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A novel index for assessment of riparian strip efficiency in agricultural landscapes using high spatial resolution satellite imagery

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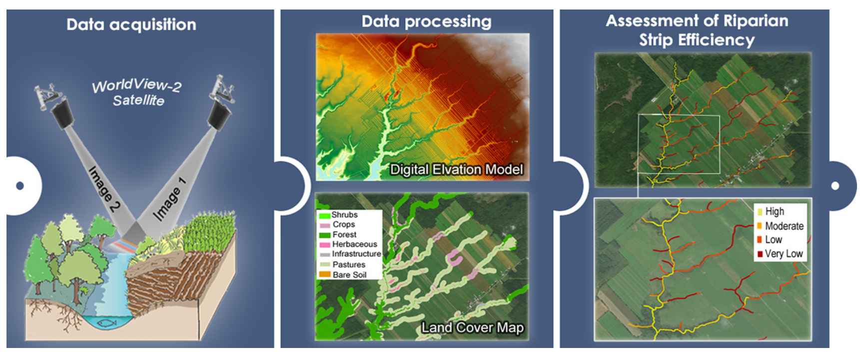
HIGHLIGHTS

- A new index RSEI is developed for riparian strip efficiency assessment.
- One set of VHRS satellite imagery is used as a single source of RSEI inputs.
- The synergy of land cover and drainage information improved the assessment of riparian strips efficiency.

GRAPHICAL ABSTRACT



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ABSTRACT

Riparian strips are used worldwide to protect riverbanks and water quality in agricultural zones because of their numerous environmental benefits. A metric called Riparian Strip Quality Index, which is based on the percentage area of riparian vegetation, is used to evaluate their ecological condition. This index measures the potential capacity of riparian strips to filter sediments, retain pollutants, and provide shelter for terrestrial and aquatic species. This research aims to improve this metric by integrating the ability of riparian strips to intercept surface runoff, which is the major cause of water pollution and erosion in productive areas. In Canada and the Nordic countries, rapid surface drainage from snow melt and spring rains is often practiced to avoid production delays and losses. This reduces the efficiency of riparian buffer strips by promoting soil erosion due to concentrated runoff. A new proposed metric called Riparian Strip Efficiency Index (RSEI), incorporates not only land cover information, but topographic and hydrologic variables to model the intensity and spatial distribution of runoff streamflow, and the capability of riparian strips to retain sediments and pollutants. The research is performed over the La Chevrotière River Basin in the Portneuf municipality in Québec (Canada) using hydrological modeling, land cover and topographic data extracted from very high spatial resolution WorldView-2 imagery as a unique source of inputs. The results show that RSEI provides a better characterization of the ecosystem services of riparian strips in terms of pollutants filtration and prevention of soil erosion in agricultural areas. RSEI will allow a better management of agricultural practices such as drainage and land leveling. Further, it will provide to land managers information to monitor environmental changes and to prioritize intervention areas, which ultimately targets to ensure optimal allocation of private or public funds toward the most inefficient and threatened riparian strips.

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1. Introduction

Riparian strips are well known for their many ecological functions that help in the protection of riparian landscapes and their biota (Naiman and Decamps, 1997; Smart et al., 2001; Boutin et al., 2003; de Sosa et al., 2018). These areas, when vegetated, serve to protect water quality controlling its temperature (Janisch et al., 2012), and their filtering capabilities reduce nonpoint source pollution in agricultural areas (Sahu and Gu, 2009; Parn et al., 2012; Aguiar et al., 2015). They have also been found effective to prevent erosion caused by water runoff (Duchemin and Hogue, 2009), to sequester large amounts of carbon and regulate stream sulfate and dissolved organic carbon when covered by forest (Fortier et al., 2010; Ledesma et al., 2016; Koopman et al., 2018). They also play a key role in preserving biodiversity when working as wildlife corridors (Borin et al., 2010). Worldwide, riparian habitats are threatened by natural and anthropogenic activities that have gradually fragmented and in some areas almost eliminated them from urban and agricultural landscapes (Vought et al., 1995; Saint-Jacques and Richard, 1998; Charron et al., 2008). In overall, riparian zone management is often applied without an accurate assessment of their condition and the ecosystem services they actually provide.

In the province of Quebec, the Ministry of Sustainable Development, Environment, Fauna, and Parks (MDDEFP, for its French acronym), through environmental laws and regulations, protects these fragile habitats, establishing standards for the width of the strips per land cover zoning and terrain slope. Widths from 10 to 15 m are specified in most land cover types, but in agricultural regions, the protected widths range from three to four meters (MDDEFP, 2002; MDDEFP, 2005).

The MDDEFP (2008) has adopted a metric called the Riparian Strip Quality Index (RSQI), developed by Saint-Jacques and Richard (1998) to evaluate the ecological condition of riparian habitats and their impact on the integrity of aquatic environments. This index is based on the correlation between the ecological conditions of benthic and fish communities across many watersheds, and the distinct types of riparian vegetation. The RSQI is widely used to create ecological portraits of watersheds, especially for further development of water protection plans. Essentially, the index is a weighted sum of land cover area percentages in the riparian strip, with greater weight given to arboreal vegetation and lesser to bare soils. The MDDEFP uses an operational, in-situ technical protocol to characterize riparian strips and evaluate the RSQI. Several researches have been conducted on creating a metric to assess the riparian conditions quality. Munné et al. (1998) have developed the QBR index (Qualitat del Bosc de Ribera, or Riparian Forest Quality), a simple method for assessing the riparian habitat quality to be used in Mediterranean streams of Spain (Suárez et al., 2002; Munné et al., 2002) and applied in several regions of the world with satisfactory results (Ocampo-Duque et al., 2007; Carvalho et al., 2011; Fennessy et al., 2016). Some adjustments have been made by several authors in order to adapt it to other geographical regions (Colwell, 2007; Sirombra and Mesa, 2012). Del Tánago and De Jalón (2011) proposed the Riparian Quality Index (RQI) methodology as a standardized field survey and scoring system method, allowing gathering qualitative and quantitative information on the structure of riparian zones for assessing their ecological status. However, the methodologies executed in the field are time-consuming, subjective, difficult to replicate, and very demanding in terms of human and material resources, facts that make it very difficult to regularly monitor the evolution of the ecological conditions of riparian lands (Ashraf et al., 2010). Besides that, these methodologies do not allow quantifying the ability of riparian strips to intercept surface runoff and retaining sediments.

Some research has been done on the usefulness and efficiency of riparian strips and the factors that influence their ability to protect water quality by reducing and preventing nonpoint source pollution (Lin et al., 2002; Hickey and Doran, 2004; Liu et al., 2008). Their efficiency is proportional to the size of the transported particles, the width of the strips, and the concentration of sediments, but inversely proportional to the magnitude of streamflow and the slope (Duchemin and Majdoub, 2004; Gumiere et al., 2011). In addition, as Lowrance et al. (1997) have shown, the hydrologic configuration of streams, riparian strips, and agricultural fields determine the efficiency of the surface water runoff filtering and sediment retaining functions of the riparian strips. Given their potential to affect the ecological functions of riparian strips, slope and water runoff are the most important topographic and hydrologic variables (Piechnik et al., 2012). In northern countries such as Canada, rapid surface drainage from snow melt and spring rainfall is often applied to avoid production delays and losses. This reduces the effectiveness of riparian buffer strips by promoting erosion due to concentrated runoff. The full range of these topographic and hydrologic parameters is rarely integrated into farm management practices (Aarons and Gourley, 2013), and the fact that surface runoff in agricultural areas is concentrated in channels or ditches long before approaching the riparian strip and water streams (Hosl et al., 2012) means that a riparian strip efficiency metric is widely required. Surface runoff variables may be used to model the efficiency of such strips, which is maximized when water runoff is homogeneously distributed along the strip, enabling it to filter and retain the greatest possible proportion of the sediments and pollutants coming from the highlands (Duchemin and Majdoub, 2004; Gumiere et al., 2011).

Geographic Information Systems (GIS) and remote sensing techniques have been used for the characterization, analysis, and monitoring of riparian landscapes, providing scientists with valuable information to understand land surface processes (Narumalani et al., 1997; Basnyat et al., 2000; Smart et al., 2001; Goetz, 2006; de Sosa et al., 2018; Murray et al., 2018). Ideally, remote sensing data should have spatial resolution and temporal resolutions that are fine enough to represent ecosystem dynamics and allow for the detection of rapid changes, correlate closely with appropriate in-situ indicators of ecosystem degradation (Murray et al., 2018). In 1999, stereoscopic satellite imagery with pixel sizes of less than 1 m became available, offering the possibility of a "one-stop" solution to obtain multispectral and ground elevation information on a regular basis and at very high spatial resolution (VHSR) (Johansen et al., 2007; Gu and Liu, 2010). Such imagery has the potential to complement or replace aerial photographs as a source of multispectral information, and it is available worldwide with very short revisit times (Goetz et al., 2003; Ghosh and Joshi, 2014). Remote sensing techniques to extract spectral indices are widely used because they are a fast, cost-effective way to obtain biophysical and morphological information from the land surface (Zawadzki et al., 2016; Wang et al., 2018; Lees et al., 2018; Chi et al., 2018). Besides, object-based image analysis is a proven alternative to per-pixel–based classifiers to extract land cover information from this highly heterogeneous imagery (Gergel et al., 2007; Johansen et al., 2010; Tormos et al., 2011).

Accordingly, hydrological modeling using gridded digital elevation models (DEM) has mostly been done at the watershed scale (El Hage et al., 2012; Rezak et al., 2012). To date, this approach has not been used to support operational, local methodologies to assess the efficiency of riparian strips at agricultural field scale, mainly because of the coarse spatial resolution and vertical accuracy of the outdated DEMs commercially available. Thus, most riparian strip assessments have focused on extracting land cover information and evaluating the ecological condition using field surveys, complemented in some cases by aerial photographs or light detection and ranging (LiDAR) data sets, to characterize these habitats (Congalton et al., 2002; Gergel et al., 2007; Yang, 2007; de Sosa et al., 2018). However, current satellite-derived spectral and altimetry information offers better spatial resolution (<1 m) and vertical accuracy ($\pm$1 m), and now presents an attractive alternative for rapid, periodic extraction of land cover, geomorphological and drainage information to assess the ecological quality and efficiency of riparian strips at local scales (Novoa et al., 2013).

The focus of this study is to assess the potential of the riparian strip to deliver efficient ecosystem services. For this purpose, we developed a new riparian strip efficiency index using drainage modeling, multispectral and stereoscopic satellite imagery at VHSR as a unique source of inputs. This index should help land managers and farmers better understand and manage their riparian strips to protect the environment.

2. Materials and methods

2.1. Study area

The La Chevrotière River Basin, located in the regional municipality of Portneuf, is 60 km west of Quebec City, on the north shore of the Saint Lawrence River (Fig. 1). There are two main urban centers within the basin, St-Marc-dès-Carrières and St-Gilbert, which together had a population of 3207 according to Statistics Canada Census 2016. The watershed covers an area of 108 km^2, and its topography ranges from flat to undulating in a landscape covered mainly by forest (60%) and agricultural land (34%). Forests in the study area are mainly composed of sugar and red maple, hemlock, fir, red and white spruce, trembling aspen, and several species of birch. There is an important presence of pastures, which are cultivated and used as animal fodder (CAPSA, 2014). The La Chevrotière River, which is composed of two main branches, runs 29 km and flows out of the Saint Lawrence River. Slopes of the watershed range from 0% in agricultural and urban areas to >8% in riparian areas. The region receives 932 mm of rainfall and 220 mm of snowfall per year. During April, when the snow starts to melt, soils in the basin become saturated and there is an increased risk of erosion induced by surface water runoff dynamics or inadequate anthropogenic drainage. This is one of the problems that healthy riparian strips may help to mitigate (Nigel et al., 2013).

The methodology takes advantage of remotely sensed information at VHSR and the analytical capabilities of object-based image analysis and GIS to evaluate the ecological quality and efficiency of riparian strips in fulfilling their ecosystem services (Fig. 2). Two main input data sets are used: land-use information collected during fieldwork and satellite-derived information (multispectral and elevation data). The result is a geospatial data set that contains polygons representing every riparian strip, along with their ecological quality and efficiency.

2.2. Field data collection

A fieldwork survey was carried out during summer 2011 to evaluate the ecological status of the riparian areas of the watershed. Using stratified random sampling, 80 locations were evaluated in-situ using the technical protocol developed by the MDDEFP (2008). The stratified sampling considered the Strahler Stream Order and the land-use zoning of the study area. Due to accessibility problems, most of the samples were collected in agricultural zones, which is why future comparisons and validations were only used for agricultural lands. Thus, land cover and topographic information were collected in-situ from both riverbanks through direct observations. The geospatial information of the current research, namely GPS coordinates, satellite imagery, land cover maps, georeferenced photographic records and field measurements was stored using ArcGIS 10 software, which is also used in the spatial analysis and the automatization of certain processes.

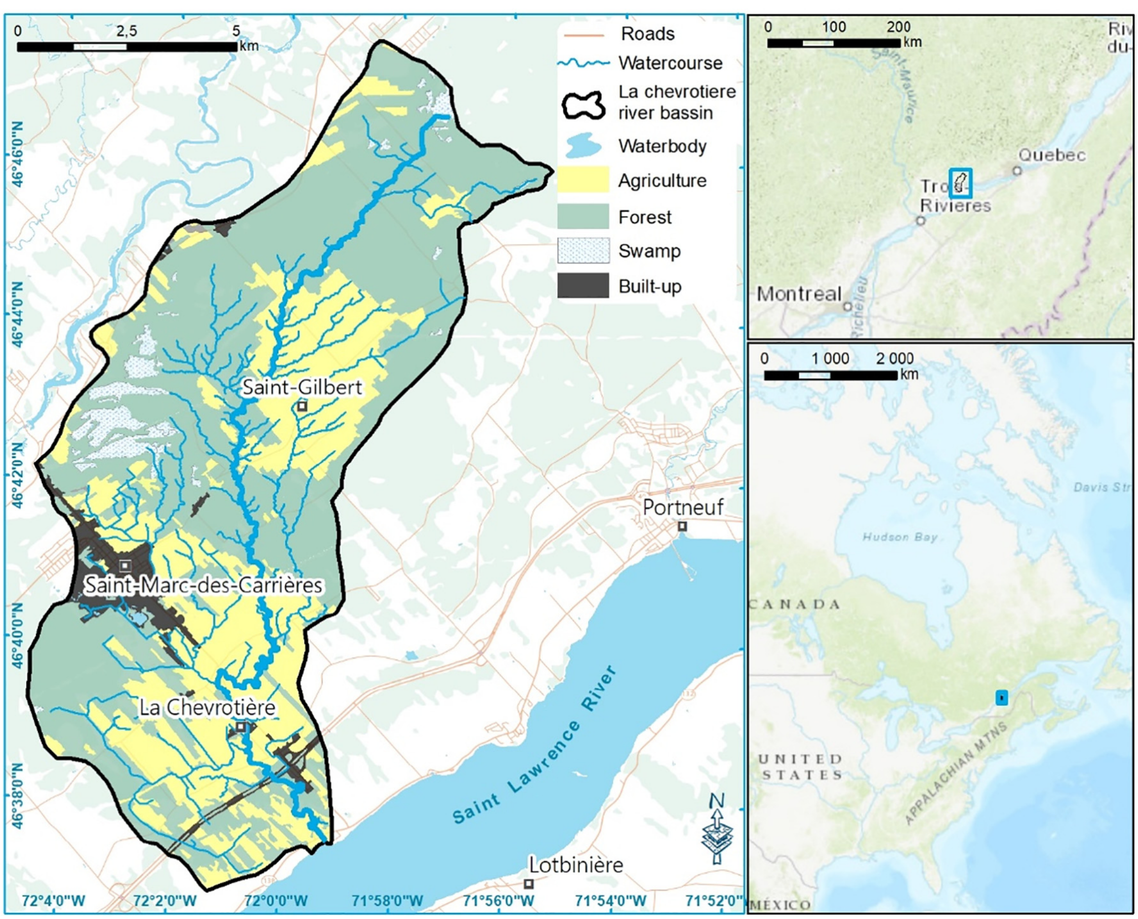

Fig. 1. La Chevrotière River Basin land use, the location is between Montreal and Quebec City, in the province of Quebec, Canada.

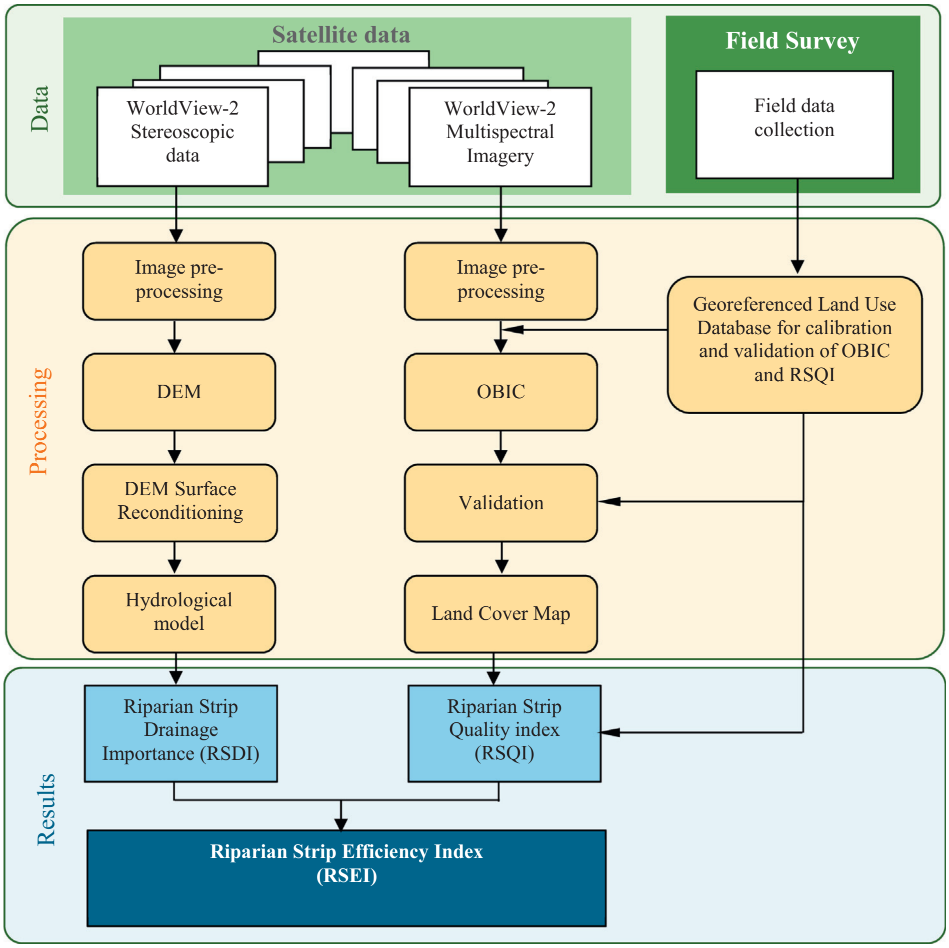

Fig. 2. Flowchart showing the technical approach used to evaluate the ecological efficiency of riparian strips in agricultural areas.

Accordingly, the information collected in the field served to calibrate the classification algorithm and to validate the land cover classification.

2.3. Image acquisition and preprocessing

Two WorldView-2 (WV-2) satellite images were acquired, one from summer 2011 and the other from spring 2012, to detect the spectral variation due to vegetation seasonality. Each image provides a high resolution panchromatic band (0.5 m) and eight multispectral bands (deep blue, blue, green, red, red edge, near infra-red 1 and near-infrared 2 at 2 m spatial resolution). Using the stereoscopic pair of spring, the image provider extracted a DEM of one-meter spatial resolution and one-meter vertical accuracy using automated images matching algorithms (Fig. 1S, Appendix A).

An atmospheric correction of the images was performed using the algorithm ATCOR2 (Richter, 1997). Afterward, using six high-precision (± 0.1 m) GPS control points, the atmospherically corrected images were orthorectified, achieving a horizontal precision of less than 1 m for both images. Then, the two eight-band images were pan-sharpened at half-meter spatial resolution using the algorithm PANSHARP2 (Zhang, 2002), which preserves the spectral characteristics of the satellite bands. This process was performed because during the assessment of riparian strips, small and narrow land cover patches had to be detected and analyzed. To reduce and synthesize the spectral variability within the eight spectral bands of each image, the first Principal Component (PC1) was computed using the Principal Component Analysis of the eight spectral bands (Ghosh and Joshi, 2014). The PC1 contains >90% of the spectral variability of its root bands (93% for summer 2011 and 97% for spring 2012). Afterward, a Normalized Difference Vegetation Index - hereinafter called RE-NDVI - was computed for both images independently using the red-edge and near-infrared bands as follows:

$$\text{RE-NDVI} = \frac{(NIR-RE)}{(NIR+RE)} \tag{1}$$

where NIR is the reflectance in the near-infrared band and RE is the reflectance in the red-edge band.

This modified vegetation index is useful for better discriminating vegetation types by avoiding the high saturation levels of the traditional NDVI (Mutanga et al., 2012). Consequently, a four-band raster file was created (henceforth called the composite raster), combining the PC1 and the RE-NDVI of each image. This combination has proven to be effective in extracting riparian vegetation (Johansen et al., 2007). Following this approach, the two multispectral images were combined into a single raster to reduce file size, spectral complexity, and computing time.

2.4. DEM surface reconditioning

Even at one-meter spatial resolution, the satellite-derived elevation model faced problems when modeling micro-topographic details such as terrain depressions or ditches (Novoa et al., 2013). Thus, to enforce DEM cells drain toward the stream and downstream, the algorithm AGREE was applied to the elevation model using a vector dataset containing all surface drainage channels (e.g. rivers, ditches) (Hellweger, 1997). Therefore, the algorithm was applied to the original DEM, dropping progressively the elevation of the cells located within a buffer around drainage vectors. This procedure improved the estimation of flow direction and accumulation, which ultimately were used to model surface water runoff intensity as a parameter to be used in the riparian strip efficiency estimate.

2.5. Object-based image classification (OBIC)

OBIC relies on the segmentation of groups of pixels to create objects (i.e. polygons) and work with them at different scales using spectral, geometric, thematic, and topological information, which create a richer framework to extract geospatial information (Benz et al., 2004; Hay et al., 2005; Blaschke, 2010). The eCognition software (Trimble, 2011), used in this research, relies on a multiresolution segmentation algorithm to group similar pixels into objects. The algorithm creates objects by consecutively merging pixels or existing image objects using a bottom-up approach based on a pairwise region-merging technique (Benz et al., 2001).

The OBIC was performed inside a geographic mask corresponding to a 50 m buffer around water streams, which was considered adequate as the required width of riparian strips in the study area ranges from 3 to a maximum of 15 m. Image segmentation is one of the most important steps in an OBIC; the parameters (i.e. scale, shape, compactness) used in segmentation are crucial to the accuracy of the objects created (Liu et al., 2012). The scale parameter controls the size of the objects to be created during segmentation. Accordingly, the use of an optimal scale parameter is imperative to not under- or over-segment the image. Thus, the software module developed by Dragut et al. (2010) was used to complete this task. It iteratively evaluates the spatial and spectral properties of the objects created at multiple scales, and reveals the optimum scale parameter that will produce the highest number of objects, without over-segmenting the image. Similarly, the shape and compactness parameters control the form of the objects created and their dependence on the spectral values of the input image. The selected scale parameter was 25, while the shape and compactness parameters were both 0.1. These values enabled the creation of small as well as elongated objects, as expected in agricultural riparian zones. For the segmentation process, the bands corresponding to the first principal component were used. This approach is supported by the findings of Lippitt et al. (2012), who tested the performance of principal components in object segmentation.

Once the composite raster was segmented, seven land cover classes were created. Sample objects were then selected for each land cover class using information collected during fieldwork. These samples were used for training the classification algorithm using the spectral information derived from the first principal component and the RE-NDVI bands (Table S1, Appendix A). Next, the information collected through these sample objects was used to perform a feature space optimization analysis. This analysis shows the sixteen spectral, topological and textural variables with the best class separation. These variables were: object area, object brightness, spectral skewness, shape index, spectral mean, spectral standard deviation, and spectral maximum difference. Hence, the nearest-neighbor algorithm was used to classify the composite raster and produce a land cover map of the riparian areas of the watershed.

2.6. Classification validation

The validation of the OBIC was performed using the WV-2 satellite imagery. Visual inspection was considered suited and effective because the satellite imagery had enough spatial resolution to help discern between the land cover categories, and to evaluate the delineation of polygons (Tiede et al., 2008). Accordingly, validation polygons (181) at the 95% confidence level and 10% margin of error were randomly selected and independently evaluated on screen. The number of validation objects selected for each land cover class was determined by the percentage of total objects in each category, as seen in Table S2 (Appendix A). A confusion matrix, producer's and user's accuracies, and the Kappa Coefficient (KC) were then calculated to show the degree of agreement between ground truth and the classified land cover (Congalton, 1991).

2.7. Riparian Strip Quality Index (RSQI)

The RSQI is a measure of the ecological quality of riparian strips, and it is commonly used to create ecological portraits of watershed riparian areas. Computed using weighted riparian land cover classes (Eq. (2)), it may also be used as a tool to verify legal compliance and to help land managers monitor changes in riparian habitats. In some jurisdictions, the riparian strips' width is based on its average slope. The RSQI is calculated as follows:

$$\mathrm{RSQI} = \frac{\sum(\%\mathrm{LU_i} \times W_i)}{10} \tag{2}$$

where $\%LU_i$ is the land cover area percentage inside the riparian strip and W_i corresponds to the land cover class weighting factor, as follows (Saint-Jacques and Richard, 1998): forest (10.0), shrubs (8.2), herbaceous vegetation (5.8), crops (1.9), pastures (3.0), bare soil (1.7), infrastructure (1.9), bedrock (3.8), and logging areas (4.3). This calculation was done automatically in a GIS on 500 m length riparian strips, except in agricultural areas, where riparian strips had the same length as the agricultural fields they went through. The RSQI ranges from 17 (lowest quality) to 100 (highest quality). The RSQI categories were defined in MDDEFP (2008) based on empirical tests as shown in Table 1.

2.8. Drainage importance analysis in agricultural zones

In addition to vegetation, topography plays an important role in modeling how riparian strips intercept runoff and retain sediments (Fernandez et al., 2012; Piechnik et al., 2012; Teufl et al., 2013). As Bereswill et al. (2013) argue, the width of a riparian strip is not enough to measure the performance of these vegetative filters. In addition, the agricultural landscape is often highly modified through fields leveling, by drainage ditches, or hydraulic works to boost productivity. Accordingly, the RSQI may be insufficient to precisely describe the filtering capabilities of riparian strips. Land cover information must be complemented by runoff metrics (flow volume and spatial distribution) to identify diffuse or concentrated runoff plot configurations.

Concentrations of surface runoff in riparian strips are commonly caused by a disadvantageous drainage configuration. Several algorithms are available to simulate water distribution and calculate the streamflow magnitude in watersheds. The accuracy of these algorithms has been extensively tested when calculating the flow direction and flow accumulation using gridded DEMs (Zhou and Liu, 2002; Wilson et al., 2008). In this research, we used the D8 flow routing algorithm (O'Callaghan and Mark, 1984), which is one of the most widely used in hydrological modeling because of its simplicity of implementation, and its performance is considered acceptable for the detection of potential streamflow concentration in agricultural fields (Wilson et al., 2007). Subsequently, we propose a new drainage quality index called The Riparian Strip Drainage Importance (RSDI), which is calculated individually for each riparian strip located in agricultural zones, as follows:

$$\mathrm{RSDI} = \frac{\sum(Drainage_{P75})}{\text{Field area}} \tag{3}$$

where $\sum(\mathrm{Drainage}_{P75})$ is the sum of the areas drained by the extreme outlets, and Field Area is the total area of the plot in contact with the riparian strip. Extreme outlets were defined as those who have a

Table 1
Categorization of RSQI.

RSQI categories	RSQI values
Very low	<40
Low	40–60
Moderate	60–80
High	>80

cumulative surface runoff area greater than the 75th percentile (P75) of the drained area. The drainage quality is defined according to the RSDI intervals, which are based on quartiles of surface runoff (Table 2).

The drainage points were classified as normal and extreme outlets. They were used to infer the potential amount of surface runoff volume in each riparian strip. All the outlets of the field (not only those inside a riparian strip) were sorted based on their drained area (Fig. 3). Then, those with drained values greater than percentile 75 were classified as extreme outlets. The micro-watersheds inside the lot have been computed to determine the amount of surface runoff received by each of the existing riparian strips. Consequently, the figure depicts areas where problems such as erosion rills, soil loss, and water pollution have the greatest potential to arise. The riparian strip with high RSDI clearly shows the small, similar-size micro-watershed because it does not have extreme outlets inside it, which might indicate a diffuse runoff and one with low RSDI because all the extreme outlets of the field are inside its boundaries, with potentially erosive surface runoff volumes.

This approach allowed us to find relative extreme outlets, which enabled us to standardize the analysis, considering the wide variation in size among agricultural fields. In this context, RSDI must be considered as a relative measure of the performance of surface drainage in agricultural fields. This metric aims to detect whether the riparian strip is delivering valuable ecosystem services related to the slope gradient (indirectly), and the surface runoff streamflow. Anbumozhi et al. (2005) demonstrated that a riparian strip is more efficient at preventing concentrated flow erosion and capturing sediments and pollutants when it has drainage composed by several outlets where flow discharge and velocity do not exceed critical values that enable the development of gullies or erosion rills.

2.9. Riparian strip efficiency assessment in agricultural zones

In environmental applications that handle complex phenomena with rare or difficult to acquire data, qualitative assessment frameworks effectively support environmental decision making. These have proven to be cost-effective in several environmental applications such as fisheries, aquatic ecosystem or watershed management (Astles et al., 2006; Kajenthira et al., 2012; Rastogi et al., 2014; Suter, 2006). This research suggests the integration of RSQI and RSDI in the computation of a new Riparian Strip Efficiency Index (RSEI). This leads an integrated assessment of the quality of vegetation coverage and the hydrological configuration of a riparian strip, which allows an improved assessment of its ecosystem services. RSEI is computed by combining RSQI and RSDI into one categorical index according to the Eq. (4) and categorized as High, Moderate, Low, and Very Low (Table S3, Appendix A).

$$\mathrm{RSEI} = \min(\mathrm{RSQI}, \mathrm{RSDI}) \quad (4)$$

3. Results and discussions

3.1. Object-based classification

The OBIC performed well, achieving an overall KC of 0.82. The use of the PC1 and the RE-NDVI of each image improved the performance with minimal sacrifice of accuracy by reducing the spectral information. The 50-meter buffer area used as the target area to extract riparian vegetation covered 15.1 km^2, which represents 13.7% of the whole river basin. Approximately 318 km of riverbanks were located within this buffer area. Forest was the dominant class within the target area, covering 59.5% of the riparian zones. The second most important land cover class extracted was Pastures, covering 32%. The remaining 8.5% corresponds to Crops (5.0%), Infrastructure (1.9%), Herbaceous (1.2%), Bare Soil (0.2%), and Shrubs (0.2%). This obtained land use distribution with large pasture cultivations is due to the fact that the main agricultural activity in La Chevrotiere River Basin is led by the dairy and cattle industry (CAPSA, 2014). As shown in Fig. 4, the Basin has an important presence of large zones of pasture and crops. In these agricultural areas, most of the ecological problems are expected to occur, because of the hydromorphological and environmental pressures as well as the land cover degradation related to human activities and agricultural practices.

Once the land cover map was extracted, a validation sample size was estimated at 95% confidence level and with a margin of error of 10% (Congalton, 1991). Validation statistics were computed using 181 samples selected randomly in proportion to the number of objects in each land cover class. Table 3 shows the confusion matrix of the image classification, showing the number of pixels classified into each land cover class against those selected in the validation process. Forest, Crops, Bare Soil, and Infrastructure were the most accurate, showing the highest KCs (KC > 0.92), while Shrubs, Herbaceous, and Pastures showed the lowest ones, ranging from 0.39 to 0.67.

The classification errors of the vegetation land cover classes with low KC are explained by the small number of spectral bands used for classifying the image (i.e. RE-NDVI, PC1). While using 4 bands speeded up the time-consuming object-based image classification process, this was 4 insufficient to provide enough spectral information to have better separability between land cover classes. The effects of these inaccurate land cover classes on the RSQI, and ultimately on the RSEI, are difficult to foresee with certainty, but the fact that they show confusion primarily against other types of natural vegetation is likely to reduce their effect on the indices, minimizing their negative impact. Refining techniques to improve the OBIC might be envisaged in the future.

3.2. Riparian strip quality assessment

The average ecological quality index RSQI in the river basin was 69, which ranks it as a watershed with a moderate ecological quality. Most of the length of the riverbanks, 205.0 km (64%), was covered by riparian strips with a high RSQI, 36.9 km (12%) of the riverbanks were covered by riparian strips with a moderate RSQI, and 76.6 km (24%) were covered by riparian strips with a low or very low RSQI (Fig. 5).

The results in the agricultural areas show that 31.8 km (28.9%) of riverbanks were covered by riparian strips with high RSQI, 17.4 km (15.8%) were covered by riparian strips with moderate RSQI, and 60.9 km (55.3%) were covered by riparian strips with a low or very low RSQI (Fig. 5). In agricultural areas, the ecological quality of riparian strips decreased considerably, presenting a mean RSQI of 56 (Low), 13 points lower than the overall watershed RSQI (Moderate). Riparian strips with a high RSQI decreases by more than half, from 64% to 29%. Riparian strips with moderate RSQI remain stable, increasing in percentage only from 12% to 16%, and low and very low RSQI riparian strips increase in the percentage by more than double, from 24% to 55%, showing a considerable deterioration of the ecological quality of riparian strips when they go through productive areas. It is also worth noting the mean RSQI of riparian strips located outside agricultural areas was 80 (High), which reinforces the fact that most of the ecological problems of riparian strips occurs in areas under anthropogenic pressure (e.g. urban areas, agricultural zones).

The results obtained from the satellite-based RSQI are highly correlated with the ones derived from fieldwork. In agricultural areas, the fieldwork-based RSQI average value was 55/100 (i.e. low ecological quality) and the satellite image-based RSQI was 56/100, demonstrating the high accuracy of the developed RSQI estimation methods. This result

Table 2
Categorization of RSDI.

RSDI category	RSDI values
Very low	>0.75
Low	0.50–0.75
Moderate	0.25–0.50
High	<0.25

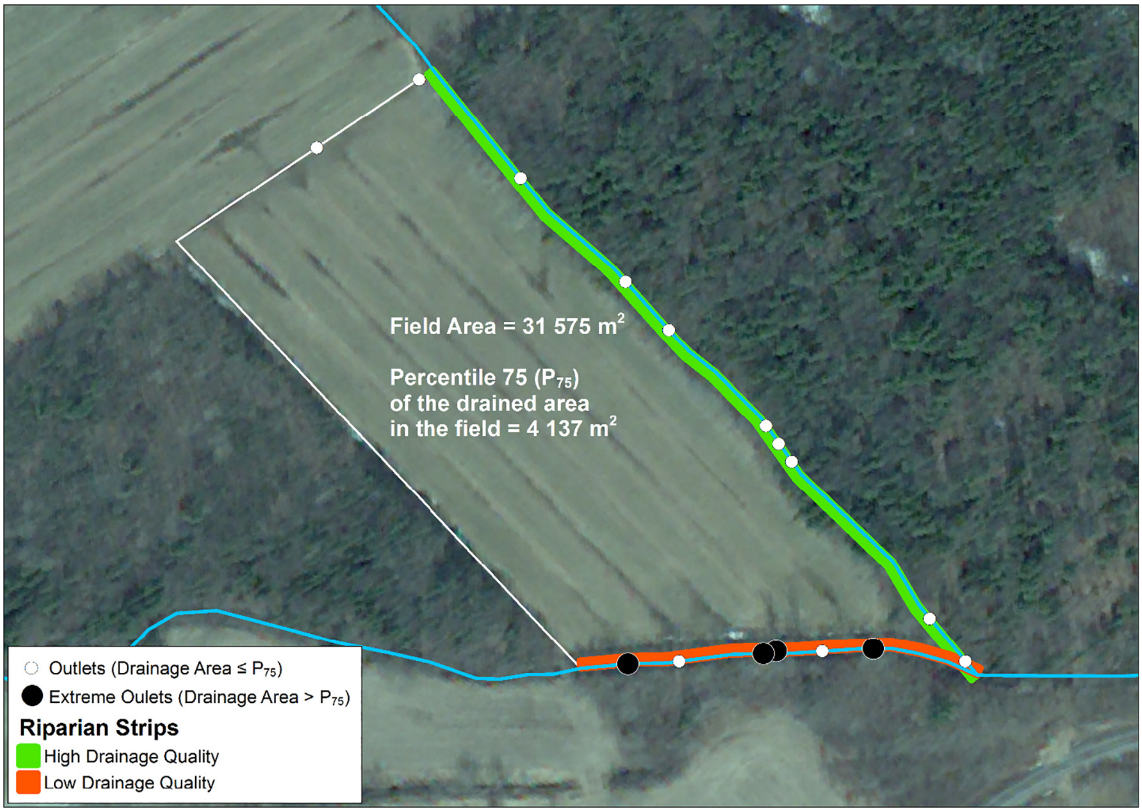

Fig. 3. Drainage quality configuration in an agricultural field. Riparian strips with high RSQI (green) have outlets (white dots) of small drainage areas, while riparian strips with low RSQI (orange) have extreme outlets (black dots) of bigger drainage areas.

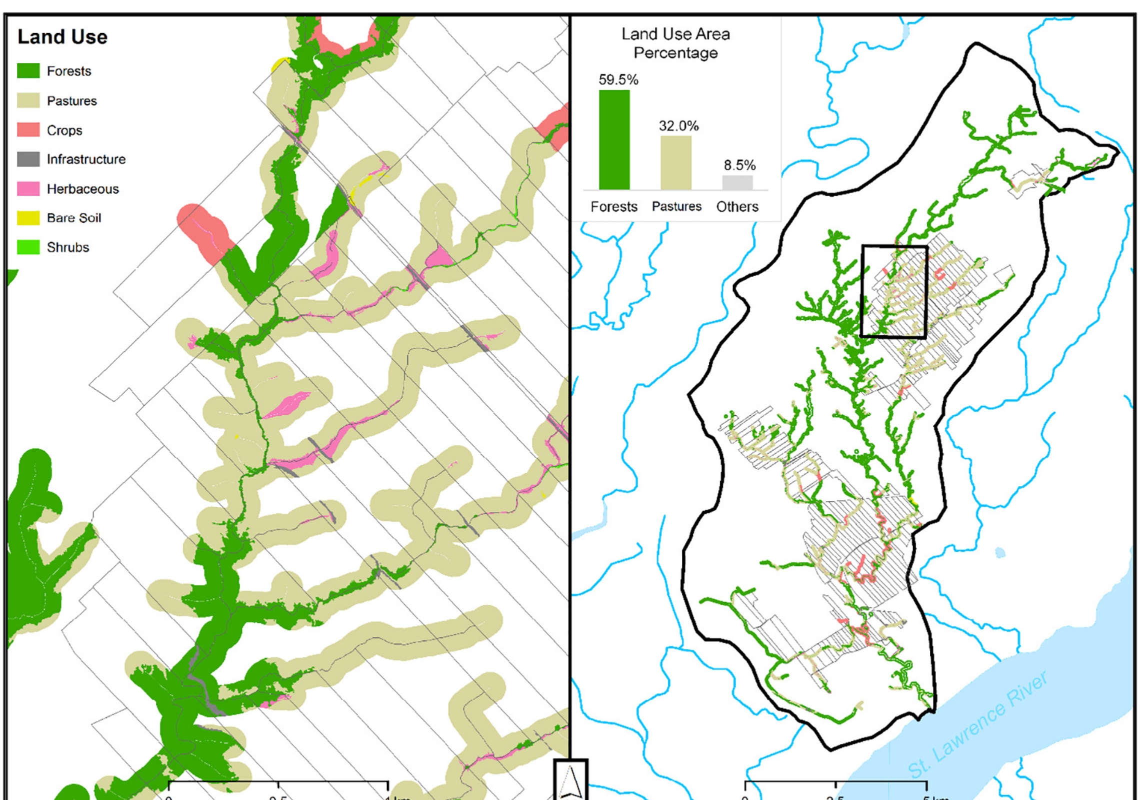

Fig. 4. Land cover map: at watershed level (right panel) and at the agricultural zone (left panel). The gray outlines represent agricultural parcels boundaries.

Table 3
Confusion matrix of the OBIC.

Land cover class	Reference class (area percentage)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1) Forest	**98.29%**	0.06%	1.65%				
(2) Shrubs	19.18%	**38.58%**	42.24%				
(3) Herbaceous	4.12%	6.61%	**89.28%**				
(4) Crops				**17.46%**	82.54%		
(5) Pastures	0.12%		0.02%		**99.86%**		
(6) Bare soil						**100.00%**	
(7) Infrastructure	0.99%					0.61%	**98.39%**
KC per class	0.99	0.54	0.39	1.00	0.67	0.92	1.00
KC	0.82						

The diagonal elements (in bold) represent the percentage for which the predicted class is equal to the reference class, while off-diagonal elements are those that are misclassified.

demonstrates the usefulness of the proposed methodology, which may reproduce the results of the in-situ methodology using fewer resources.

As the only input parameter to calculate the RSQI is the land cover map, future improvements and implementations of this methodology must have special attention to its accuracy and time to completion. Land cover mapping in riparian strips faced with two main difficulties: (1) the availability of cloud-free satellite imagery, and (2) the spectrally-optimized approach to extract land cover information using an object-based image classification. Indeed, cloud-free images are difficult to obtain with optical sensors, and this can potentially obstruct retrieving and monitoring the land cover information. Thus, methodologies using new optical and radar sensors or combination of them, to derive land cover information may help improve the overall accuracy and availability. Concerning the timeliness of completion, the use of only two spectral bands (i.e. RE-NDVI, PC1) speeded up the land cover OBIC but caused an acceptable minor loss in accuracy in the final map. However, there are opportunities for improvement on this matter. Currently, scientists have at their fingertips very high computing power to perform big technical tasks using scalable, distributed data infrastructure through cloud computing systems, which could promote the use of bigger multispectral datasets by optimizing timeliness and processing accuracies. In addition, the recent success of deep learning classifiers, namely the convolutional neural network (CNN) may promote retrieving land cover map accurately and rapidly compared to state-of-the-art classification methods (Weng et al., 2018).

3.3. Riparian strip efficiency assessment

The efficiency of riparian strips at filtering surface runoff and retaining sediments in agricultural zones was computed using hydrologic information such as potential predisposition to generate surface runoff. These variables were extracted from the satellite-derived DEM and used to compute the drainage quality according to RSDI equation. Over approximately 110 km of riverbanks in agricultural areas, 65.1 km (59%) had a high RSDI, 33.8 km (31%) had a moderate RSDI, and 11.2 km (10%) had a low or very low RSDI. The drainage

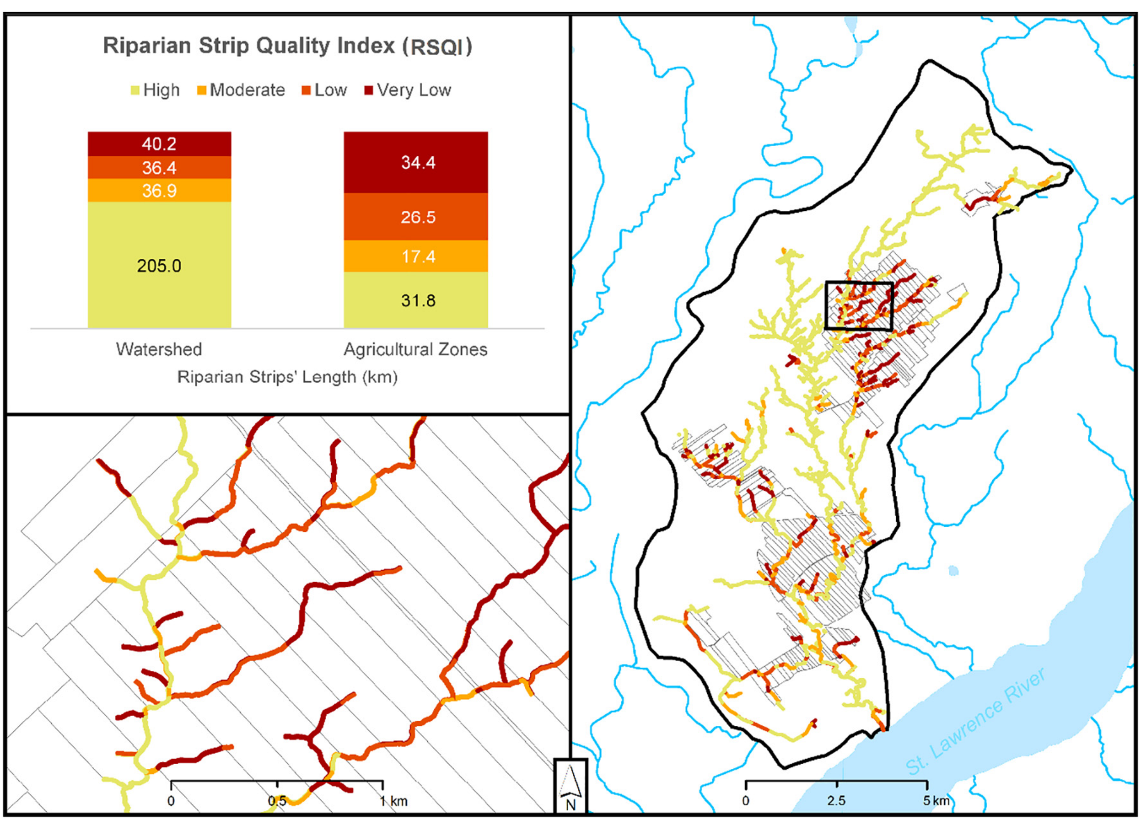

Fig. 5. RSQI spatial distribution: at watershed level (right panel), and a section of the agricultural zone (bottom left panel). The top left panel shows the number of kilometers of riparian strips by RSQI category in the watershed (left chart) and in the agricultural zone (right chart). The gray outlines represent agricultural parcel boundaries.

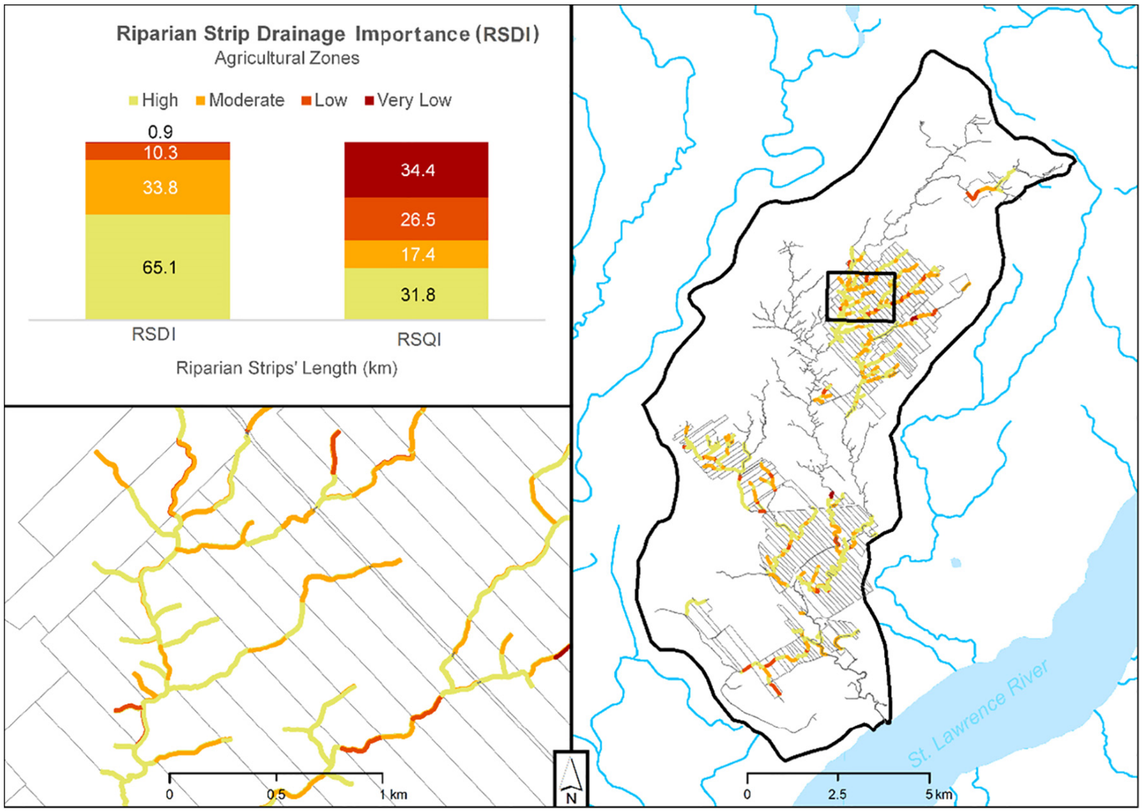

Fig. 6. RSDI spatial distribution: at watershed level (right panel), and a section of at the agricultural zone (bottom left panel). The top left panel shows the number of kilometers of riparian strips in the agricultural zone, by RSDI (left chart) and by RSQI (right chart). The gray outlines represent agricultural parcel boundaries.

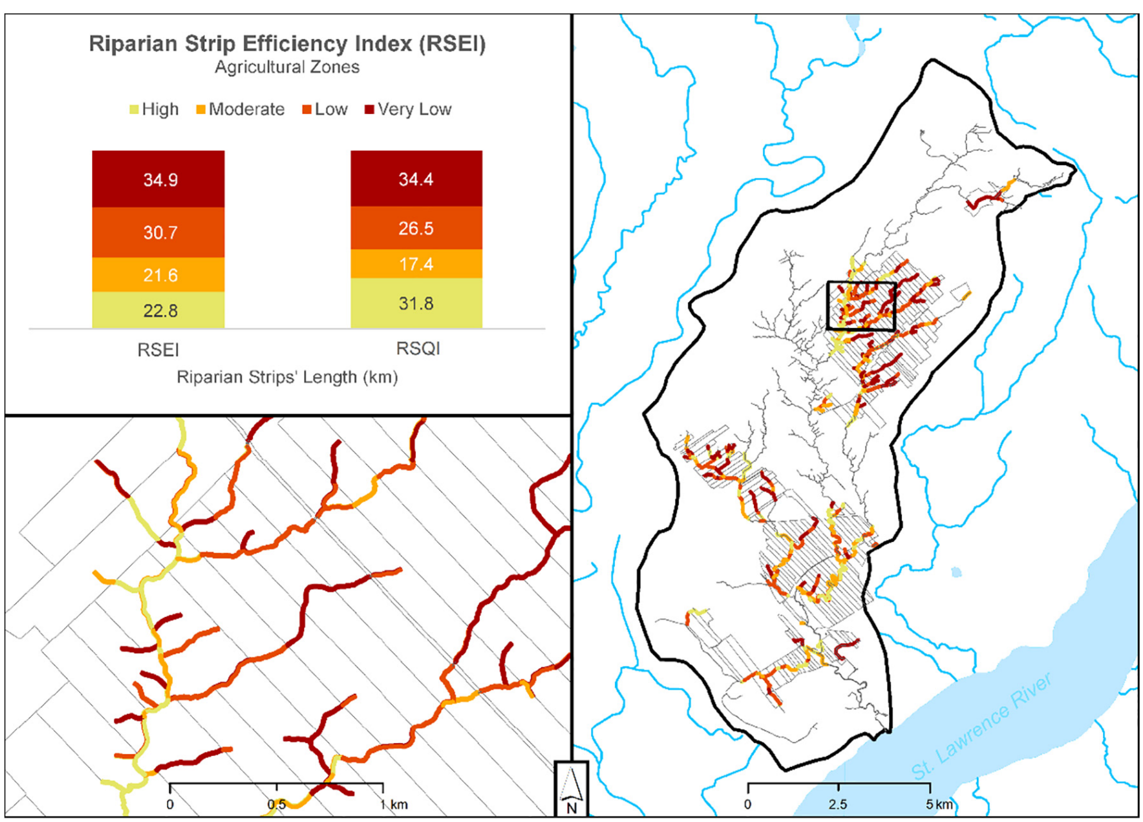

Fig. 7. RSEI spatial distribution: at watershed level (right panel), and at a section of the agricultural zone (bottom left panel). The top left panel shows the number of kilometers of riparian strips in the agricultural zone, by RSEI (left chart) and RSQI (right chart). The gray outlines represent agricultural parcel boundaries.

configuration of agricultural land in this watershed seems therefore to be acceptable, but the RSDI calculations indicate that there are 11.2 km of riverbanks with potential runoff concentration problems, which might induce to soil loss or water pollution (Fig. 6). In this way, the RSQI drainage quality metric assists in detection of riverbanks negatively influenced by their upland drainage system, and provides to land managers interesting insights about how the hydrologic configuration may influence filtering capacity of riparian strips.

Each riparian strip crossing cropland was assigned either its RSQI or RSDI category, whichever was the lowest. As a consequence of the inclusion of the drainage quality metric, some riparian strips previously categorized as high quality (High RSQI) were downgraded to a Moderate or even to a Low or Very Low category. Fig. 7 shows how the hydrologic configuration could be used to improve the discrimination and categorization of the potential ecological performance of riparian strips.

New insights were revealed by using the RSEI as a substitute for the RSQI. Although 31.8 km (29%) of the riverbanks were classified with a High RSQI, only 22.8 km (21%) were assessed as highly efficient by the RSEI. This represents a difference of 9 km, a probably not insignificant amount when budgeting annual maintenance and mitigation plans in the watershed. Besides, 17.4 km (15.8%) of moderate RSQI increased to 21.6 km (19.6%) of moderate RSEI, and 60.9 km (55.4%) of the lowest RSQI increased to 65.6 km (59.6%) of the lowest RSEI. These changes in percentage distribution indicate that the RSQI overestimates the ecosystem services of riparian areas. Thus, one might consider the RSEI more complete and comprehensive for discriminating the efficiency of riparian strips to fulfill their hydrological and ecological services.

There are several opportunities to improve the RSEI by further processes in the calculation of the RSDI, especially on the input parameter (i.e. DEM), and in the optimal selection of the flow accumulation algorithm, which helps identifying drainage points and their potential runoff volume. The LiDAR elevation measurements using aircrafts or drones are becoming more accessible and could be a crucial source of elevation datasets to perform such hydrological analysis. Another important fact to have in mind is the correct registration of all man-made agricultural drainages systems, otherwise considerable errors can be added to the calculations such as defining inexistent drainage points or assigning them unrealistic drainage volumes. In addition, the RSDI thresholds currently used (i.e. quartiles) could be modified to adjust empirical data about runoff volume. The RSDI methodology is easy to adjust and reproducing it with quantitative data will improve the outcomes and be suitable for a wider range of watersheds in terms of size and hydrological configuration.

The results showed that RSEI Index is promising and powerful tool, which allows to overcome the limitations of existing traditional indicators such as RSQI, QBR and RQI. These indicators rely on in-situ measurements, field forms and scoring system, which makes them subjective and dependent on the operator's performance. They may give accurate results thanks to their concentrated application over a few hundreds of meters, which is in return very laborious when trying to assess the whole watershed, long river corridors or frequent environmental monitoring needs. Accordingly, Fernández et al. (2014) have developed a land cover based model to predict the riparian strip quality as a faster and easier alternative. Their models correlate significantly with the QBR index when using high-spatial-resolution land-cover data. However, hydromorphological pressures related to human activities played a very small role in their models. The novel approach presented in this paper offers a more objective, comprehensive, easily reproducible methodology that integrates land cover and drainage quality to gain a better understanding of riparian strips and their ecological services in agricultural zones.

The characterization of riparian strips using VHSR satellite imagery is an operational and reliable methodological alternative that produces good results and allows regular and effective monitoring of these ecosystems at lower costs. The choice of using a single source of information of the multispectral image data and the elevation data for the development of the methodology favors its use since these limits the costs of data acquisition and processing (around \$1.5/ha). Traditional approaches involve different suppliers for image data (aerial photos, around 1.3\$/ha) and elevation data (Lidar, around 0.75\$/ha–3\$/ha, depending on the density of the sowing points), with different acquisition protocols and processing tools, which ultimately are financially more onerous.

The developed methodology may be applied to any stereoscopic satellite image with VHSR and generalized to different watersheds and larger riparian areas. However, it should be adapted according to the amount and complexity of riparian strip datasets on a large scale. It also may be applied using other multispectral sensors for computing the RSQI, but the results are highly dependent on the spatial resolution of the obtained land-cover dataset (Fernández et al., 2014). Besides, other elevation datasets may be used for performing the RSDI. While this is achievable, it is worth noting that using a unique input image stereo pair to derive all the required datasets have advantages in terms of error propagation and overall accuracy, over a "multi-source" approach. The methodology uses only standard remote sensing techniques and geographic information processing and analysis systems available in most commercial and free software. Some of free alternatives that could be used to perform this methodology are: SNAP/OrfeoToolbox, for image calibrations, corrections, image segmentation, and image classification; SAGA/QGIS/GRASS/WhiteboxGAT/ILWIS for hydrological and GIS analysis; Python/R for process automation; and a modified version of NASA's ASP software (Shean et al., 2016) for the creation of a DEM from a stereoscopic pair.

This research will provide natural resources managers with an operational decision-making tool to ensure that the ecological knowledge, the environmental processes of protection and governance are effectively considered in the establishment, maintenance or restoration of riparian strips. Thus, the managers can properly assess the resources required and the implementation methods. Incorporated into the integrated water management cycle, the methodology developed is an effective tool for monitoring and assessing actions concerning riparian strips designed and implemented during the previous iteration of the management cycle. Such a methodology will enable watershed managers to produce an exhaustive inventory of riparian strips, assess the state of health of these vulnerable ecosystems and analyze their compliance with current recommendations and/or regulations. In addition, it will measure the effectiveness of riparian areas in relation to actual field runoff conditions.

In addition to contributing to the judicious application of water and soil conservation practices and improving the productivity of watershed management organizations, the knowledge developed through this work will help promote the use of earth observation data, space technologies and geomatics tools in the agricultural applications. This will allow watershed organizations and agri-environmental stakeholders to have access, at reasonable costs, to decision support tools that will enable them to perform wisely, economically and environmentally.

4. Conclusions

This paper proposes a new index for riparian strip efficiency assessment RSEI, which combines an intrinsic quality index RSQI and a drainage quality index RSDI. Those indices were computed using a single set of VHSR (0.5 m) stereoscopic WV-2 satellite image data as a unique source of inputs. The results of this research have demonstrated the performance of RSEI in assessing the efficiency of riparian strips to fulfill their hydrological and ecological services in productive areas, where agricultural practices are placing increasing pressure on riparian habitats, causing ecological problems such as erosion and water pollution. In addition to remotely sensed land cover data, the integration of satellite-based drainage information in the RSEI has improved the assessment of riparian strips health and allowed a better characterization of their efficiency.

The RSQI was calibrated and validated using the land cover collected during the field survey. In agricultural areas, the fieldwork-based RSQI average value was 55/100, corresponding to a Low ecological quality, while the satellite image-based RSQI was 56/100, demonstrating the high accuracy of the developed RSQI estimation approach. However, the RSQI index only allows the intrinsic quality assessment of the riparian strip and does not provide information on whether surface runoff is diffuse or concentrated in a limited number of outlets and bypassing the riparian strip barrier. To deal with this issue, we proposed a new drainage quality index RSDI on the basis of the high resolution WV-2 derived DEM (1×1 m). The RSDI demonstrated its performance in assessing the drainage quality of riparian strips in agricultural zones by extracting the position of extreme outlets (defined as those who have a cumulative surface runoff area greater than the 75th percentile of the plot area). This allowed assessing the potential of the riparian strip to intercept surface runoff and retaining sediments. Subsequently, the final RSEI efficiency index combines the RSQI and the RSDI by retaining the lowest RSQI or RSDI category to each riparian strip. The combined use of land cover information and hydrologic variables by RSEI enabled a better identification of the most threatened riparian strips even though they show good intrinsic quality (high RSQI), which provides a more accurate measurement of the riparian strip efficiency to play its fundamental role as filtering barriers of surface runoff. Qualitative assessment, as the one used in this research, provide an effective way to categorize and prioritize complex environmental phenomena when data is scarce and mixed effects cannot be quantified or modeled without more quantitative data. These qualitative categorizations provide scientists, managers, and other stakeholders useful information and new insights about the riparian strips performance, which ultimately will promote further empirical research endeavors. Because of it is accurate, indirect, less expensive, faster and synoptic technique, the proposed approach constitutes a promising tool for estimating the efficiency of the riparian strip in the agricultural landscapes.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.scitotenv.2018.07.069.

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