 (≤ 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
General information	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)
Type of remote sensing data	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
Extent of the study area	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"> • Local: Length < 10 km

				<ul style="list-style-type: none"> • River segment: Length 10-100 km OR Area < 100 km² • Subregional: Length 100-1000 km OR Area 100-1000 km² • Regional: Length > 10,000 km OR Area 1000-10,000 km² • Very large scale: Area > 10,000 km²
Type of indicator	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	
Multi-temporality	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

186

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

189

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

190

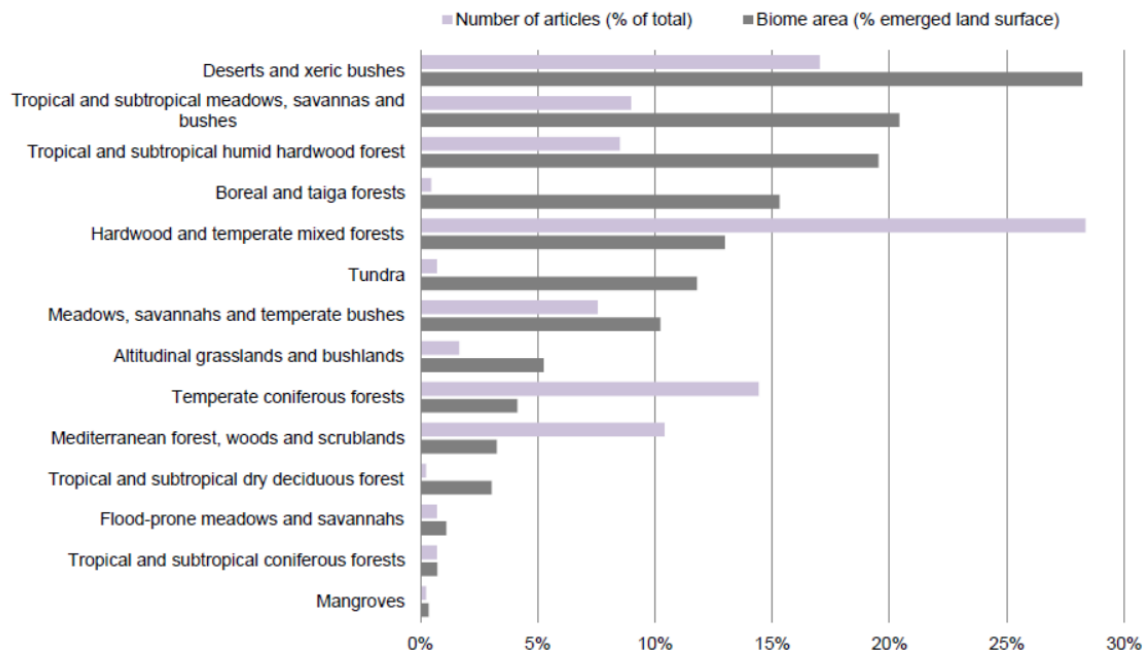
emerged land area), few studies focused on them.



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*

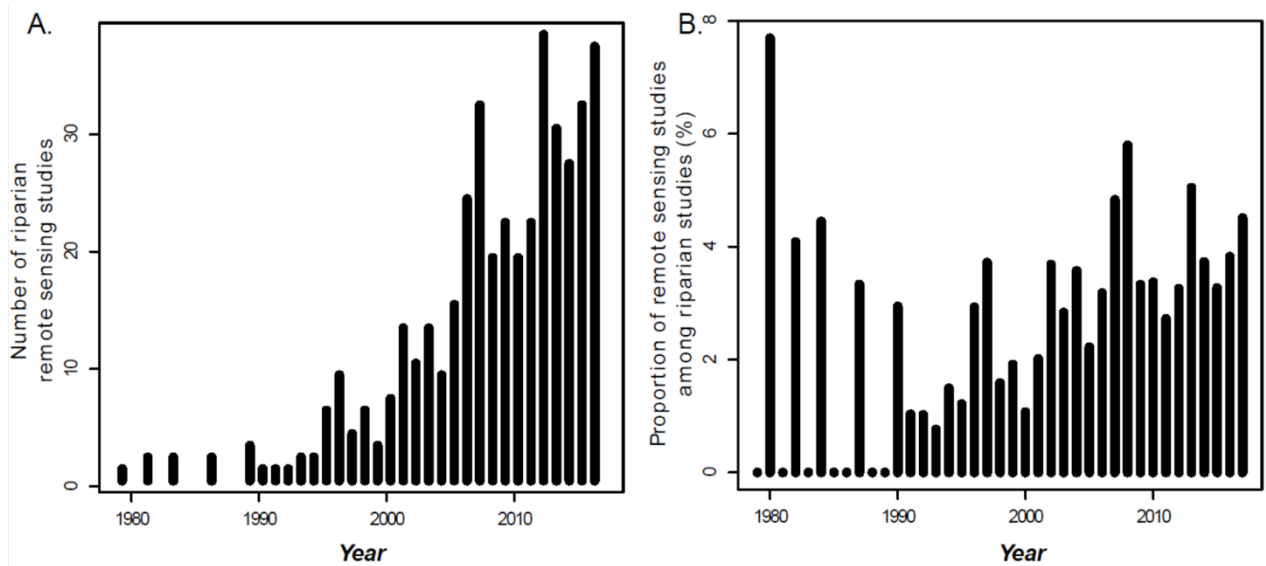
195 This result highlights the lack of knowledge and studies about tropical and boreal riparian forests,
 196 perhaps due to the location of laboratories, which are often located in developed countries and
 197 temperate climates. Our results are similar to those of Dufour et al. (2019) for all riparian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

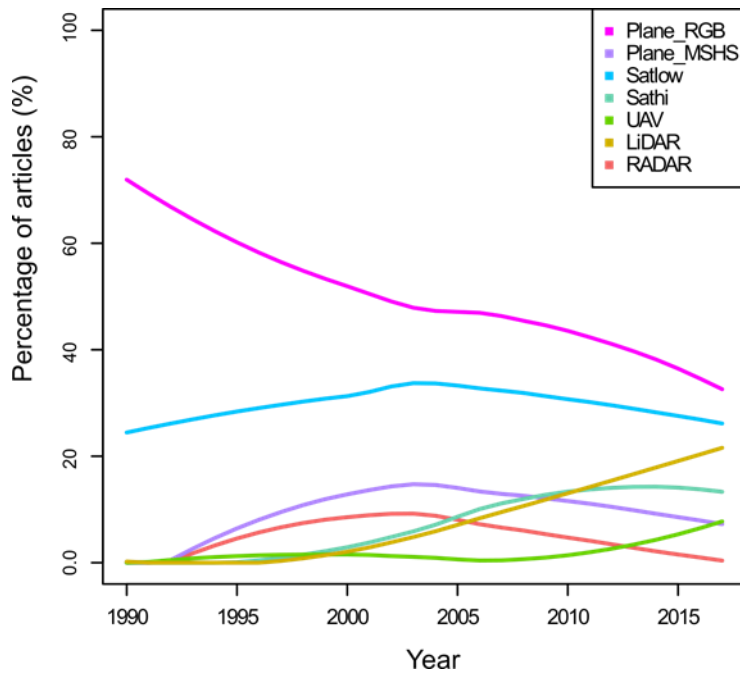


232

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.



245

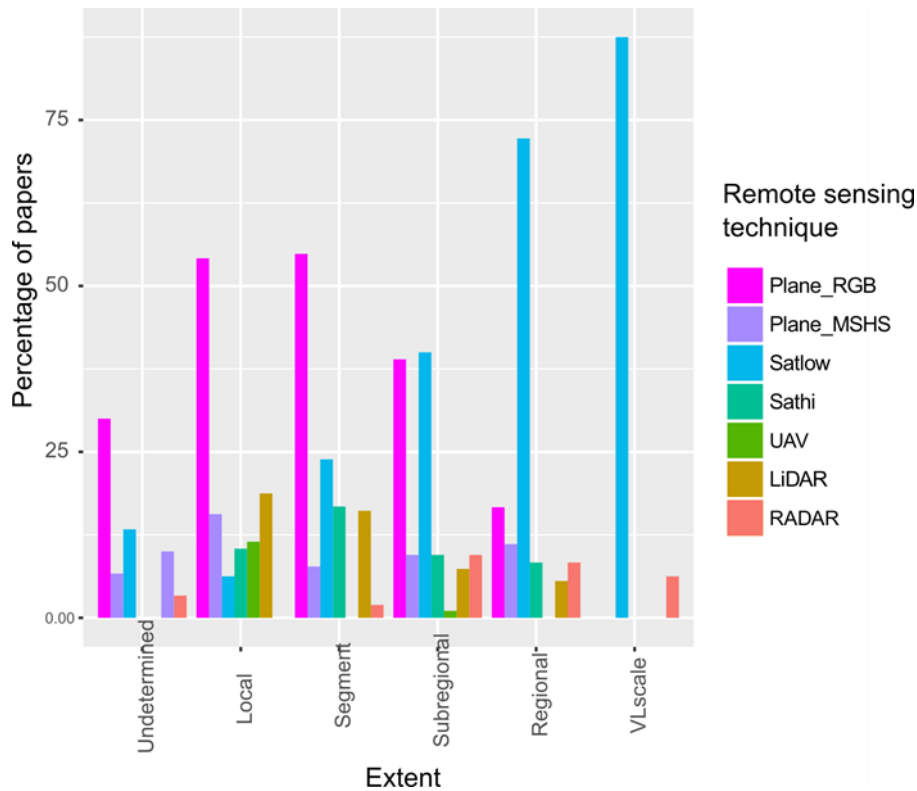
246 *Figure 6. Percentage of studies that used a given technology per year. The curve was smoothed using a loess regression.*

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).

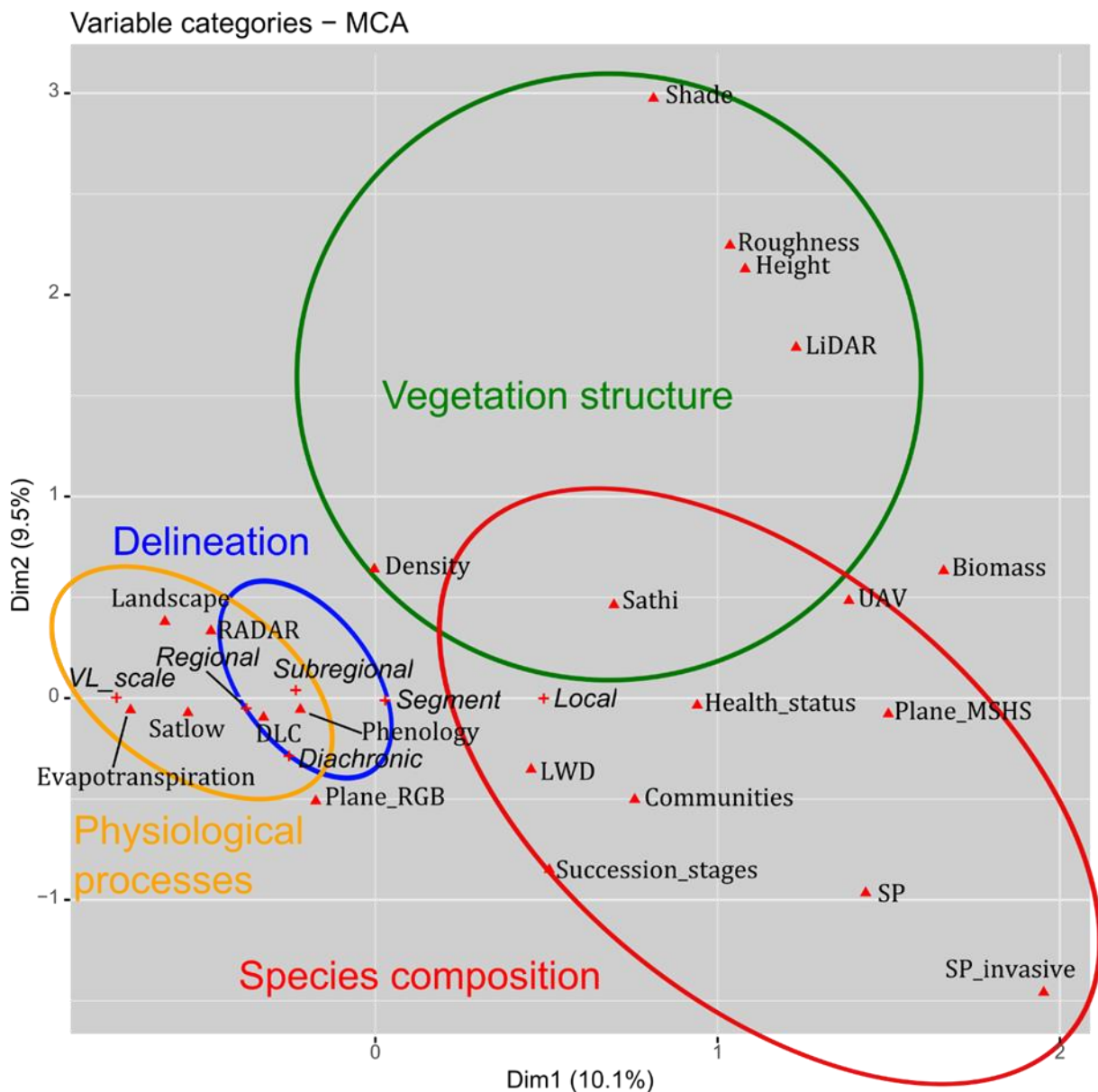
315 **3.4.3. Large scale: satellite images**

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 pansharpening
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.



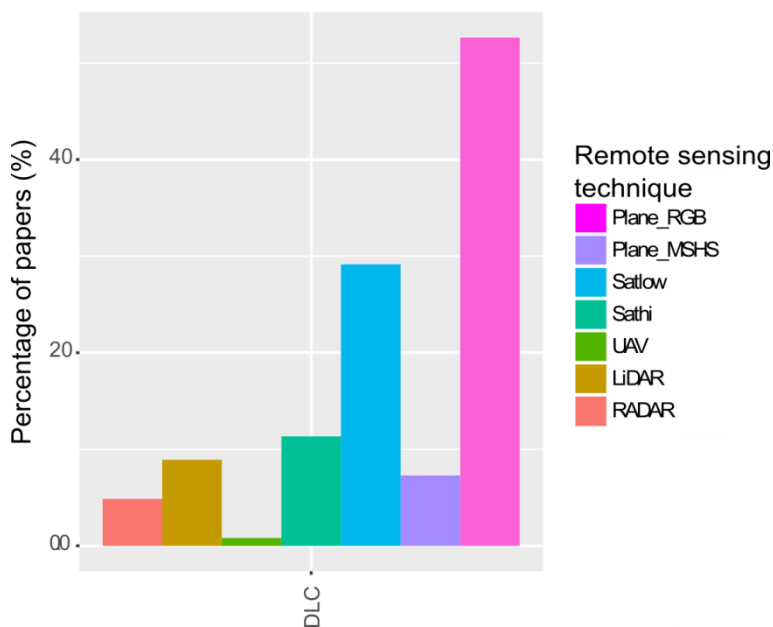
342

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).

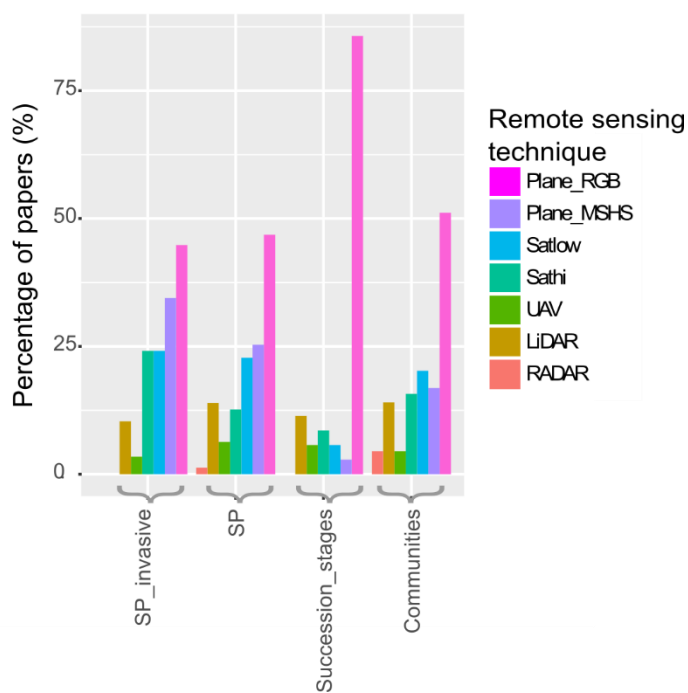


361
 362 *Figure 9. Percentage of studies that used given remote sensing data to delineate riparian vegetation (i.e. distinguish riparian*
 363 *vegetation from other land-cover types)*

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).

403 Table 2. Examples of remote sensing methods used to classify riparian species in different settings and their accuracy

<u>Reference</u>	<u>Data</u>	<u>Classes</u>	<u>Accuracy</u>	<u>Comment</u>
Mature riparian forests				
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 ²) LiDAR point cloud	8 tree species in a temperate riparian agricultural/forested landscape	67%	
Pioneer/species-poor riparian settings				
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%	

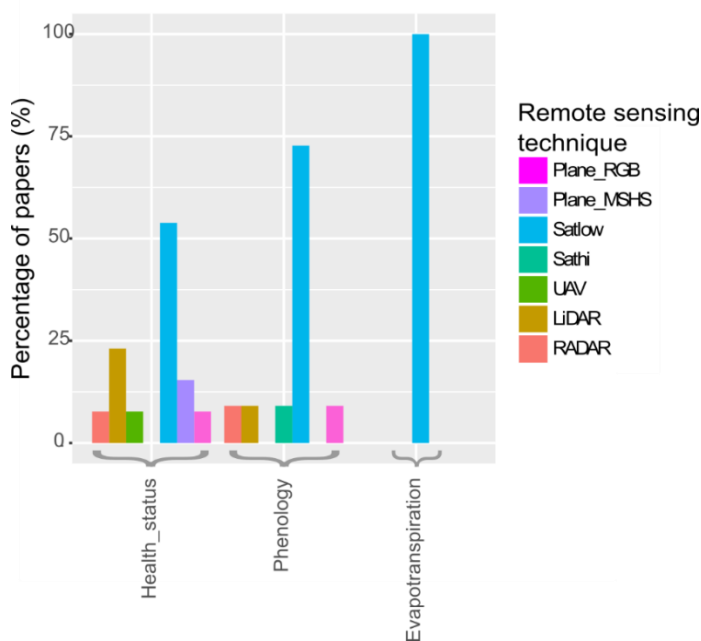
Invasive species				
Narumalani et al. (2009)	Hyperspectral aerial imagery (62 bands, 1.5 m resolution)	<i>Tamarix, Elaeagnus angustifolia, Cirsium arvense, Carduus nutans</i> and mixed classes	74%	Mixed classes are not well classified and decrease overall accuracy
Fernandes et al. (2014)	RGB-NIR aerial 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).

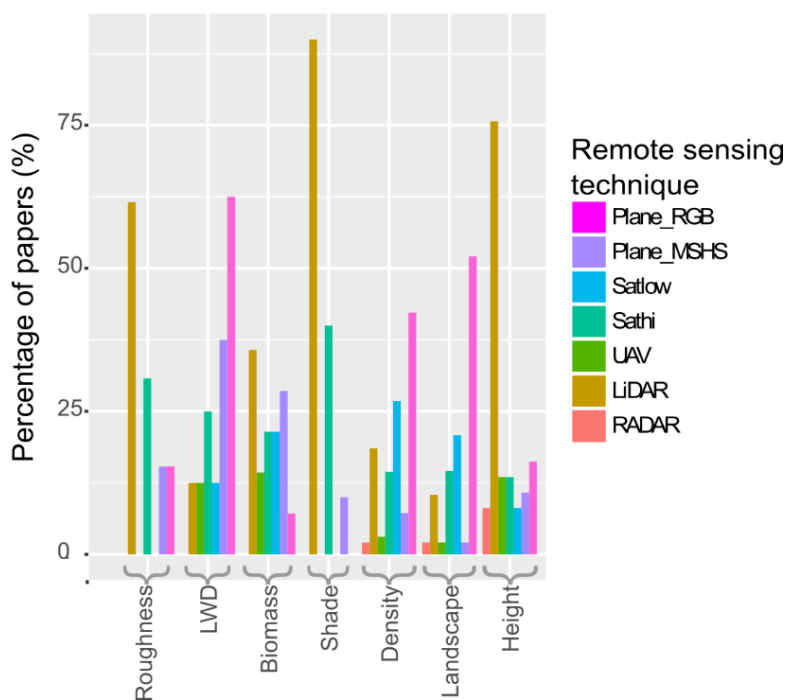


429

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).

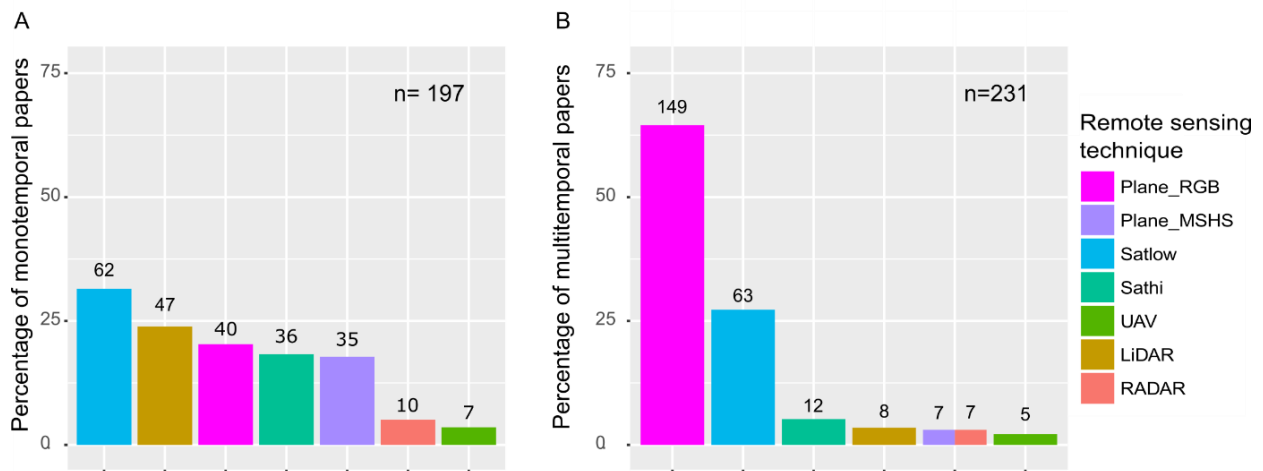
447 LiDAR data have been used in 90% of studies (Figure 12) to map riparian shade, which is a major
448 parameter that influences stream water temperature (Poole and Berman, 2001). Temperature
449 regulates the habitat of aquatic species such as the brown trout (*Salmo trutta fario* L.) (Caissie, 2006;
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 km² 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.

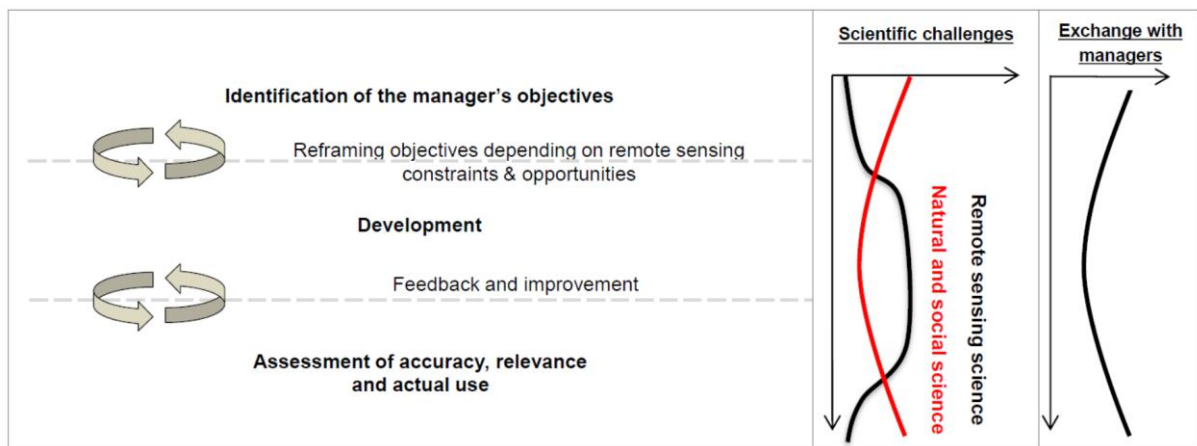
589 One example (hereinafter referred to as example 4) includes a legal map produced to describe the
590 maximum roughness of vegetation cover allowed within the floodplains of major Dutch rivers. The
591 legal map uses a historical situation as a target reference (Rijkswaterstaat, 2014). To support 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.

787 **Acknowledgement**

788 The collaboration that led to the writing of this article was initiated during a short term scientific
789 mission financed by the Converges COST action (CA16208). This work received financial support from
790 the Province of Liège, the Province of Luxembourg and the Agence de l'eau Seine Normandie.

791 **References**

792 Akasaka, T., Akasaka, M., Yanagawa, H., 2010. Relative importance of the environmental factors at
793 site and landscape scales for bats along the riparian zone. *Landsc. Ecol. Eng.* 6, 247–255.

794 <https://doi.org/10.1007/s11355-010-0105-4>

795 Alaibakhsh, M., Emelyanova, I., Barron, O., Sims, N., Khiadani, M., Mohyeddin, A., 2017. Delineation
796 of riparian vegetation from Landsat multi-temporal imagery using PCA. *Hydrol. Process.* 31,

797 800–810. <https://doi.org/10.1002/hyp.11054>

798 Anderson, K., Gaston, K.J., 2013. Lightweight unmanned aerial vehicles will revolutionize spatial
799 ecology. *Front. Ecol. Environ.* 11, 138–146. <https://doi.org/10.1890/120150>

800 Antonarakis, A.S., Richards, K.S., Brasington, J., 2008. Object-based land cover classification using
801 airborne LiDAR. *Remote Sens. Environ.* 112, 2988–2998.
802 <https://doi.org/10.1016/j.rse.2008.02.004>

803 Arroyo, L.A., Johansen, K., Armston, J., Phinn, S., 2010. Integration of LiDAR and QuickBird imagery
804 for mapping riparian biophysical parameters and land cover types in Australian tropical
805 savannas. *For. Ecol. Manag.* 259, 598–606. <https://doi.org/10.1016/j.foreco.2009.11.018>

806 Ashraf, S., Brabyn, L., Hicks, B.J., Collier, K., 2010. Satellite remote sensing for mapping vegetation in
807 New Zealand freshwater environments: A review. *N. Z. Geogr.* 66, 33–43.
808 <https://doi.org/10.1111/j.1745-7939.2010.01168.x>

809 Beechie, T., Pess, G., Roni, P., Giannico, G., 2008. Setting river restoration priorities: a review of
810 approaches and a general protocol for identifying and prioritizing actions. *North Am. J. Fish.*
811 *Manag.* 28, 891–905.

812 Belletti, B., Dufour, S., Piégay, H., 2015a. What is the Relative Effect of Space and Time to Explain the
813 Braided River Width and Island Patterns at a Regional Scale? *River Res. Appl.* 31, 1–15.
814 <https://doi.org/10.1002/rra.2714>

815 Belluco, E., Camuffo, M., Ferrari, S., Modenese, L., Silvestri, S., Marani, A., Marani, M., 2006. Mapping
816 salt-marsh vegetation by multispectral and hyperspectral remote sensing. *Remote Sens.*
817 *Environ.* 105, 54–67. <https://doi.org/10.1016/j.rse.2006.06.006>

818 Bendix, J., Stella, J.C., 2013. Riparian Vegetation and the Fluvial Environment: A Biogeographic
819 Perspective. *Treatise Geomorphol.* 53–74. [https://doi.org/10.1016/B978-0-12-374739-](https://doi.org/10.1016/B978-0-12-374739-6.00322-5)
820 [6.00322-5](https://doi.org/10.1016/B978-0-12-374739-6.00322-5)

821 Bertoldi, W., Drake, N.A., Gurnell, A.M., 2011. Interactions between river flows and colonizing
822 vegetation on a braided river: exploring spatial and temporal dynamics in riparian vegetation

823 cover using satellite data. *Earth Surf. Process. Landf.* 36, 1474–1486.
824 <https://doi.org/10.1002/esp.2166>

825 Bowler, D.E., Mant, R., Orr, H., Hannah, D.M., Pullin, A.S., 2012. What are the effects of wooded
826 riparian zones on stream temperature? *Environ. Evid.* 1, 3. [https://doi.org/10.1186/2047-](https://doi.org/10.1186/2047-2382-1-3)
827 [2382-1-3](https://doi.org/10.1186/2047-2382-1-3)

828 Brogna, D., Dufrêne, M., Michez, A., Latli, A., Jacobs, S., Vincke, C., & Dendoncker, N. (2018). Forest
829 cover correlates with good biological water quality. Insights from a regional study (Wallonia,
830 Belgium). *Journal of Environmental Management*, 211, 9–21.
831 <https://doi.org/10.1016/j.jenvman.2018.01.017>

832 Bucha, T., Slávik, M., 2013. Improved methods of classification of multispectral aerial photographs:
833 Evaluation of floodplain forests in the inundation area of the Danube. *Folia For. Pol. Ser. -*
834 *For.* 55. <https://doi.org/10.2478/ffp-2013-0007>

835 Bunn, S.E., Abal, E.G., Smith, M.J., Choy, S.C., Fellows, C.S., Harch, B.D., Kennard, M.J., Sheldon, F.,
836 2010. Integration of science and monitoring of river ecosystem health to guide investments
837 in catchment protection and rehabilitation. *Freshw. Biol.* 55, 223–240.
838 <https://doi.org/10.1111/j.1365-2427.2009.02375.x>

839 Cadol, D., Wine, M.L., 2017. Geomorphology as a first order control on the connectivity of riparian
840 ecohydrology. *Geomorphology, Connectivity in Geomorphology from Binghamton 2016* 277,
841 154–170. <https://doi.org/10.1016/j.geomorph.2016.06.022>

842 Caissie, D., 2006. The thermal regime of rivers: a review. *Freshw. Biol.* 51, 1389–1406.
843 <https://doi.org/10.1111/j.1365-2427.2006.01597.x>

844 Capon, S.J., Pettit, N.E., 2018. Turquoise is the new green: Restoring and enhancing riparian function
845 in the Anthropocene. *Ecol. Manag. Restor.* 19, 44–53. <https://doi.org/10.1111/emr.12326>

846 Carbonneau, P., Piégay, H., 2012. Future prospects and challenges for river scientists and managers,
847 in: *Fluvial Remote Sensing for Science and Management*. John Wiley & Sons, Ltd.
848 <https://doi.org/10.1002/9781119940791>

849 Carli, C.M., Bayley, S.E., 2015. River connectivity and road crossing effects on floodplain vegetation of
850 the upper Columbia River, Canada. *Écoscience* 22, 97–107.
851 <https://doi.org/10.1080/11956860.2015.1121705>

852 Claggett, P.R., Okay, J.A., Stehman, S.V., 2010. Monitoring Regional Riparian Forest Cover Change
853 Using Stratified Sampling and Multiresolution Imagery1. *JAWRA J. Am. Water Resour. Assoc.*
854 46, 334–343. <https://doi.org/10.1111/j.1752-1688.2010.00424.x>

855 Congalton, R.G., Birch, K., Jones, R., Schriever, J., 2002. Evaluating remotely sensed techniques for
856 mapping riparian vegetation. *Comput. Electron. Agric.* 37, 113–126.
857 [https://doi.org/10.1016/S0168-1699\(02\)00108-4](https://doi.org/10.1016/S0168-1699(02)00108-4)

858 Cunningham, S.C., Griffioen, P., White, M.D., Nally, R.M., 2018. Assessment of ecosystems: A system
859 for rigorous and rapid mapping of floodplain forest condition for Australia’s most important
860 river. *Land Degrad. Dev.* 29, 127–137. <https://doi.org/10.1002/ldr.2845>

861 Curran, J.C., Hession, W.C., 2013. Vegetative impacts on hydraulics and sediment processes across
862 the fluvial system. *J. Hydrol.* 505, 364–376. <https://doi.org/10.1016/j.jhydrol.2013.10.013>

863 Cushnie, J. L., 1987. The interactive effect of spatial resolution and degree of internal variability
864 within land-cover types on classification accuracies. *International Journal of Remote Sensing*,
865 8(1), 15–29. <https://doi.org/10.1080/01431168708948612>

866 Dahm, C.N., Cleverly, J.R., Coonrod, J.E.A., Thibault, J.R., McDonnell, D.E., Gilroy, D.J., 2002.
867 Evapotranspiration at the land/water interface in a semi-arid drainage basin. *Freshw. Biol.*
868 47, 831–843. <https://doi.org/10.1046/j.1365-2427.2002.00917.x>

869 Dauwalter, D.C., Fesenmyer, K.A., Bjork, R., 2015. Using Aerial Imagery to Characterize Redband
870 Trout Habitat in a Remote Desert Landscape. *Trans. Am. Fish. Soc.* 144, 1322–1339.
871 <https://doi.org/10.1080/00028487.2015.1088471>

872 Debruxelles, N., Claessens, H., Lejeune, P., & Rondeux, J., 2009. Design of a watercourse and riparian
873 strip monitoring system for environmental management. *Environmental Monitoring and*
874 *Assessment*, 156(1–4), 435–450. <https://doi.org/10.1007/s10661-008-0496-y>

875 Décamps, H., 2001. How a riparian landscape finds form and comes alive. *Landscape and Urban*
876 *Planning*, 57(3), 169–175. [https://doi.org/10.1016/S0169-2046\(01\)00202-X](https://doi.org/10.1016/S0169-2046(01)00202-X)

877 Dixon, S. J., Sear, D. A., Odoni, N. A., Sykes, T., & Lane, S. N., 2016. The effects of river restoration on
878 catchment scale flood risk and flood hydrology. *Earth Surface Processes and Landforms*,
879 41(7), 997–1008. <https://doi.org/10.1002/esp.3919>

880 Doody, T.M., Lewis, M., Benyon, R.G., Byrne, G., 2014. A method to map riparian exotic vegetation
881 (*Salix* spp.) area to inform water resource management. *Hydrol. Process.* 28, 3809–3823.
882 <https://doi.org/10.1002/hyp.9916>

883 Dufour, S., Piégay, H., 2009. From the myth of a lost paradise to targeted river restoration: forget
884 natural references and focus on human benefits. *River Res. Appl.* 25, 568–581.
885 <https://doi.org/10.1002/rra.1239>

886 Dufour, S., Muller, E., Straatsma, M., Corgne, S., 2012. Image Utilisation for the Study and
887 Management of Riparian Vegetation: Overview and Applications, in: *Fluvial Remote Sensing*
888 *for Science and Management*. John Wiley & Sons, Ltd.
889 <https://doi.org/10.1002/9781119940791>

890 Dufour, S., Bernez, I., Betbeder, J., Corgne, S., Hubert-Moy, L., Nabucet, J., Rapinel, S., Sawtschuk, J.,
891 Trollé, C., 2013. Monitoring restored riparian vegetation: how can recent developments in
892 remote sensing sciences help? *Knowl. Manag. Aquat. Ecosyst.* 10.
893 <https://doi.org/10.1051/kmae/2013068>

894 Dufour, S., Rinaldi, M., Piégay, H., Michalon, A., 2015. How do river dynamics and human influences
895 affect the landscape pattern of fluvial corridors? Lessons from the Magra River, Central–
896 Northern Italy. *Landsc. Urban Plan.* 134, 107–118.
897 <https://doi.org/10.1016/j.landurbplan.2014.10.007>

898 Dufour, S., Rodríguez-González, P.M., Laslier, M., 2019. Tracing the scientific trajectory of riparian
899 vegetation studies: Main topics, approaches and needs in a globally changing world. *Sci. Total*
900 *Environ.* 653, 1168–1185. <https://doi.org/10.1016/j.scitotenv.2018.10.383>

901 Dunford, R., Michel, K., Gagnage, M., Piégay, H., Trémelo, M.-L., 2009. Potential and constraints of
902 Unmanned Aerial Vehicle technology for the characterization of Mediterranean riparian
903 forest. *Int. J. Remote Sens.* 30, 4915–4935. <https://doi.org/10.1080/01431160903023025>

904 Dutta, D., Wang, K., Lee, E., Goodwell, A., Woo, D.K., Wagner, D., Kumar, P., 2017. Characterizing
905 Vegetation Canopy Structure Using Airborne Remote Sensing Data. *IEEE Trans. Geosci.*
906 *Remote Sens.* 55, 1160–1178. <https://doi.org/10.1109/TGRS.2016.2620478>

907 Fairhead, J., Leach, M., 1998. Reconsidering the extent of deforestation in twentieth century West
908 Africa. *Unasylva* 49192 38-46.

909 Fassnacht, F.E., Latifi, H., Stereńczak, K., Modzelewska, A., Lefsky, M., Waser, L.T., Straub, C., Ghosh,
910 A., 2016. Review of studies on tree species classification from remotely sensed data. *Remote*
911 *Sens. Environ.* 186, 64–87. <https://doi.org/10.1016/j.rse.2016.08.013>

912 Fausch, K.D., Torgersen, C.E., Baxter, C.V., Li, H.W., 2002. Landscapes to Riverscapes: Bridging the
913 Gap between Research and Conservation of Stream Fishes. *BioScience* 52, 483–498.
914 [https://doi.org/10.1641/0006-3568\(2002\)052\[0483:LTRBTG\]2.0.CO;2](https://doi.org/10.1641/0006-3568(2002)052[0483:LTRBTG]2.0.CO;2)

915 Fédération des Conservatoires d’espaces naturels, 2018. Les nouvelles technologies dans l’étude des
916 milieux humides : exemples d’applications.

917 Fernandes, M.R., Aguiar, F.C., Ferreira, M.T., Pereira, J.M.C., 2013a. Spectral separability of riparian
918 forests from small and medium-sized rivers across a latitudinal gradient using multispectral
919 imagery. *Int. J. Remote Sens.* 34, 2375–2401.
920 <https://doi.org/10.1080/01431161.2012.744491>

921 Fernandes, M.R., Aguiar, F.C., Silva, J.M.N., Ferreira, M.T., Pereira, J.M.C., 2013b. Spectral
922 discrimination of giant reed (*Arundo donax* L.): A seasonal study in riparian areas. *ISPRS J.*
923 *Photogramm. Remote Sens.* 80, 80–90. <https://doi.org/10.1016/j.isprsjprs.2013.03.007>

924 Fernandes, M.R., Aguiar, F.C., Silva, J.M.N., Ferreira, M.T., Pereira, J.M.C., 2014. Optimal attributes
925 for the object based detection of giant reed in riparian habitats: A comparative study

926 between Airborne High Spatial Resolution and WorldView-2 imagery. *Int. J. Appl. Earth Obs.*
927 *Geoinformation* 32, 79–91. <https://doi.org/10.1016/j.jag.2014.03.026>

928 Forzieri, G., Castelli, F., Preti, F., 2012. Advances in remote sensing of hydraulic roughness. *Int. J.*
929 *Remote Sens.* 33, 630–654. <https://doi.org/10.1080/01431161.2010.531788>

930 Forzieri, G., Tanteri, L., Moser, G., Catani, F., 2013. Mapping natural and urban environments using
931 airborne multi-sensor ADS40–MIVIS–LiDAR synergies. *Int. J. Appl. Earth Obs. Geoinformation*
932 23, 313–323. <https://doi.org/10.1016/j.jag.2012.10.004>

933 Fullerton, A.H., Beechie, T.J., Baker, S.E., Hall, J.E., Barnas, K.A., 2006. Regional patterns of riparian
934 characteristics in the interior Columbia River basin, Northwestern USA: applications for
935 restoration planning. *Landsc. Ecol.* 21, 1347–1360. [https://doi.org/10.1007/s10980-006-](https://doi.org/10.1007/s10980-006-0017-8)
936 0017-8

937 Georges, B., Brostaux, Y., Claessens, H., Degré, A., Huylenbroeck, L., Lejeune, P., Piégay, H., Michez,
938 A., 2019. Can water level stations be used for thermal assessment in aquatic ecosystem?
939 *River Res. Appl.* 1 - 14. <https://doi.org/10.1002/rra.3520>

940 Gergel, S.E., Stange, Y., Coops, N.C., Johansen, K., Kirby, K.R., 2007. What is the Value of a Good Map?
941 An Example Using High Spatial Resolution Imagery to Aid Riparian Restoration. *Ecosystems*
942 10, 688–702. <https://doi.org/10.1007/s10021-007-9040-0>

943 Goetz, W.E., 2002. Developing a predictive model for identifying riparian communities at an
944 ecoregion scale in Idaho and Wyoming. Unpublished master thesis, Utah State University,
945 Logan.

946 Goetz, S.J., 2006. Remote Sensing of Riparian Buffers: Past Progress and Future Prospects. *JAWRA J.*
947 *Am. Water Resour. Assoc.* 42, 133–143. <https://doi.org/10.1111/j.1752-1688.2006.tb03829.x>

948 Gong, P., Wang, J., Yu, Le, Zhao, Yongchao, Zhao, Yuanyuan, Liang, L., Niu, Z., Huang, X., Fu, H., Liu, S.,
949 Li, C., Li, X., Fu, W., Liu, C., Xu, Y., Wang, X., Cheng, Q., Hu, L., Yao, W., Zhang, Han, Zhu, P.,
950 Zhao, Z., Zhang, Haiying, Zheng, Y., Ji, L., Zhang, Y., Chen, H., Yan, A., Guo, J., Yu, Liang, Wang,
951 L., Liu, X., Shi, T., Zhu, M., Chen, Y., Yang, G., Tang, P., Xu, B., Giri, C., Clinton, N., Zhu, Z.,

952 Chen, Jin, Chen, Jun, 2013. Finer resolution observation and monitoring of global land cover:
953 first mapping results with Landsat TM and ETM+ data. *Int. J. Remote Sens.* 34, 2607–2654.
954 <https://doi.org/10.1080/01431161.2012.748992>

955 Gong, Z., Cui, T., Pu, R., Lin, C., Chen, Y., 2015. Dynamic simulation of vegetation abundance in a
956 reservoir riparian zone using a sub-pixel Markov model. *Int. J. Appl. Earth Obs.*
957 *Geoinformation* 35, 175–186. <https://doi.org/10.1016/j.jag.2014.09.004>

958 González del Tánago, M., García de Jalón, D., 2011. Riparian Quality Index (RQI): a methodology for
959 characterising and assessing the environmental conditions of riparian zones. *Limnética* 30,
960 0235–0254.

961 González del Tánago, M., Bejarano, M.D., García de Jalón, D., Schmidt, J.C., 2015. Biogeomorphic
962 responses to flow regulation and fine sediment supply in Mediterranean streams (the
963 Guadalete River, southern Spain). *J. Hydrol.* 528, 751–762.
964 <https://doi.org/10.1016/j.jhydrol.2015.06.065>

965 González, E., González-Sanchis, M., Cabezas, Á., Comín, F.A., Muller, E., 2010. Recent Changes in the
966 Riparian Forest of a Large Regulated Mediterranean River: Implications for Management.
967 *Environ. Manage.* 45, 669–681. <https://doi.org/10.1007/s00267-010-9441-2>

968 González, E., Sher, A.A., Tabacchi, E., Masip, A., Poulin, M., 2015. Restoration of riparian vegetation:
969 A global review of implementation and evaluation approaches in the international, peer-
970 reviewed literature. *J. Environ. Manage.* 158, 85–94.
971 <https://doi.org/10.1016/j.jenvman.2015.04.033>

972 Groeneveld, D.P., Watson, R.P., 2008. Near-infrared discrimination of leafless saltcedar in wintertime
973 Landsat TM. *Int. J. Remote Sens.* 29, 3577–3588.
974 <https://doi.org/10.1080/01431160701711078>

975 Hamandawana, H., Chanda, R., 2013. Environmental change in and around the Okavango Delta
976 during the nineteenth and twentieth centuries. *Reg. Environ. Change* 13, 681–694.
977 <https://doi.org/10.1007/s10113-012-0367-5>

978 Harwell, E., 2000. Remote Sensibilities: Discourses of Technology and the Making of Indonesia's
979 Natural Disaster. *Dev. Change* 31, 307–340. <https://doi.org/10.1111/1467-7660.00156>

980 Henshaw, A. J., Gurnell, A. M., Bertoldi, W., & Drake, N. A., 2013. An assessment of the degree to
981 which Landsat TM data can support the assessment of fluvial dynamics, as revealed by
982 changes in vegetation extent and channel position, along a large river. *Geomorphology*, 202,
983 74–85. <https://doi.org/10.1016/j.geomorph.2013.01.011>

984 Hering, D., Borja, A., Carstensen, J., Carvalho, L., Elliott, M., Feld, C.K., Heiskanen, A.-S., Johnson, R.K.,
985 Moe, J., Pont, D., Solheim, A.L., de Bund, W. van, 2010. The European Water Framework
986 Directive at the age of 10: A critical review of the achievements with recommendations for
987 the future. *Sci. Total Environ.* 408, 4007–4019.
988 <https://doi.org/10.1016/j.scitotenv.2010.05.031>

989 Hill, D. J., Tarasoff, C., Whitworth, G. E., Baron, J., Bradshaw, J. L., & Church, J. S., 2017. Utility of
990 unmanned aerial vehicles for mapping invasive plant species: A case study on yellow flag iris
991 (*Iris pseudacorus* L.). *International Journal of Remote Sensing*, 38(8–10), 2083–2105.
992 <https://doi.org/10.1080/01431161.2016.1264030>

993 Hill, D. J., Babbar-Sebens, M., 2019. Promise of UAV-Assisted Adaptive Management of Water
994 Resources Systems. *J. Water Resour. Plan. Manag.* 145, 02519001.
995 [https://doi.org/10.1061/\(ASCE\)WR.1943-5452.0001081](https://doi.org/10.1061/(ASCE)WR.1943-5452.0001081)

996 Holmes, P. M., Richardson, D. M., Esler, K. J., Witkowski, E. T. F., & Fourie, S., 2005. A decision-making
997 framework for restoring riparian zones degraded by invasive alien plants in South Africa:
998 Review article. *South African Journal of Science*, 101(11–12), 553–564.

999 Honey-Rosés, J., Acuña, V., Bardina, M., Brozović, N., Marcé, R., Munné, A., Sabater, S., Termes, M.,
1000 Valero, F., Vega, À., & Schneider, D. W., 2013. Examining the Demand for Ecosystem Services:
1001 The Value of Stream Restoration for Drinking Water Treatment Managers in the Llobregat
1002 River, Spain. *Ecological Economics*, 90, 196–205.
1003 <https://doi.org/10.1016/j.ecolecon.2013.03.019>

- 1004 Hughes, F. M. R., del Tánago, M. G., & Mountford, J. O., 2012. Restoring Floodplain Forests in Europe.
1005 In J. Stanturf, P. Madsen, & D. Lamb (Eds.), *A Goal-Oriented Approach to Forest Landscape*
1006 *Restoration* (pp. 393–422). Springer Netherlands. [https://doi.org/10.1007/978-94-007-5338-](https://doi.org/10.1007/978-94-007-5338-9_15)
1007 [9_15](https://doi.org/10.1007/978-94-007-5338-9_15)
- 1008 Hupp, C.R., 1992. Riparian Vegetation Recovery Patterns Following Stream Channelization: A
1009 Geomorphic Perspective. *Ecology* 73, 1209–1226. <https://doi.org/10.2307/1940670>
- 1010 Jalonen, J., Järvelä, J., Virtanen, J.-P., Vaaja, M., Kurkela, M., Hyypä, H., 2015. Determining
1011 Characteristic Vegetation Areas by Terrestrial Laser Scanning for Floodplain Flow Modeling.
1012 *Water* 7, 420–437. <https://doi.org/10.3390/w7020420>
- 1013 Jansen, B.J.M., Backx, J.J.G.M., 1998. Biologische monitoring zoete rijkswateren : ecotopenkartering
1014 Rijntakken-oost 1997, RIZA rapport;98.054. RIZA, Lelystad.
- 1015 Johansen, K., Phinn, S., Dixon, I., Douglas, M., Lowry, J., 2007. Comparison of image and rapid field
1016 assessments of riparian zone condition in Australian tropical savannas. *For. Ecol. Manag.* 240,
1017 42–60. <https://doi.org/10.1016/j.foreco.2006.12.015>
- 1018 Johansen, K., Phinn, S., Witte, C., 2010. Mapping of riparian zone attributes using discrete return
1019 LiDAR, QuickBird and SPOT-5 imagery: Assessing accuracy and costs. *Remote Sens. Environ.*
1020 114, 2679–2691. <https://doi.org/10.1016/j.rse.2010.06.004>
- 1021 Kalliola, R., Puhakka, M., 1988. River Dynamics and Vegetation Mosaicism: A Case Study of the River
1022 Kamajohka, Northernmost Finland. *J. Biogeogr.* 15, 703–719.
1023 <https://doi.org/10.2307/2845334>
- 1024 Kennedy, R.E., Townsend, P.A., Gross, J.E., Cohen, W.B., Bolstad, P., Wang, Y.Q., Adams, P., 2009.
1025 Remote sensing change detection tools for natural resource managers: Understanding
1026 concepts and tradeoffs in the design of landscape monitoring projects. *Remote Sens.*
1027 *Environ., Monitoring Protected Areas* 113, 1382–1396.
1028 <https://doi.org/10.1016/j.rse.2008.07.018>

1029 Klein, L. R., Hendrix, W. G., Lohr, V. I., Kaytes, J. B., Sayler, R. D., Swanson, M. E., Elliot, W. J., &
1030 Reganold, J. P., 2015. Linking ecology and aesthetics in sustainable agricultural landscapes:
1031 Lessons from the Palouse region of Washington, U.S.A. *Landscape and Urban Planning*, 134,
1032 195–209. <https://doi.org/10.1016/j.landurbplan.2014.10.019>

1033 Koenig, K., Höfle, B., 2016. Full-Waveform Airborne Laser Scanning in Vegetation Studies—A Review
1034 of Point Cloud and Waveform Features for Tree Species Classification. *Forests* 7, 198.
1035 <https://doi.org/10.3390/f7090198>

1036 Lallias-Tacon, S., Liébault, F., Piégay, H., 2017. Use of airborne LiDAR and historical aerial photos for
1037 characterising the history of braided river floodplain morphology and vegetation responses.
1038 *CATENA*, Geoecology in Mediterranean mountain areas. Tribute to Professor José María
1039 García Ruiz 149, 742–759. <https://doi.org/10.1016/j.catena.2016.07.038>

1040 Landon, N., Piégay, H., Bravard, J.P., 1998. The Drôme river incision (France): from assessment to
1041 management. *Landsc. Urban Plan.* 43, 119–131. [https://doi.org/10.1016/S0169-](https://doi.org/10.1016/S0169-2046(98)00046-2)
1042 [2046\(98\)00046-2](https://doi.org/10.1016/S0169-2046(98)00046-2)

1043 Laslier, M., Hubert-Moy, L., Dufour, S., 2019. Mapping Riparian Vegetation Functions Using 3D
1044 Bispectral LiDAR Data. *Water* 11, 483. <https://doi.org/10.3390/w11030483>

1045 Lattin, P. D., Wigington, P. J., Moser, T. J., Peniston, B. E., Lindeman, D. R., & Getter, D. R., 2004.
1046 Influence of Remote Sensing Imagery Source on Quantification of Riparian Land Cover/Land
1047 Use1. *JAWRA Journal of the American Water Resources Association*, 40(1), 215–227.
1048 <https://doi.org/10.1111/j.1752-1688.2004.tb01020.x>

1049 Lee, P., Smyth, C., Boutin, S., 2004. Quantitative review of riparian buffer width guidelines from
1050 Canada and the United States. *J. Environ. Manage.* 70, 165–180.
1051 <https://doi.org/10.1016/j.jenvman.2003.11.009>

1052 Loicq, P., Moatar, F., Jullian, Y., Dugdale, S.J., Hannah, D.M., 2018. Improving representation of
1053 riparian vegetation shading in a regional stream temperature model using LiDAR data. *Sci.*
1054 *Total Environ.* 624, 480–490. <https://doi.org/10.1016/j.scitotenv.2017.12.129>

1055 Macfarlane, W.W., McGinty, C.M., Laub, B.G., Gifford, S.J., 2017. High-resolution riparian vegetation
1056 mapping to prioritize conservation and restoration in an impaired desert river. *Restor. Ecol.*
1057 25, 333–341. <https://doi.org/10.1111/rec.12425>

1058 Nally, R. M., Cunningham, S. C., Baker, P. J., Horner, G. J., & Thomson, J. R., 2011. Dynamics of
1059 Murray-Darling floodplain forests under multiple stressors: The past, present, and future of
1060 an Australian icon. *Water Resources Research*, 47(12).
1061 <https://doi.org/10.1029/2011WR010383>

1062 Maillard, P., Alencar-Silva, T., 2013. A method for delineating riparian forests using region-based
1063 image classification and depth-to-water analysis. *Int. J. Remote Sens.* 34, 7991–8010.
1064 <https://doi.org/10.1080/01431161.2013.827847>

1065 Manfreda, S., McCabe, M.F., Miller, P.E., Lucas, R., Pajuelo Madrigal, V., Mallinis, G., Ben Dor, E.,
1066 Helman, D., Estes, L., Ciraolo, G., Müllerová, J., Tauro, F., De Lima, M.I., De Lima, J.L.M.P.,
1067 Maltese, A., Frances, F., Caylor, K., Kohv, M., Perks, M., Ruiz-Pérez, G., Su, Z., Vico, G., Toth,
1068 B., 2018. On the Use of Unmanned Aerial Systems for Environmental Monitoring. *Remote*
1069 *Sens.* 10, 641. <https://doi.org/10.3390/rs10040641>

1070 Manners, R., Schmidt, J., Wheaton, J.M., 2013. Multiscalar model for the determination of spatially
1071 explicit riparian vegetation roughness. *J. Geophys. Res. Earth Surf.* 118, 65–83.
1072 <https://doi.org/10.1029/2011JF002188>

1073 Marcus, W.A., Fonstad, M.A., 2008. Optical remote mapping of rivers at sub-meter resolutions and
1074 watershed extents. *Earth Surf. Process. Landf.* 33, 4–24. <https://doi.org/10.1002/esp.1637>

1075 Martin, F.-M., Müllerová, J., Borgniet, L., Dommanget, F., Breton, V., Evette, A., 2018. Using Single-
1076 and Multi-Date UAV and Satellite Imagery to Accurately Monitor Invasive Knotweed Species.
1077 *Remote Sens.* 10, 1662. <https://doi.org/10.3390/rs10101662>

1078 Matsuura, T., Suzuki, W., 2013. Analysis of topography and vegetation distribution using a digital
1079 elevation model: case study of a snowy mountain basin in northeastern Japan. *Landsc. Ecol.*
1080 *Eng.* 9, 143–155. <https://doi.org/10.1007/s11355-012-0187-2>

1081 Miao, X., Patil, R., Heaton, J.S., Tracy, R.C., 2011. Detection and classification of invasive saltcedar
1082 through high spatial resolution airborne hyperspectral imagery. *Int. J. Remote Sens.* 32,
1083 2131–2150. <https://doi.org/10.1080/01431161003674618>

1084 Michez, A., Piégay, H., Lisein, J., Claessens, H., Lejeune, P., 2016a. Mapping of riparian invasive
1085 species with supervised classification of Unmanned Aerial System (UAS) imagery. *Int. J. Appl.*
1086 *Earth Obs. Geoinformation* 44, 88–94. <https://doi.org/10.1016/j.jag.2015.06.014>

1087 Michez, A., Piégay, H., Lisein, J., Claessens, H., Lejeune, P., 2016b. Classification of riparian forest
1088 species and health condition using multi-temporal and hyperspatial imagery from unmanned
1089 aerial system. *Environ. Monit. Assess.* 188, 146. <https://doi.org/10.1007/s10661-015-4996-2>

1090 Michez, A., Piégay, H., Lejeune, P., Claessens, H., 2017. Multi-temporal monitoring of a regional
1091 riparian buffer network (>12,000 km) with LiDAR and photogrammetric point clouds. *J.*
1092 *Environ. Manage.* 202, 424–436. <https://doi.org/10.1016/j.jenvman.2017.02.034>

1093 Morgan, J.L., Gergel, S.E., Coops, N.C., 2010. Aerial Photography: A Rapidly Evolving Tool for
1094 Ecological Management. *BioScience* 60, 47–59. <https://doi.org/10.1525/bio.2010.60.1.9>

1095 Muller, E., Décamps, H., Dobson, M.K., 1993. Contribution of space remote sensing to river studies.
1096 *Freshw. Biol.* 29, 301–312. <https://doi.org/10.1111/j.1365-2427.1993.tb00766.x>

1097 Munné, A., Prat, N., Solà, C., Bonada, N., Rieradevall, M., 2003. A simple field method for assessing
1098 the ecological quality of riparian habitat in rivers and streams: QBR index. *Aquat. Conserv.*
1099 *Mar. Freshw. Ecosyst.* 13, 147–163. <https://doi.org/10.1002/aqc.529>

1100 Nagler, P.L., Brown, T., Hultine, K.R., van Riper, C., Bean, D.W., Dennison, P.E., Murray, R.S., Glenn,
1101 E.P., 2012. Regional scale impacts of Tamarix leaf beetles (*Diorhabda carinulata*) on the water
1102 availability of western U.S. rivers as determined by multi-scale remote sensing methods.
1103 *Remote Sens. Environ.* 118, 227–240. <https://doi.org/10.1016/j.rse.2011.11.011>

1104 Nagler, P.L., Doody, T.M., Glenn, E.P., Jarchow, C.J., Barreto-Muñoz, A., Didan, K., 2016. Wide-area
1105 estimates of evapotranspiration by red gum (*Eucalyptus camaldulensis*) and associated

1106 vegetation in the Murray–Darling River Basin, Australia. *Hydrol. Process.* 30, 1376–1387.
1107 <https://doi.org/10.1002/hyp.10734>

1108 Naiman, R.J., Décamps, H., 1997. The Ecology of Interfaces: Riparian Zones. *Annu. Rev. Ecol. Syst.* 28,
1109 621–658. <https://doi.org/10.1146/annurev.ecolsys.28.1.621>

1110 Naiman, R.J., Decamps, H., McClain, M.E., 2005. *Riparia: Ecology, Conservation, and Management of*
1111 *Streamside Communities*. Elsevier.

1112 Nardi, F., Annis, A., Di Baldassarre, G., Vivoni, E.R., Grimaldi, S., 2019. GFPLAIN250m, a global high-
1113 resolution dataset of Earth’s floodplains. *Sci. Data* 6, 180309.
1114 <https://doi.org/10.1038/sdata.2018.309>

1115 Narumalani, S., Mishra, D.R., Wilson, R., Reece, P., Kohler, A., 2009. Detecting and Mapping Four
1116 Invasive Species along the Floodplain of North Platte River, Nebraska. *Weed Technol.* 23, 99–
1117 107. <https://doi.org/10.1614/WT-08-007.1>

1118 National Research Council, 2002. *Riparian Areas: Functions and Strategies for Management*.
1119 Washington (DC): National Academies Press. <https://doi.org/10.17226/10327>

1120 Palmquist, E.C., Ralston, B.E., Merritt, D.M., Shafroth, P.B., 2018. Landscape-scale processes influence
1121 riparian plant composition along a regulated river. *J. Arid Environ.* 148, 54–64.
1122 <https://doi.org/10.1016/j.jaridenv.2017.10.001>

1123 Parent, J.R., Volin, J.C., Civco, D.L., 2015. A fully-automated approach to land cover mapping with
1124 airborne LiDAR and high resolution multispectral imagery in a forested suburban landscape.
1125 *ISPRS J. Photogramm. Remote Sens.* 104, 18–29.
1126 <https://doi.org/10.1016/j.isprsjprs.2015.02.012>

1127 Peerbhay, K., Mutanga, O., Lottering, R., Ismail, R., 2016. Mapping *Solanum mauritianum* plant
1128 invasions using WorldView-2 imagery and unsupervised random forests. *Remote Sens.*
1129 *Environ.* 182, 39–48. <https://doi.org/10.1016/j.rse.2016.04.025>

- 1130 Penning, E., 2018. Interactions between flow and vegetation: Translating knowledge from academic
1131 research to daily water management. *E3S Web Conf.* 40, 01001.
1132 <https://doi.org/10.1051/e3sconf/20184001001>
- 1133 Piégay, H., Landon, N., 1997. Promoting ecological management of riparian forests on the Drôme
1134 River, France. *Aquat. Conserv. Mar. Freshw. Ecosyst.* 7, 287–304.
1135 [https://doi.org/10.1002/\(SICI\)1099-0755\(199712\)7:4<287::AID-AQC247>3.0.CO;2-S](https://doi.org/10.1002/(SICI)1099-0755(199712)7:4<287::AID-AQC247>3.0.CO;2-S)
- 1136 Piégay, H., Arnaud, F., Belletti, B., Bertrand, M., Bizzi, S., Carbonneau, P., Dufour, S., Liébault, F., Ruiz-
1137 Villanueva, V., & Slater, L., 2020. Remotely sensed rivers in the Anthropocene: State of the
1138 art and prospects. *Earth Surface Processes and Landforms*, 45(1), 157–188.
1139 <https://doi.org/10.1002/esp.4787>
- 1140 Poff, B., Koestner, K. A., Neary, D. G., & Henderson, V., 2011. Threats to Riparian Ecosystems in
1141 Western North America: An Analysis of Existing Literature¹. *JAWRA Journal of the American*
1142 *Water Resources Association*, 47(6), 1241–1254. [https://doi.org/10.1111/j.1752-](https://doi.org/10.1111/j.1752-1688.2011.00571.x)
1143 [1688.2011.00571.x](https://doi.org/10.1111/j.1752-1688.2011.00571.x)
- 1144 Pontius, R.G.J., Millones, M., 2011. Death to Kappa: birth of quantity disagreement and allocation
1145 disagreement for accuracy assessment. *Int. J. Remote Sens.* 32, 4407–4429.
1146 <https://doi.org/10.1080/01431161.2011.552923>
- 1147 Poole, G.C., Berman, C.H., 2001. An Ecological Perspective on In-Stream Temperature: Natural Heat
1148 Dynamics and Mechanisms of Human-Caused Thermal Degradation. *Environ. Manage.* 27,
1149 787–802. <https://doi.org/10.1007/s002670010188>
- 1150 Rajão, R., 2013. Representations and discourses: the role of local accounts and remote sensing in the
1151 formulation of Amazonia’s environmental policy. *Environ. Sci. Policy, SI: Environmental and*
1152 *Developmental Discourses: Technical knowledge, discursive spaces and politics* 30, 60–71.
1153 <https://doi.org/10.1016/j.envsci.2012.07.019>

1154 Rapinel, S., Mony, C., Lecoq, L., Clément, B., Thomas, A., Hubert-Moy, L., 2019. Evaluation of
1155 Sentinel-2 time-series for mapping floodplain grassland plant communities. *Remote Sens.*
1156 *Environ.* 223, 115–129. <https://doi.org/10.1016/j.rse.2019.01.018>

1157 Richardson, D.M., Holmes, P.M., Esler, K.J., Galatowitsch, S.M., Stromberg, J.C., Kirkman, S.P., Pyšek,
1158 P., Hobbs, R.J., 2007. Riparian vegetation: degradation, alien plant invasions, and restoration
1159 prospects. *Divers. Distrib.* 13, 126–139. <https://doi.org/10.1111/j.1366-9516.2006.00314.x>

1160 Richardson, J.J., Moskal, L.M., Kim, S.-H., 2009. Modeling approaches to estimate effective leaf area
1161 index from aerial discrete-return LIDAR. *Agric. For. Meteorol.* 149, 1152–1160.
1162 <https://doi.org/10.1016/j.agrformet.2009.02.007>

1163 Richardson, J.J., Torgersen, C.E., Moskal, L.M., 2019. Lidar-based approaches for estimating solar
1164 insolation in heavily forested streams. *Hydrol. Earth Syst. Sci.* 23, 2813–2822.
1165 <https://doi.org/10.5194/hess-23-2813-2019>

1166 Richter, R., Reu, B., Wirth, C., Doktor, D., Vohland, M., 2016. The use of airborne hyperspectral data
1167 for tree species classification in a species-rich Central European forest area. *Int. J. Appl. Earth*
1168 *Obs. Geoinformation* 52, 464–474. <https://doi.org/10.1016/j.jag.2016.07.018>

1169 Riedler, B., Pernkopf, L., Strasser, T., Lang, S., Smith, G., 2015. A composite indicator for assessing
1170 habitat quality of riparian forests derived from Earth observation data. *Int. J. Appl. Earth Obs.*
1171 *Geoinformation, Special Issue on Earth observation for habitat mapping and biodiversity*
1172 *monitoring* 37, 114–123. <https://doi.org/10.1016/j.jag.2014.09.006>

1173 Rijkswaterstaat, 2014. Vegetatielegger : instrument voor veilige en natuurlijke uiterwaarden.

1174 Rood, S.B., Braatne, J.H., Goater, L.A., 2010. Responses of obligate versus facultative riparian shrubs
1175 following river damming. *River Res. Appl.* 26, 102–117. <https://doi.org/10.1002/rra.1246>

1176 Rubol, S., Ling, B., Battiato, I., 2018. Universal scaling-law for flow resistance over canopies with
1177 complex morphology. *Sci. Rep.* 8, 1–15. <https://doi.org/10.1038/s41598-018-22346-1>

1178 Rutherford, J.C., Meleason, M.A., Davies-Colley, R.J., 2018. Modelling stream shade: 2. Predicting the
1179 effects of canopy shape and changes over time. *Ecol. Eng.* 120, 487–496.
1180 <https://doi.org/10.1016/j.ecoleng.2018.07.008>

1181 Sá, C., Grieco, J., 2016. Open Data for Science, Policy, and the Public Good. *Rev. Policy Res.* 33, 526–
1182 543. <https://doi.org/10.1111/ropr.12188>

1183 Sankey, T.T., Sankey, J.B., Horne, R., Bedford, A., 2016. Remote Sensing of Tamarisk Biomass, Insect
1184 Herbivory, and Defoliation: Novel Methods in the Grand Canyon Region, Arizona [WWW
1185 Document]. <https://doi.org/info:doi/10.14358/PERS.82.8.645>

1186 Scott, M.L., Nagler, P.L., Glenn, E.P., Valdes-Casillas, C., Erker, J.A., Reynolds, E.W., Shafroth, P.B.,
1187 Gomez-Limon, E., Jones, C.L., 2009. Assessing the extent and diversity of riparian ecosystems
1188 in Sonora, Mexico. *Biodivers. Conserv.* 18, 247–269. [https://doi.org/10.1007/s10531-008-](https://doi.org/10.1007/s10531-008-9473-6)
1189 [9473-6](https://doi.org/10.1007/s10531-008-9473-6)

1190 Seddon, J.A., Zerger, A., Doyle, S.J., Briggs, S.V., 2007. The extent of dryland salinity in remnant
1191 woodland and forest within an agricultural landscape. *Aust. J. Bot.* 55, 533–540.
1192 <https://doi.org/10.1071/BT06100>

1193 Shendryk, I., Broich, M., Tulbure, M.G., McGrath, A., Keith, D., Alexandrov, S.V., 2016. Mapping
1194 individual tree health using full-waveform airborne laser scans and imaging spectroscopy: A
1195 case study for a floodplain eucalypt forest. *Remote Sens. Environ.* 187, 202–217.
1196 <https://doi.org/10.1016/j.rse.2016.10.014>

1197 Shields, F.D., Coulton, K.G., Nepf, H., 2017. Representation of Vegetation in Two-Dimensional
1198 Hydrodynamic Models. *J. Hydraul. Eng.* 143, 02517002.
1199 [https://doi.org/10.1061/\(ASCE\)HY.1943-7900.0001320](https://doi.org/10.1061/(ASCE)HY.1943-7900.0001320)

1200 Sims, N.C., Colloff, M.J., 2012. Remote sensing of vegetation responses to flooding of a semi-arid
1201 floodplain: Implications for monitoring ecological effects of environmental flows. *Ecol. Indic.*
1202 18, 387–391. <https://doi.org/10.1016/j.ecolind.2011.12.007>

1203 Solins, J.P., Thorne, J.H., Cadenasso, M.L., 2018. Riparian canopy expansion in an urban landscape:
1204 Multiple drivers of vegetation change along headwater streams near Sacramento, California.
1205 *Landsc. Urban Plan.* 172, 37–46. <https://doi.org/10.1016/j.landurbplan.2017.12.005>

1206 Sridhar, B.B.M., Vincent, R.K., Clapham, W.B., Sritharan, S.I., Osterberg, J., Neale, C.M.U., Watts, D.R.,
1207 2010. Mapping saltcedar (*Tamarix ramosissima*) and other riparian and agricultural
1208 vegetation in the Lower Colorado River region using multi-spectral Landsat TM imagery.
1209 *Geocarto Int.* 25, 649–662. <https://doi.org/10.1080/10106049.2010.521857>

1210 Staben, G.W., Evans, K.G., 2008. Estimates of tree canopy loss as a result of Cyclone Monica, in the
1211 Magela Creek catchment northern Australia. *Austral Ecol.* 33, 562–569.
1212 <https://doi.org/10.1111/j.1442-9993.2008.01911.x>

1213 Starkey, E. N., 2016. Upper Columbia Basin Network stream channel characteristics and riparian
1214 condition annual report 2013: John Day Fossil Beds National Monument (JODA). Natural
1215 Resource Data Series NPS/UCBN/NRDS—2015/808. National Park Service, Fort Collins,
1216 Colorado.

1217 Steiniger, S., Hay, G.J., 2009. Free and open source geographic information tools for landscape
1218 ecology. *Ecol. Inform.* 4, 183–195. <https://doi.org/10.1016/j.ecoinf.2009.07.004>

1219 Stella, J.C., Bendix, J., 2019. Chapter 5 - Multiple Stressors in Riparian Ecosystems, in: Sabater, S.,
1220 Elosegi, A., Ludwig, R. (Eds.), *Multiple Stressors in River Ecosystems*. Elsevier, pp. 81–110.
1221 <https://doi.org/10.1016/B978-0-12-811713-2.00005-4>

1222 Stöcker, C., Bennett, R., Nex, F., Gerke, M., Zevenbergen, J., 2017. Review of the Current State of UAV
1223 Regulations. *Remote Sens.* 9, 459. <https://doi.org/10.3390/rs9050459>

1224 Straatsma, M.W., Baptist, M.J., 2008. Floodplain roughness parameterization using airborne laser
1225 scanning and spectral remote sensing. *Remote Sens. Environ.* 112, 1062–1080.
1226 <https://doi.org/10.1016/j.rse.2007.07.012>

1227 Straatsma, M.W., Kleinhans, M.G., 2018. Flood hazard reduction from automatically applied
1228 landscaping measures in RiverScape, a Python package coupled to a two-dimensional flow
1229 model. *Environ. Model. Softw.* 101, 102–116. <https://doi.org/10.1016/j.envsoft.2017.12.010>

1230 Straatsma, M.W., Fliervoet, J.M., Kabout, J.A.H., Baart, F., Kleinhans, M.G., 2019. Towards multi-
1231 objective optimization of large-scale fluvial landscaping measures. *Nat. Hazards Earth Syst.*
1232 *Sci.* 19, 1167–1187. <https://doi.org/10.5194/nhess-19-1167-2019>

1233 Strasser, T., Lang, S., 2015. Object-based class modelling for multi-scale riparian forest habitat
1234 mapping. *Int. J. Appl. Earth Obs. Geoinformation* 37, 29–37.

1235 Tabacchi, E., Correll, D.L., Hauer, R., Pinay, G., Planty-Tabacchi, A.-M., Wissmar, R.C., 1998.
1236 Development, maintenance and role of riparian vegetation in the river landscape. *Freshw.*
1237 *Biol.* 40, 497–516. <https://doi.org/10.1046/j.1365-2427.1998.00381.x>

1238 Tillack, A., Clasen, A., Kleinschmit, B., Förster, M., 2014. Estimation of the seasonal leaf area index in
1239 an alluvial forest using high-resolution satellite-based vegetation indices. *Remote Sens.*
1240 *Environ.* 141, 52–63. <https://doi.org/10.1016/j.rse.2013.10.018>

1241 Tompalski, P., Coops, N.C., White, J.C., Wulder, M.A., Yuill, A., 2017. Characterizing streams and
1242 riparian areas with airborne laser scanning data. *Remote Sens. Environ.* 192, 73–86.
1243 <https://doi.org/10.1016/j.rse.2017.01.038>

1244 Tomsett, C., Leyland, J., 2019. Remote sensing of river corridors: A review of current trends and
1245 future directions. *River Res. Appl.* 35, 779–803. <https://doi.org/10.1002/rra.3479>

1246 Tormos, T., Kosuth, P., Durrieu, S., Villeneuve, B., Wasson, J.G., 2011. Improving the quantification of
1247 land cover pressure on stream ecological status at the riparian scale using High Spatial
1248 Resolution Imagery. *Phys. Chem. Earth Parts ABC* 36, 549–559.

1249 Townsend, P.A., Walsh, S.J., 2001. Remote sensing of forested wetlands: application of
1250 multitemporal and multispectral satellite imagery to determine plant community
1251 composition and structure in southeastern USA. *Plant Ecol.* 157, 129–149.
1252 <https://doi.org/10.1023/A:1013999513172>

1253 Townsend, P.A., 2002. Relationships between forest structure and the detection of flood inundation
1254 in forested wetlands using C-band SAR. *Int. J. Remote Sens.* 23, 443–460.
1255 <https://doi.org/10.1080/01431160010014738>

1256 Turner, M.D., Taylor, P.J., 2003. Critical Reflections on the Use of Remote Sensing and GIS
1257 Technologies in Human Ecological Research. *Hum. Ecol.* 31, 177–182.
1258 <https://doi.org/10.1023/A:1023958712140>

1259 Turner, W., Rondinini, C., Pettorelli, N., Mora, B., Leidner, A.K., Szantoi, Z., Buchanan, G., Dech, S.,
1260 Dwyer, J., Herold, M., Koh, L.P., Leimgruber, P., Taubenboeck, H., Wegmann, M., Wikelski,
1261 M., Woodcock, C., 2015. Free and open-access satellite data are key to biodiversity
1262 conservation. *Biol. Conserv.* 182, 173–176. <https://doi.org/10.1016/j.biocon.2014.11.048>

1263 Vande Kamp, K., Rigge, M., Troelstrup, N.H., Smart, A.J., Wylie, B., 2013. Detecting Channel Riparian
1264 Vegetation Response to Best-Management-Practices Implementation in Ephemeral Streams
1265 With the Use of Spot High-Resolution Visible Imagery. *Rangel. Ecol. Manag.* 66, 63–70.
1266 <https://doi.org/10.2111/REM-D-11-00153.1>

1267 Vanden Borre, J., Paelinckx, D., Mûcher, C.A., Kooistra, L., Haest, B., De Blust, G., Schmidt, A.M., 2011.
1268 Integrating remote sensing in Natura 2000 habitat monitoring: Prospects on the way
1269 forward. *J. Nat. Conserv.* 19, 116–125. <https://doi.org/10.1016/j.jnc.2010.07.003>

1270 Varga, K., Dévai, G., Tóthmérész, B., 2013. Land use history of a floodplain area during the last
1271 200 years in the Upper-Tisza region (Hungary). *Reg. Environ. Change* 13, 1109–1118.
1272 <https://doi.org/10.1007/s10113-013-0424-8>

1273 Vaz, A.S., Alcaraz-Segura, D., Campos, J.C., Vicente, J.R., Honrado, J.P., 2018. Managing plant
1274 invasions through the lens of remote sensing: A review of progress and the way forward. *Sci.*
1275 *Total Environ.* 642, 1328–1339. <https://doi.org/10.1016/j.scitotenv.2018.06.134>

1276 Verry, E.S., Dolloff, C.A., Manning, M.E., 2004. Riparian ecotone: A functional definition and
1277 delineation for resource assessment. *Water Air Soil Pollut. Focus* 4, 67–94.
1278 <https://doi.org/10.1023/B:WAFO.0000012825.77300.08>

1279 Vivier, A., Breton, L., Grivel, S., Melun, G., Piégay, H., Demarchi, L., Adrien, M., Séjour, A.,
1280 Thommeret, N., Tormos, T., Cazals, C., Koehl, M., Lague, D., Rapinel, S., Ville, A., Chevillier, B.,
1281 Tarrío, D., Guerri, O., Laslier, M., Dupont, P., 2018. Actes de la journée technique "Avancées,
1282 apports et perspectives de la télédétection pour la caractérisation physique des corridors
1283 fluviaux".

1284 Vollmer, D., Prescott, M. F., Padawangi, R., Girot, C., & Grêt-Regamey, A., 2015. Understanding the
1285 value of urban riparian corridors: Considerations in planning for cultural services along an
1286 Indonesian river. *Landscape and Urban Planning*, 138, 144–154.
1287 <https://doi.org/10.1016/j.landurbplan.2015.02.011>

1288 Wagner-Lücker, I., Lanz, E., Förster, M., Janauer, G.A., Reiter, K., 2013. Knowledge-based framework
1289 for delineation and classification of ephemeral plant communities in riverine landscapes to
1290 support EC Habitat Directive assessment. *Ecol. Inform.*, The analysis and application of spatial
1291 ecological data to support the conservation of biodiversity 14, 44–47.
1292 <https://doi.org/10.1016/j.ecoinf.2012.11.003>

1293 Wallace, C.S.A., Villarreal, M.L., Iii, C. van R., 2013. Influence of monsoon-related riparian phenology
1294 on yellow-billed cuckoo habitat selection in Arizona. *J. Biogeogr.* 40, 2094–2107.
1295 <https://doi.org/10.1111/jbi.12167>

1296 Wan, Y., Wan, C., Hedgepeth, M., 2015. Elucidating multidecadal saltwater intrusion and vegetation
1297 dynamics in a coastal floodplain with artificial neural networks and aerial photography.
1298 *Ecohydrology* 8, 309–324. <https://doi.org/10.1002/eco.1509>

1299 Wang, L., Silván-Cárdenas, J.L., Yang, J., Frazier, A.E., 2013. Invasive Saltcedar (*Tamarisk* spp.)
1300 Distribution Mapping Using Multiresolution Remote Sensing Imagery. *Prof. Geogr.* 65, 1–15.
1301 <https://doi.org/10.1080/00330124.2012.679440>

1302 Wasser, L., Chasmer, L., Day, R., Taylor, A., 2015. Quantifying land use effects on forested riparian
1303 buffer vegetation structure using LiDAR data. *Ecosphere* 6, art10.
1304 <https://doi.org/10.1890/ES14-00204.1>

1305 Wawrzyniak, V., Allemand, P., Bailly, S., Lejot, J., Piégay, H., 2017. Coupling LiDAR and thermal
1306 imagery to model the effects of riparian vegetation shade and groundwater inputs on
1307 summer river temperature. *Sci. Total Environ.* 592, 616–626.
1308 <https://doi.org/10.1016/j.scitotenv.2017.03.019>

1309 Weissteiner, C.J., Ickerott, M., Ott, H., Probeck, M., Ramminger, G., Clerici, N., Dufourmont, H., De
1310 Sousa, A.M.R., 2016. Europe’s Green Arteries—A Continental Dataset of Riparian Zones.
1311 *Remote Sens.* 8, 925. <https://doi.org/10.3390/rs8110925>

1312 Willaarts, B., Ballesteros, M., & Hernández-Mora, N., 2014. Ten years of the Water Framework
1313 Directive in Spain: An overview of the ecological and chemical status of surface water bodies.
1314 In P. Martinez-Santos, M. Aldaya, M. Llamas, & L. Thuy (Eds.), *Integrated Water Resources*
1315 *Management in the 21st Century: Revisiting the paradigm* (pp. 99–120). CRC Press.
1316 <https://doi.org/10.1201/b16591-10>

1317 Wohl, E., 2017. Bridging the gaps: An overview of wood across time and space in diverse rivers.
1318 *Geomorphology, Dynamics and ecology of Wood in World Rivers* 279, 3–26.
1319 <https://doi.org/10.1016/j.geomorph.2016.04.014>

1320 Wohl, E., Bledsoe, B.P., Fausch, K.D., Kramer, N., Bestgen, K.R., Gooseff, M.N., 2016. Management of
1321 Large Wood in Streams: An Overview and Proposed Framework for Hazard Evaluation.
1322 *JAWRA J. Am. Water Resour. Assoc.* 52, 315–335. <https://doi.org/10.1111/1752-1688.12388>

1323 Wulder, M.A., White, J.C., Nelson, R.F., Næsset, E., Ørka, H.O., Coops, N.C., Hilker, T., Bater, C.W.,
1324 Gobakken, T., 2012. Lidar sampling for large-area forest characterization: A review. *Remote*
1325 *Sens. Environ.* 121, 196–209. <https://doi.org/10.1016/j.rse.2012.02.001>

1326 Yang, X., 2007. Integrated use of remote sensing and geographic information systems in riparian
1327 vegetation delineation and mapping. *Int. J. Remote Sens.* 28, 353–370.
1328 <https://doi.org/10.1080/01431160600726763>

- 1329 Yousefi, S., Mirzaee, S., Keesstra, S., Surian, N., Pourghasemi, H. R., Zakizadeh, H. R., & Tabibian, S.,
1330 2018. Effects of an extreme flood on river morphology (case study: Karoon River, Iran).
1331 *Geomorphology*, 304, 30–39. <https://doi.org/10.1016/j.geomorph.2017.12.034>
- 1332 Zahidi, I., Yusuf, B., Cope, M., Ahmed Mohamed, T., Mohd Shafri, H.Z., 2018. Effects of depth-varying
1333 vegetation roughness in two-dimensional hydrodynamic modelling. *Int. J. River Basin Manag.*
1334 16, 413–426. <https://doi.org/10.1080/15715124.2017.1394313>
- 1335 Zaimes, G. N., Schultz, R. C., & Isenhardt, T. M., 2004. Stream bank erosion adjacent to riparian forest
1336 buffers, row-crop fields, and continuously-grazed pastures along Bear Creek in central Iowa.
1337 *Journal of Soil and Water Conservation*, 59(1), 19–27.
- 1338 Zaimes, G. N., Gounaridis, D., & Symeonakis, E., 2019. Assessing the impact of dams on riparian and
1339 deltaic vegetation using remotely-sensed vegetation indices and Random Forests modelling.
1340 *Ecological Indicators*, 103, 630–641. <https://doi.org/10.1016/j.ecolind.2019.04.047>
- 1341 Zogaris, S., Markogianni, V., Özeren, S.C., Dimitriou, E., 2015. Assessment of riparian zone and river
1342 island conditions in a trans-boundary greenbelt: the Evris/Meriç River (Greece - Turkey).
1343 *Fresenius Environ. Bull.* 24, 10.