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Original Research Article

Evaluating the riparian forest quality index (QBR) in the Luchena River by integrating remote sensing, machine learning and GIS techniques

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ABSTRACT

The Water Framework Directive (WFD 2000/60/EU) is a mandatory standard that aims to improve and protect water quality in Europe. It covers, among other issues, the need to establish particular reference conditions for assessing river ecosystems and defines the ecological status of water bodies and conserve the hydromorphological characteristics of rivers. The quality of riparian vegetation is an important component of stream status and contributes directly to a river's ecological stability. QBR index ("Qualitat del Bosc de Ribera") is one of the most widely used methods of evaluating riparian quality. This paper presents a new methodological version of the QBR index (QBR-GIS) to assess the ecological status of riparian forests. For this purpose, we have considered the four major conceptual blocks of the QBR index (total vegetation cover, cover structure, cover quality and channel alteration) using geographically referenced information, remote sensing and machine learning techniques. To obtain the cover quality indicator, several vegetation indices were calculated and a sensitivity analysis was performed. The QBR-GIS was validated from the results obtained from the QBR index. QBR-GIS provides greater reliability and objectivity in the results. Furthermore, it reduces the time spent on field visits and increases accuracy in obtaining the status of riparian quality. Furthermore, it is a useful tool for landscape planning and management, improved ability to apply the QBR Index to larger areas of the river catchment, resulting in more information on riparian quality.

1. Introduction

Riparian zones are land–water ecosystem interfaces along inland streams (Cavaillé et al., 2013). Similarly, riparian forests are an ecologically significant component of river systems characterised by high levels of productivity and biological diversity (Bren, 1993), supporting multiple habitats for a wide variety of species (Magdaleno, 2014). In addition, they contribute to consolidating an area's tree mass, as they increase the capacity to fix bank soil, improve water quality and prevent erosion (Welsch, 1991). Notably, much attention has been focused on potential erosion prevention measures in these areas (Anders et al., 2020). However, freshwater habitats worldwide are in a deteriorating ecological condition, necessitating urgent management efforts and legislative changes to reverse the current trend (Tolkkinen et al., 2021). Despite their importance, riparian habitats, especially those in semi-arid

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Mediterranean regions, are under threat because they are extremely sensitive to disturbances and anthropogenic effects (Garófano-Gómez et al., 2013).

The WFD (European Commission, 2000) and other directives recognise the structure of riparian regions as one of the key features to consider in the hydromorphological and ecological status of freshwater bodies (Magdaleno, 2014). Thus, the WFD establishes the standards for evaluating the ecological status of rivers (Valero, 2014), which is closely related to the quality of the riparian area. Vegetated riparian zones create a natural buffer next to rivers, and they are crucial for preserving high biodiversity levels and good water quality (Tolkkinen et al., 2021).

Water and natural resource managers in Europe are required to ensure the protection of riparian vegetation using various water and biodiversity decrees and legislation. Several steps must be implemented to preserve the quality of riparian forests. (Magdaleno, 2014). Thus, several indices have been created and are used to evaluate the ecological health of water bodies (Vidal-Abarca et al., 2016). For example, the River Habitat Survey (RHV) provides a solid structure for characterising the physical characteristics and evaluating the habitat quality of a 500 m length of river (Raven et al., 1998). The Rapid Appraisal of Riparian Condition (RARC) established an index of river condition based on 18 markers that track changes to a stream's hydrology, physical shape, floodplain vegetation, water quality and biota (Jansen, 2005). The Riparian Condition Index (RCI) is also a qualitive index comprised of 13 attributes which are evaluated for both banks and then averaged (Burdon et al., 2013). Stream ecological responses can be related to their summed total (Burdon et al., 2020) and has been proven to correlate with spatially explicit measures of riparian vegetation, such as buffer width (Forio et al., 2020). The Riparian Macrophyte Protocol (RMP) is focused on flora structure, riparian habitats and human pressures. Their cover and influence are assessed both banks and the riverbed and its information can complement other protocol data with valuable insights (Kazoglou et al., 2011). The Riparian Quality Index (RQI) method was developed for use in sections, where a fairly uniform riparian structure can be observed as a function of landscape (geology, vegetation and land use), valley and river type, flow conditions and floodplain characteristics (González del Tánago and García de Jalón, 2011). The QBR index (Qualitat del Bosc de Ribera) was developed to evaluate the quality of riparian forest along Mediterranean rivers in Spain (Munné et al., 1998) and is based on four conceptual blocks: total vegetation cover, cover structure, cover quality and channel alteration. Several researchers have since improved and adjusted the index for their specific study regions (Belletti et al., 2015; Kazoglou et al., 2010) and used it to identify reference conditions or measure a stressor gradient within analyses of the WFD's biological quality elements, such as benthic macroinvertebrates, fishes and macrophytes (Chatzinikolaou et al., 2011). The technique is not restricted to field tests; it can also be with combined with geographically referenced information and remote sensing techniques (Wiatkowski and Tomczyk, 2018).

Despite such numerous existing indices, the methodologies conducted in the field are mostly qualitative and rely on subjective evaluations (Novoa et al., 2018). The application of these indices is often focused on a local scale and cannot properly assess the evolution of riparian land conditions (Ashraf et al., 2010). Furthermore, using geographically referenced information from techniques including GIS and remote sensing to characterise, analyse and monitor riparian landscapes provides scientists with valuable information for understanding land surface processes (Goetz et al., 2003; Murray et al., 2018). Yet these techniques are not explicitly aligned with traditional methods based on field habitat assessments. It is essential to develop a method that exploits the potential of spatially explicit information (i.e., GIS and remote sensing) and machine learning and adapt it to one of the existing riparian indices, such as QBR. It will provide greater flexibility for managers and technicians in measuring riparian conditions and their evolution. Thus, here we present an integrated version of the QBR index, the QBR-GIS index. It is new methodological tool for determining the quality of riparian forests based on traditional QBR index. Its data collection and evaluation criteria have been modified based on current techniques, high-resolution data, and GIS software to achieve a more spatially accurate index of river riparian quality. Accordingly, automatic learning techniques (random forest) have been used to identify vegetation cover from high spatial resolution data (LIDAR point clouds and orthophotos) obtained by remote sensing. The riparian zone was delimited from a DEM together with an orthophoto, and invasive species were identified. Other techniques developed to obtain different vegetation indices, for example, are noted in the methodology section.

The area of the Luchena River in south-eastern Spain has been the subject of analysis on several occasions due to existing erosion in natural and cultivated zones (Anders et al., 2020), making this area interesting for assessing the quality of its riparian habitat.

This paper has the following primary objectives: (i) to provide a new, easy-to-use methodology for an accurate and distributed evaluation of the quality of riparian forests, (ii) to develop a quick and objective tool to assess and interpret changes in riparian zones and (iii) to provide a procedure based on current techniques, high-resolution data, and GIS software to determine the quality of riparian vegetation, enabling technicians and managers to take practical measures to protect and restore these areas.

2. Material and Methods

2.1. Study area

The Luchena River is located in the Segura River basin, which is situated in the Murcia province, south-eastern Spain (Fig. 1). It lies between 1° 56′ to 1° 51′ W longitude and 37° 47′ to 37° 45′ N latitude. The Luchena River floodplain covers 108.05 ha. The stretch of the river used to analyse the riparian forest is 11,829 m in length and approximately 85 m in width. The Luchena River has an elevation of 575 m at its source and ends at the outlet of the

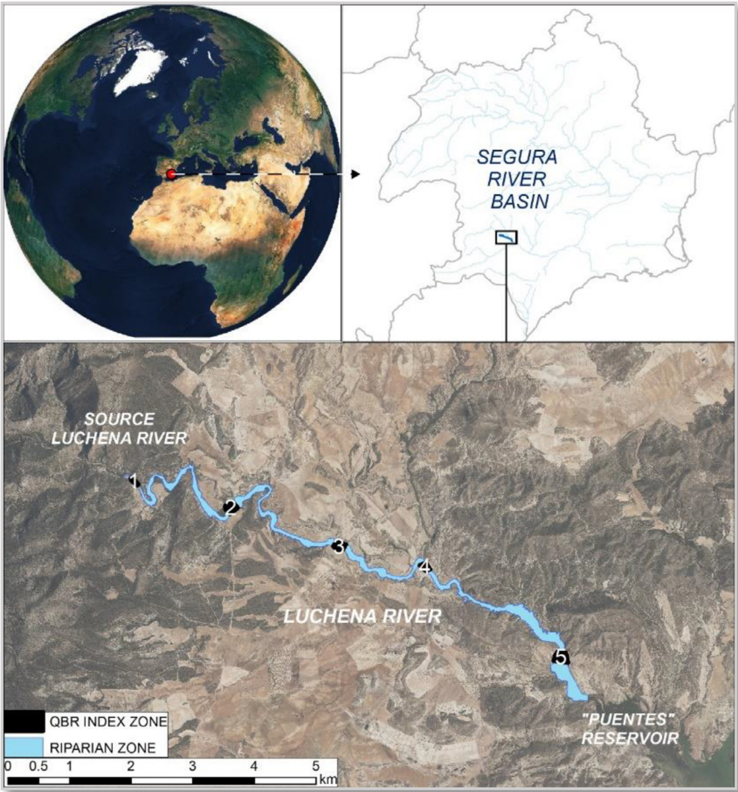

Figure 1. Location of the Luchena riparian zone and sections where the QBR index was calculated (1, 2, 3, 4, 5).

Puentes reservoir at an elevation of 463 m above mean sea level (MSL) with an average slope of 0.94%.

The average annual precipitation in the area is 335 mm, and there is little variation throughout the year, with the wettest month (October) receiving an average of 43 mm and the driest month (July) receiving 5 mm. The mean temperature is 16 °C, with maximum temperatures approximately 25 °C, while minimum temperatures can reach 0 °C (Fick and Hijmans, 2017).

The study area is located in the Betic Cordillera, an orogenically inclined mountain range running from northeast to southwest formed by the convergence of the African and Iberian plates. The predominant soil classes are Cambisols, Regosols and calcareous Fluvisols, Calcisols (petrosols), Gypsisols (petrosols) and Leptosols. Most of the land is used for irrigated crops and dryland farming (cereals, olives, almonds, vines and horticultural crops). Forest and natural bushes (mostly *Stipa tenacissima*) comprise the majority of the research area's semi-natural vegetation (*Pinus halepensis*) (Baartman et al., 2011).

Five zones approximately 150 m in length, representing different sections of the Luchena River, were selected to determine the QBR index. Zone 1 lies in the Luchena River headwaters and corresponds to a section in which the riparian habitat predominantly comprises a dense tree and shrub stratum, as is the case in tarays. Zone 2 is characterised by a much wider riparian zone, reaching 150 metres in width, where invasive plant species such as *Arundo donax* are dominant in the band close to direct contact with the water, while the shrub layer predominates behind it, and the tree layer has little presence. Zone 3 lies downstream and has an average width of approximately 120 m with a meandering morphology. As in the previous section, it is defined by a low density of trees and shrubs with the presence of *Arundo donax*. Zone 4 represents an area where the riverbed is somewhat narrower than in sections 2 and 3 with an average width of 90 m. It is characterised by dense vegetation in the areas adjacent to the river while its left bank is sparsely vegetated with a predominance of bare soil and a xerophytic shrub stratum. Finally, zone 5 is an area close to the mouth of the Puentes reservoir. It is the widest of the selected sections with an average width of 195 m. In addition, it is characterised by high anthropisation with a road that runs parallel to the Luchena River on its right bank. It also has a dense band of vegetation near the river course and another very well-differentiated band in which abandoned crops predominate.

2.2. Methodology and data

Assessing the quality of riparian zones using GIS, remote sensing and machine learning techniques provides further spatial resolution of their ecological status and gridded information for the entire study area rather than the partial representative values for sections obtained using the traditional QBR index. Figure 2 presents the

Figure 2. QBR index indicators vs. QBR-GIS indicators and sub-indicators.

methodological process of adapting QBR to QBR-GIS based on estimating a series of remote indicators using the above-mentioned technologies. This methodology makes it possible to determine the spatially extensive riparian quality throughout the study area rather than the localised results obtained using the QBR method. This focus offers a truly explicit evaluation from a spatial point of view while preserving the possibility of identifying individual indicator-level decomposition.

2.2.1. QBR index

The QBR index (Munné et al., 1998) is a riparian quality index widely used in stream and river management that can also help determine ecological status in the context of the WFD. Before estimating the QBR index, the main channel and floodplain zones must be identified to determine the bankfull zone. The observer should use all indications of the riparian zone, including river terraces, the presence of riparian plants and indications of the consequences of major flooding, although delineating the riparian zone is not always straightforward (Munné et al., 2003). Once the riparian zone had been delimited, five spatially distributed sections (Figure 2) were determined to which the QBR index was applied. In the case of the Luchena River, the length of each section was approximately 150 m.

This method is based on four main indicators: total vegetation cover, cover structure, cover quality and channel alterations. To obtain the QBR index, several field trips were made to the Luchena River to identify and score the necessary indicators for each block. The block is 150 m long but varies in width because the extent of the riparian zone was determined from the DEM. The width varies due to the morphology of each zone. Prior to the field visit, the orthophoto of the PNOA and the DEM identified the areas to be analysed with the QBR index. For each of the five sections analysed, the four blocks were summed to provide the final QBR index (the maximum score per block was 25 points, and the minimum was 0). To assist the fieldwork, a scoring sheet for the QBR Index was used, which can be consulted in the supplementary materials. Total vegetation cover evaluates both the riparian zone and the riverbed and includes any type of tree (Saha et al., 2020). The riparian zones of the different stretches were surveyed, and the percentage of coverage and approximate degree of connectivity were assigned. The cover structure block predominantly evaluates the vertical structure of vegetation with other sub-indicators such as the presence of consolidated undergrowth and concentrations of helophyte plants on the shore. Cover quality depends on the analysed section's geomorphological type and considers the presence of autochthonous trees. This block can be assigned a maximum score of 25 points. This score can be reduced to account for the presence of allochthonous species, dumping and waste, for example, by subtracting 10 points. Channel alterations evaluate anthropic changes in the riparian zone, such as constant obstructions between riparian zones and the riverbed or the existence of continuous structures, which are detrimental to the quality of the riparian forest and the naturalness of the river channel (Jáimez-Cuéllar, 2002). A maximum score of 25 is obtained if the river channel has not been modified. However, the presence of transverse infrastructures would reduce the score by 10 points.

The total score per block was summed and ranked (see Table 1). According to the QBR index methodology, the scores for riparian forest range from 0 (poorest) to 100 (best). Subsequently, five riparian habitat quality classes, correlating roughly with those recommended in the WFD (Colwell and Hix, 2008), were differentiated as illustrated in Table 1 (Sirombra et al., 2005).

2.2.2. QBR-GIS

This index is an adaptation of the traditional QBR method with modified data collection and evaluation crite-

Table 1
Riparian habitat quality class and QBR index.

Riparian habitat quality class	QBR Index range
Riparian habitat in natural condition	≥ 95
Some disturbance, good quality	75-90
Significant disturbance, fair quality	55-70
Strong alteration, poor quality	30-50
Extreme degradation, bad quality	≤ 25

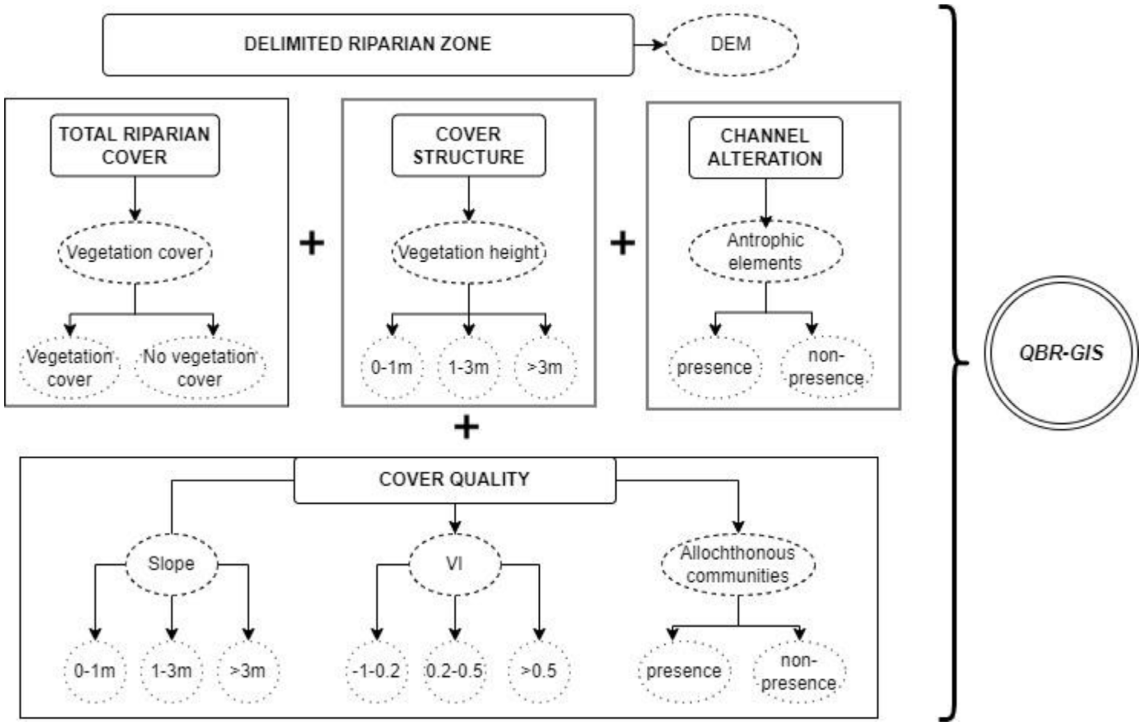

Figure 3. Flowchart: QBR-GIS methodology.

ria based on current techniques (machine learning), high-resolution data (LIDAR PNOA) and GIS software to obtain the necessary values for determining four indicators and six sub-indicators of the QBR-GIS index (Figure 2).

The riparian zone was determined from a digital elevation model generated from openly available LIDAR (light detection and ranging) data from the National Aerial Orthophotography Plan of Spain (LIDAR PNOA, 2016). These digital point cloud files (.laz) with X, Y and Z LIDAR coordinates with national coverage coloured with true colour (RGB) or with infrared (IRC) were obtained by airborne LIDAR sensors. The density of points is 0.5–4 points/m², with exceptions in which the density is even higher. The altimetric accuracy obtained was better than 20 cm RMSE Z. CloudCompare open-source software (CloudCompare, 2022) was used to obtain the digital elevation model. The Luchena River's riparian zone was accurately delimited by creating contour lines using the orthophoto. A flowchart of the QBR-GIS index methodology is presented in Figure 3. Each of the sub-indicators was obtained in high spatial resolution using a raster format (0.25 × 0.25 m cell size). The sub-indicators were classified, assigned a rating and summed using the QGIS raster calculator. A distributed QBR-GIS raster was obtained, to which, depending on the score, a riparian habitat quality class was attributed, as in Table 2.

As observed in Tables 1 and 2, the maximum score obtained using the QBR index is 100 while QBR-GIS assigns a maximum score of 50. This is because QBR-GIS has fewer sub-indicators. Hence, the score weighting for each indicator would be more sensitive in scores ranging from 0–100. Therefore, it was decided that QBR-GIS should have a rating between 0 and 50 points.

To validate the results obtained using QBR-GIS, the average value for each of the five sections in the QBR index was obtained. The score obtained using the QBR index was divided by two to establish a relationship with the different QBR indices calculated.

2.2.2.1. Total vegetation cover. An orthophoto (Orthophoto PNOA, 2019) was used to classify the soil based on whether it was bare soil or covered with vegetation. The classification was carried out using the random forest algorithm (Ho, 1995). This algorithm has been progres-

Table 2
Riparian habitat quality class and QBR-GIS index.

Riparian habitat quality class	QBR-GIS range
Riparian habitat in natural condition	40-50
Some disturbance, good quality	30-40
Significant disturbance, fair quality	20-30
Strong alteration, poor quality	10-20
Extreme degradation, bad quality	≤ 10

Table 3
QBR-GIS indicators.

Total vegetation cover	Rating
Vegetation cover	10
No vegetation cover	0
Vegetation cover structure	
Vegetation height between 0 and 1 meter	0
Vegetation height between 1 and 3 meters	5
Vegetation height greater than 3 meters	10
Slope	
Slope 0-45 degrees	0
Slope 45-75 degrees	5
Slope >75 degrees	10
VI	
-1-0.2	0
0.2-0.5	5
>0.5	10
Arundo donax presence	
Yes	-10
No	0
Channel alterations	
Non-antropic riparian area changes	10
Antropic riparian area changes	0

sively used for satellite and aerial image classification, as well as generating continuous field datasets such as the percentage of tree cover and biomass (Horning, 2010) (Delalay et al., 2019; Horning, 2010). is often favoured over these most widely used approaches because of its processing effectiveness, ruggedness, and simplicity (Alonso et al., 2021). SAGA 8.1.3 software was used to obtain the vegetation zones from the VIGRA random forest classification (Köthe, 2012). An array of training areas for bare and vegetated soil have previously been established. Once the vegetated and bare soil areas had been classified in raster format, a Gaussian filter (Ringeler, 2003) was applied to soften the data and remove detail and noise (Brenner, 2003; Deng and Cahill, 1993). Finally, the classified and filtered rasters for the two vegetation cover classes were scored as shown in Table 3.

2.2.2.2. Cover structure. Cover structure was assessed by determining riparian vegetation height; the differences between the DEM and the Digital Surface Model (DSM) were obtained using CloudCompare (CloudCompare, 2022) and QGIS software (QGIS Geographic Information System, 2021). Three metres have been established as the threshold for distinguishing a tree from a shrub (Keeley, 1986; Körner, 2012). The assigned values are 0 for shrubs less than 1 m in height, 5 for shrubs and bushes between 1 and 3 m and 10 for vegetation taller than 3 m (Table 3). Thus, the vegetation height can be determined objectively, in contrast with the subjectivity of the QBR index, which primarily depends on visual perception with manual field measurements.

2.2.2.3. Cover quality: slope, VI, Arundo donax presence. Cover quality was based on sub-indicators reflecting slope and the characteristics of the main allochthonous vegetation community. In addition, it has been considered appropriate to incorporate plant condition as a sub-indicator of canopy quality. Thus, the following sub-indicators were calculated to determine the canopy quality: slope, vegetation index (VI) and allochthonous communities of invasive species Giant reed (Arundo donax).". The method of obtaining each of these sub-indicators is described in the following sections.

- *Slope*

The slope was determined from the DEM using the GDAL slope algorithm and QGIS 3.16 software. It was then classified through a series of geoprocesses using the QGIS tool (see Table 3).

- *Vegetation Index (VI).*

The VI is the basic arithmetic combination of two or more bands related to the spectral signatures of vegetation. It has been extensively used for phonologic monitoring, vegetation classification and the biophysical derivation of radiometric and structural vegetation parameters (Matsushita et al., 2007). Two or more spectral bands are combined based on two general categories: slope-based and distance-based vegetation indices (Qi et al., 1994; Silleos et al., 2006). Vegetation indices based on slope are simple mathematical combinations focusing on the contrast between the spectral reactions of vegetation in the red and infrared regions of the electromagnetic spectrum (Jackson and Huete, 1991). Each point's location in 2-dimensional NIR-Red space is geometrically equivalent to the slope (tangent) of the line leading from the point's location on a scattergram to the origin of reference (Mróz and Sobieraj, 2004).Compared to the slope group, the distance group measures the amount of vegetation present by determining the difference between the reflectance of a pixel and that of bare soil (Jackson and Huete, 1991). The soil line must be drawn, and each point's distance from this line from a perpendicular axis must be measured. The points of the soil form a line at roughly 45 degrees that passes through the origin on scattergrams showing soils and different plants (Mróz and Sobieraj, 2004).

To obtain this sub-indicator, it was useful to acquire several VIs based on slope and distance to determine

Table 4
Vegetation indices calculated for the Luchena River.

VI	Reference	Symbol
$NDVI = \frac{NIR - R}{NIR + R}$	(Rouse, J. W., Jr. et al., 1974)	R=Red band B=Blue band
$EVI = G\frac{NIR - R}{NIR + C1R - C2B + L}(1 + L)$	(Huete et al., 1999)	NIR=Near infrared L= Soil
$SAVI = \frac{NIR - R}{NIR + R}(1 + L)$	(Huete, A., 1988)	G= Gain factor C1, C2= Adjustment factors a = Slope of the soil line
$TSAVI2 = \frac{a(NIR - aR - b)}{R + aNIR - ab + 0.08(1 + a^2)}$	(Baret, F. and Guyot, G., 1991)	b = Intercept of the soil line

its sensitivity within QBR-GIS (Zhen et al., 2021). The normalised difference (NDVI), enhanced (EVI) and soil-adjusted (SAVI) VIs were calculated from the slope. Furthermore, a distance-based index, the transformed soil-adjusted vegetation index (TSAVI2), was evaluated due to its significance in arid and semi-arid environments, as in the study area. This index is based on the ground line concept, which represents a description of the typical signatures in a red–near-infrared bi-spectral plot (Silleos et al., 2006). The NDVI is prominent because it is considered a valid index of the global vegetative state; in studies limited to the regional scale, datasets have a higher resolution, so background effects can increase, influencing the index values (Li and Guo, 2010; Vani and Mandla, 2017). The SAVI was developed to remove the soil factor in vegetation reflectance in areas with low vegetative cover (Nagy et al., 2021).

Most VIs use two spectral bands, the nearby red and infrared bands (Baret and Guyot, 1991), as in the case of the NDVI, while the EVI and TSAVI2 incorporate the blue band. Their values reflect the biomass and condition of green vegetation cover (Silleos et al., 2006). The database used for these calculations was based on PNOA's LIDAR (CIR, RGB 2016). Table 4 presents the formula used to calculate the Vis with software SAGA GIS (Version 8.1.3).

After calculation, the VIs are classified (Table 3). The highest rating (10) corresponds to VI values above 0.5, where riparian vegetative quality is good or very good. The lowest rating (0) was assigned to VI values lower than 0.2, which may correspond to areas without vegetation (arid regions, built-up areas and road networks) (Hashim et al., 2019; Eid et al., 2020).

A QBR-GIS was calculated for each vegetation index, obtaining a final QBR-GIS based on the NDVI, EVI, SAVI and TSAVI2, respectively, to assess the VIs' sensitivity in the QBR-GIS method.

- *Arundo donax.*

Invasive alien species constitute one of the main factors influencing biodiversity loss; *Arundo donax* is a significant vegetative community detrimental to biodiversity in the Mediterranean zone (Bruno et al., 2018). This species has steadily invaded the riparian areas of Mediterranean rivers with negative consequences for terrestrial and aquatic biodiversity (Bruno et al., 2019). This invasive species has been considered in the cover quality assessment due to its significant presence in the Luchena River's riparian zone.

The vegetal community was identified using remote sensing techniques with the random forest algorithm. This detection method consists of numerous interconnected decision trees that work together. Each tree independently predicts a class that groups the most frequently occurring trees (Carbonell-Rivera et al., 2020; Pal, 2005; Tridawati et al., 2020). SAGA GIS (Version 8.1.3) was used to apply a Gaussian filter to the classified raster detecting *Arundo donax* to smooth the results (Conrad et al., 2015). Since this species is a detrimental indicator of riparian quality, a negative score of 10 points was applied (Table 3).

2.3. Channel alterations

This indicator was determined using the orthophoto of the PNOA data and QGIS software to vector areas indicating the presence of anthropogenic activity (roads, highways or crops). These areas were then transformed into rasters and classified by attributing a value of 0, while areas maintaining their naturalness were assigned a value of 10 (Table 3).

3. Results and discussion

3.1. QBR index

The results of the QBR index obtained after the field visit are presented in Table 5. Section 1 has more than 80% vegetation cover in the riparian zone and more than 50% connectivity between riparian forest and the forest ecosystem, giving a score of 30. Section 2 has approximately 60% vegetation cover and more than 50% connectivity between riparian forest and the ecosystem, giving a score of 15. Section 3 has the lowest score for total riparian cover, with approximately 60% vegetation cover, while connectivity between riparian forest and the ecosystem is approximately 30%, giving a score of 5. Section 4 is characterised by 60% vegetative cover in the riparian zone and connectivity between riparian forest and the adjacent ecosystem, obtaining a score of 20. Finally, section 5 presents similar characteristics to section 2 and obtains the same score (15 points).

Section 1 has the best total riparian cover indicator score, corresponding to areas of high vegetation density. Conversely, section 3 has the lowest score of the sections analysed, as it corresponds to areas where bare soil predominates.

Table 5
QBR index score by section/indicator for the Luchena River.

Traditional QBR Index	SECTION 1	SECTION 2	SECTION 3	SECTION 4	SECTION 5
1 Total riparian cover	30	15	5	20	15
2 Cover structure	20	10	5	15	10
3 Cover Quality	15	10	10	15	5
4 Channel alteration	25	25	25	25	25
Final Score	**90**	**60**	**45**	**75**	**55**
Riparian Habitat Quality Class	GOOD	FAIR	POOR	GOOD	FAIR

In terms of cover structure, section 1 has the highest score (20 points) and is characterised by a tree and shrub stratum of approximately 60% and 30%, respectively, with a concentration of halophytes and shrub undergrowth. Section 3 has the lowest score with a value of 5 points. This section comprises 40% trees and 20% shrubs, although it lacks a certain continuity. The remaining sections (2, 4 and 5) have a similar tree-shrub composition (40% and 20%), although with a higher concentration of shrubs.

Regarding the quality of coverage, section 1 has the narrowest riparian area and morphology, with the presence of autochthonous trees and a longitudinal continuity of around 80%. However, the presence of allochthonous species is isolated, giving it a score of 15. Conversely, section 5 has the lowest score as it presents a flatter riparian morphology, and communities of allochthonous species are observed. This is also the case in section 3.

Sections 1 and 4 have the highest values for cover quality, while section 3 has the lowest score, primarily due to low vegetation density. The low score in section 5 is predominantly due to existing crop breakage and a wider and flatter riparian zone, as well as its proximity to the reservoir.

It should be noted that there is no channel alteration in the analysed sections since no anthropic alterations have been observed. Therefore, this indicator has the maximum score (25 points).

In the riparian quality class, the headwaters of the Luchena River (section 1) has the highest score (90 points) since it is the least anthropised section, in which native riparian vegetation species are naturally dominant. Notably, this section has a narrow floodplain and a high density of vegetation cover, making it closest to the natural state of riparian forest (Figure 4). Section 3 has the lowest score due to the substantial presence of *Arundo donax* in the riparian zone, which is wider than in section 1 and predominantly bare soil. Hence, this section obtains low scores, particularly in terms of riparian cover and canopy structure. Section 4 has good quality riparian forest with some *Arundo donax* present, although riparian vegetation dominates. Sections 3 and 5 have a wider floodplain with large areas lacking vegetation, giving these sections poor quality (Figure 4). The scarcity of anthropic activity in the sections analysed is primarily due to the fact that the site lies in a rural area that is difficult to access by car, has a low population and little economic activity.

The average QBR index for the five sections of the Luchena River is 64, indicating that the riparian habitat quality class corresponds to fair quality. This classification reflects significant disturbance (Table 1).

3.2. QBR-GIS

Figure 4 presents the distributed values for each sub-indicator along the Luchena River. The upper section of the river has the best rating for the total vegetation cover indicator (Figure 5a), while the middle section (sections 3 and 4) reveals greater discontinuity. Near the outlet (section 5), the section widens, and the proportion of bare soil increases. Hence, this zone has the lowest vegetation cover indicator score.

In terms of cover structure (Figure 5b), the areas with the highest growing vegetation (green colour) are closest to the headwaters of the Luchena River. It is also noteworthy that a significant area with high trees lies between sections 4 and 5. The remaining vegetative zones have the lowest height (brown colour), corresponding to a score of 0.

Considering the slope indicator (Figure 5c), the highest scores are obtained in the areas with the greatest slope (red colour). The lowest scores correspond to the low-lying areas (yellow colour), as is the case in the lower section (section 5), where the geomorphology is smoother. This section has a wider flood plain than the upper section, which presents a more embedded riparian zone.

As previously stated, there is little anthropic activity in the Luchena River (Figure 5d), with the occasional presence of paths and roads that cross the riverbed, giving a score of 10 (light green colour) for the majority of the Luchena River. Anthropic activity is notably higher (brown colour) near the river mouth (near section 5), where extensive ploughed areas are present.

The presence of *Arundo donax* in the river is indicated in red (Figure 5e). Since this species is damaging to riparian forest, it has a negative score as a sub-indicator of cover quality. There is a strong presence in section 3, which has the lowest score among the sections analysed. *Arundo donax* is one of the most serious threats to riparian ecosystems in Mediterranean climate zones and presents multiple risks (Coffman et al., 2010), such as decreasing the value of wildlife habitat and consuming considerable amounts of water (Coffman, 2007).

The calculated VIs (NDVI, EVI, SAVI and TSAVI) provide an overview of the vegetative state of the riparian zones.

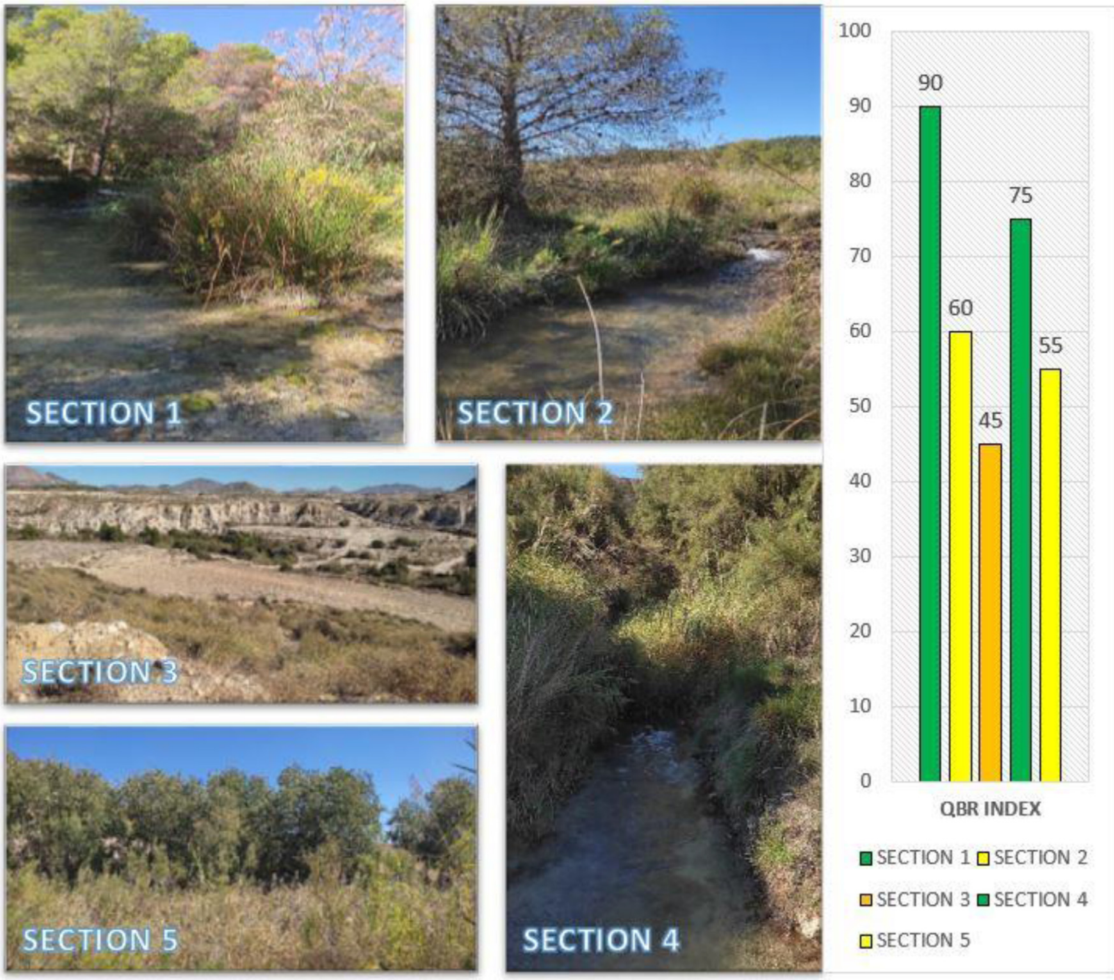

Figure 4. QBR index scores and sections landscapes.

The highest values are obtained in the most vigorous vegetation zones, such as the headwater zone (green colour). In contrast, the lowest values are obtained in the middle–lower sections (red colour), coinciding with bare soil or unhealthy vegetation (Figure 6).

The EVI differs significantly from the other calculated VIs with very low scores (red colour) indicating areas that do not correspond with the vegetative state of the study area (Figure 6b). As observed during the field visits, areas such as the headwaters, where the vegetation is generally healthy, as demonstrated by the NDVI, SAVI and TSAVI results, diverge from the EVI values. This finding could be due to the fact that the soil adjustment factor (L) in the EVI makes this index more sensitive than the NDVI to topographic conditions, as it was developed to optimise the vegetation signal with improved sensitivity in regions of high biomass (Huete et al., 2002; Matsushita et al., 2007; Mokarram and Sathyamoorthy, 2015). In addition, the NDVI (Figure 6a) and SAVI (Figure 6c) reveal similar results, although the SAVI has slightly higher values, in which the green colour predominates (score 10). The results obtained for the NDVI and SAVI are fairly representative of riparian zone quality globally and in semi-arid environments (Vani and Mandla, 2017). The TSAVI (Figure 6d) results with a predominantly yellow colour indicate intermediate vegetation quality (value 5). It could be considered a valid VI, although it did not detect several areas of bare soil, which it interpreted as vegetation, for example, between sections 1 and 2 and an area close to section 5. This failing could be because it minimises the effects of soil brightness on vegetation estimation (Baret et al., 1989) and thus interprets the soil as vegetation.

The results of the QBR-GIS calculated for each of the VIs are presented in Figure 7. The QBR-GIS (EVI) obtained a poorer evaluation with a predominance of orange colour influenced by the VI EVI sub-indicator, which has the lowest scores (Figure 6). Therefore, it is not advisable to use this VI in study areas with similar characteristics to the one analysed in this study. On the contrary, the other QBR-GIS indices demonstrate very little variation between them; they are not especially sensitive in the final QBR-GIS computation, as can be seen in Figure 7. The highest values were obtained between sections 1 and 2, which correspond to the Luchena River headwaters, with a predomi-

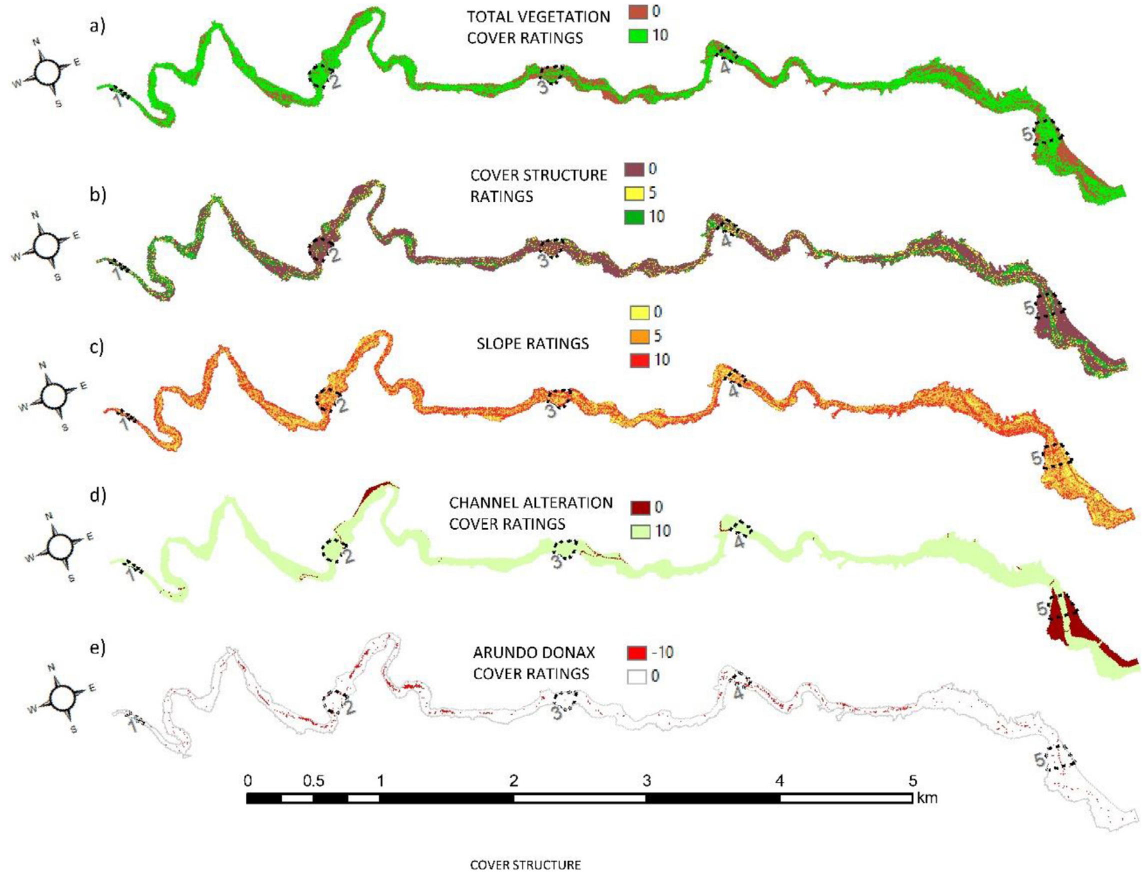

Figure 5. QBR-GIS indicator ratings: a) total vegetation, b) cover structure, c) slope, d) channel alteration and e) Arundo donax. The sections used in the QBR-index are represented by black polygons with dashed lines.

nance of green colour, denoting good quality, and the presence of blue spots, indicating the natural condition of the riparian forest. There is no clear predominance of riparian quality in the middle course of the river (sections 2–4), although an orange zone is identified in the vicinity of section 3, which is indicative of poor riparian forest quality. Green and yellow colours are predominant in the rest of the middle segment, indicating that the riparian forest has fair and good quality. Finally, the lowest values are observed in section 5, near the connection with the reservoir area, with scores below 10 points (red colour), indicating poor riparian forest quality.

4. Discussion

The validation of the proposed index was assessed by comparing the average value of the QBR-GIS for each of the five sections with the QBR index obtained at the same locations. Due to the narrower range in QBR-GIS, the QBR index was divided by two to compare both values. The calculated QBRs are summarised in Table 6.

The values of the different indices in section 1 were above 35, indicating that the quality of the riparian forest is good, regardless of the index used. This section is considered to be of high riparian quality since it corresponds to an area near the source of the Luchena River that is very little or not at all altered. In section 2, the results present the same global assessment, except in the case of QBR-SAVI, which obtained a result slightly higher than 30, assessing the riparian quality as good. Conversely, the remaining scores are below 30, reflecting poor riparian quality. Section 3 is remarkable because the different QBR-GIS do not coincide; according to the QBR index, the final rating would be poor, while the different GIS QBRs obtained ratings of fair quality. In section 4, the values obtained using the different QBR indices and QBR-GIS reflect good quality, except QBR-EVI with a score corresponding to fair riparian forest quality. Finally, in section 5, the QBR index and QBR-GIS obtain the same rating of fair quality. However, the QBR-EVI rating indicates poor riparian forest.

It is advisable to calculate the QBR-GIS using the VI indicator that best suits the study area and the available data. QBR-EVI is not recommended for this case study since its results deviate significantly from the average obtained from the remaining QBR-GIS (NDVI, SAVI, TSAVI). Hence, this index could provide erroneous results in the final qualification. The QBR-GIS should be calculated using the VI indicator best suited to the riparian zone's conditions and the data available for the study area. For example, the EVI is recommended in riparian areas with high biomass (Matsushita et al., 2007). However, it would not be possible to calculate this VI without the blue band of the

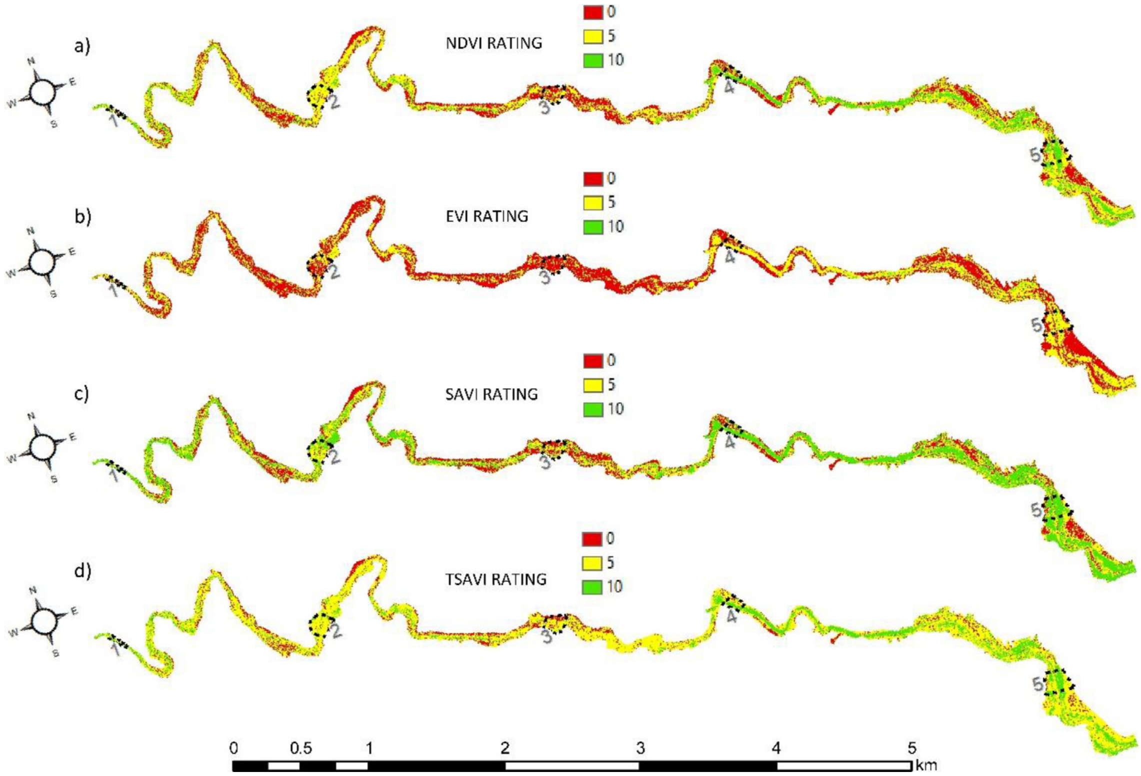

Figure 6. QBR-GIS rating for the vegetation index indicators: a) NDVI rating, b) EVI rating, c) SAVI rating and d) TSAVI rating.

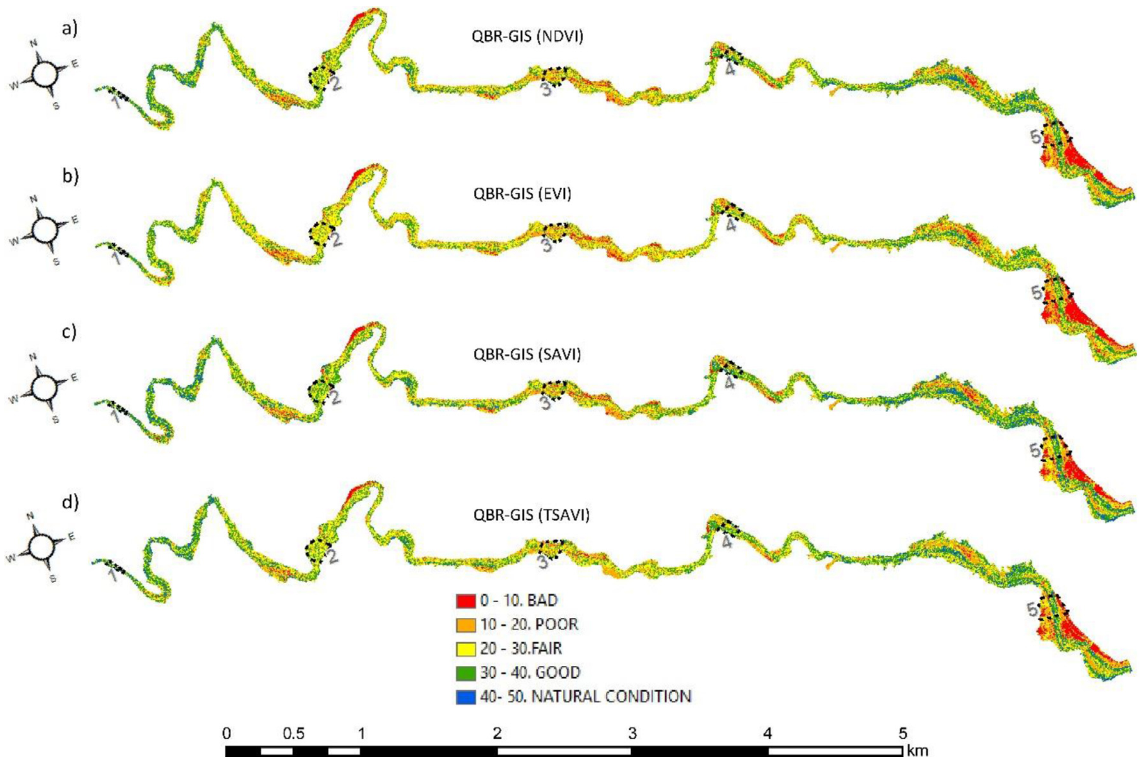

Figure 7. Riparian habitat quality class (QBR-GIS): a) QBR-GIS (NDVI), b) QBR-GIS (EVI), c) QBR-GIS (SAVI) and d) QBR-GIS (TSAVI).

Table 6
QBR index and QBR-GIS (TSAVI, SAVI, NDVI and EVI) results.

	SECTION 1	SECTION 2	SECTION 3	SECTION 4	SECTION 5
QBR_Index	90	60	45	75	55
QBR_Index/2	45	30	22.5	37.5	27.5
QBR-GIS (TSAVI)	37	29	26	32	23
QBR-GIS (SAVI)	38	31	25	32	24
QBR-GIS (NDVI)	37	29	25	31	23
QBR-GIS (EVI)	35	27	23	28	20

image. Therefore, several authors argue that the NDVI obtains good results in riparian zones globally (Albano et al., 2020; Fu and Burgher, 2015; Liu et al., 2022).

This study has shown that machine-learning techniques provide a valuable tool in riparian ecosystem assessment. Indeed, random forest algorithms have also been successfully used to identify land-use categories and nutrient concentrations in the Tagus River (Valerio et al., 2021) or land-use coverage in Cantabria rivers (Fernández et al., 2014) and in the Granada province (Rodriguez-Galiano et al., 2012), all of which are in Spain. Recent research in Mediterranean regions has also indicated that their performance is good (Zaimes et al., 2019; Cid et al., 2016; Akay et al., 2014).

Likewise, high-resolution satellite and aerial imagery in riparian quality evaluation are becoming increasingly significant. Studies on the WorldView satellite (Rivas-Fandiño et al., 2022), Landsat scenes (Ioana-Toroimac et al., 2022) and the Google Earth satellite (Pace et al., 2022) comprise some of the recently used research related to riverine monitoring. Similarly, LIDAR data has shown good results worldwide (Latella et al., 2022; Akturk et al., 2020; Zurqani et al., 2020; Hartling et al., 2019), and PNOA has indicated positive results in Spain (Acuña-Alonso et al., 2022; Pérez-Silos et al., 2019).

Regarding applying the proposed methodology to other regions, the limitations of identifying invasive species due to their similarity to native species with the same tone or morphology should also be considered. Furthermore, seasonal variations in vegetative growth involve comparisons of imagery at different times of the year. Accurate, timely information is also essential to a well-performing performance model.

Further evaluations should focus on the potential of other machine learning techniques, such as neural net classification (Salo et al., 2020), supported vector machines (Eskandari and Pourghasemi, 2022; Ba et al., 2020) and a reduced-error pruning tree (Pal and Sarda, 2022; Islam et al., 2021). Likewise, other research issues that will be addressed in the near future will consider climate change effects and citizen science to democratise riparian quality and management (Rood et al., 2020)."

5. Conclusions

This paper underscores the usefulness of the QBR index as a valid tool for evaluating the state of riparian vegetation. It also proposes the use of an innovative method (QBR-GIS) that adapts the QBR index to new technologies such as GIS, machine learning and remote sensing. This new method can be applied in any riparian zone provided the data necessary to obtain the indicators, such as aerial and satellite images, and DEMs, are available. These data sources can be freely obtained at the global level from Sentinel at the European Space Agency Signature or Landsat from NASA, beyond other, more precise, products available in particular countries or regions. The use of artificial intelligence to detect invasive species using the random forest algorithm provided a particularly significant sub-indicator of riparian quality. Random forest it is one of the most popular techniques for land cover classification due to its processing productivity, and ease of application. In this study, the presence of Arundo donax in the riparian zones. Similarly, using the VI to assess cover quality gives more weight, credibility and depth to the methodology. In this regard, due to its importance, several VIs were calculated to evaluate its sensitivity and influence on the index, avoiding the EVI. Nevertheless, the choice of VI should be subject to the orographic, climatic and environmental conditions of the study area.

Notwithstanding, the QBR index method uses more sub-indicators in its evaluation and calculations, which is both advantageous and inconvenient regarding the amount of information considered and necessary. However, QBR-GIS demonstrated similar results to QBR. Therefore, QBR-GIS is considered a powerful alternative to QBR.

The methodology described in this study makes a significant contribution to environmental management and policymaking as it provides a valid tool for analysing the status of riparian forests, promoting their conservation, preventing further degradation and mitigating soil erosion.

The new approach harnesses the power of geographically referenced information and machine learning to obtain estimates of riparian condition over large areas of the river network. This approach will help managers and practitioners target degraded areas for restoration and other management interventions."

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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