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Analysis of qualitative and quantitative assessment methods for shoreline extraction

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Abstract
The shoreline is an important geographical zone, and knowledge of its accurate location can be crucial for coastal management and mapping. The ever-increasing number of aerial and satellite sensors is leading to research related to the development of new methods for the automatic extraction of the shoreline. Currently, there is a lot of research in this area with different research methodologies. In this paper, an analysis of shoreline extraction methods was carried out. Based on the analysis undertaken, current research processes in this field can be verified. This enabled the further evaluation of the research methodologies studied, including the identification of basic assessment elements for shoreline extraction accuracy. Practical aspects of this work include the ability to establish the correct methods to assess the accuracy of extracted shorelines for both research and production processes related to data extracted from remotely sensed images.

Introduction

The knowledge of accurate shoreline location is essential both globally and regionally. Information on the geometric profile of continental coasts, including Antarctica, is important for shipping and aviation (Liu & Jezek, 2004a), and may be an important climate indicator too (Mercer, 1978; Williams, Ferrigno & Foley, 1995). Changing climatic conditions, contributing to climate warming, lead to changes in water levels and glacier melting, and consequently to flooding in areas below sea level. In this context, shoreline mapping by Liu & Jezek (Liu & Jezek, 2004a) was the first mission for mapping Antarctica and required 30 days in 1997 by the Canadian RADARSAT-1 (Jezek, 1999). This mission was essential for future research in this area and for studying climate change.

Shoreline mapping is essential for the economic activity of coastal areas, required for planning and executing investment projects in its vicinity. Shoreline monitoring, especially in erosion-affected places indicated from historical reference data, enables the planning of shore strengthening and protecting projects, to prevent coastal erosion. Based on historical data, the size of flood tides and storms can be simulated, and these results are useful for specifying shore-protecting measures (Yang, Hwang

& Cordell, 2012). The knowledge of accurate shoreline locations is also used in marine and inland transport which relies on navigational charts.

On the regional scale, shoreline mapping is used for a slightly different task. For instance, actions related to flood risk maps and flood hazards maps. EU countries are obliged by the Directive 2007/60/EC (European Commission, 2007) to establish such maps. The significance of making flood risk and hazard maps is confirmed by data from the Atlas of the Human Planet 2017, which indicates that approximately one billion of the world's population in 155 countries are exposed to floods (Pesaresi et al., 2017). At a national level, the importance of shoreline mapping lies in the need to create widely used hydrographic maps, necessary in projects such as water supply, site design of industrial estates, hydropower stations, and irrigation/melioration projects or spatial development planning. At a regional level, from the viewpoint of the real estate cadastre map in Poland, surface flowing waters are one of its elements. Therefore, based on current shoreline data, cadastral maps, are a main source of data for land boundaries and should be continuously updated (Mika, Siejka & Leń, 2016). To date, shorelines are the subject of many studies which have had various objectives, from global glacier range monitoring to the accurate determination of the shoreline for real estate records. A growing number of available high-resolution satellite platforms and algorithms for developing these data have permitted new research to be conducted for terrain mapping, and shorelines in particular (Alicandro et al., 2019).

Today there is a great variety of surveys, different interpretations, and definitions of the shoreline as a geographical object, with the use of different remote sensing materials, different approaches, and methods to acquire them with different survey objectives and methods to assess accuracy. However, research into automatic shoreline extraction sometimes lacks research into the accuracy obtained and often the practical use of the materials obtained. Thus, this paper considers different types of remote sensing data from shoreline extractions, along with the different shoreline types, to analyze the parameters used for the qualitative and quantitative analyses used to assess the accuracy of shoreline extraction. This paper also draws attention to the importance of carrying out such assessment in order to obtain reliable extraction products that can be used for more precise purposes, e.g. production of electronic navigation charts. The reference materials used as a basis for qualitative evaluation of the obtained products are also presented. Finally, the results of the analysis performed are summarized.

Shoreline definition

The most common definition of a shoreline, most frequently found in the literature, says that it is the boundary between land and water (Boak & Turner, 2005). This definition is not precise, because it does not consider variations of the shoreline in time and refers only to its instantaneous state. The shoreline is characterized by short-term and long-term variability. The changeable nature of the shoreline is affected by wave motion, tides, wind, erosion, deposition, stormy waves, and sediment accumulation (Alicandro et al., 2019). The problem of shoreline detection and extraction is widely discussed in scientific publications. Because the shoreline varies in time, the problem of its detection and the continuous updating of existing datasets requires creating new algorithms, which apart from detecting the instantaneous state of the land-water interface, also takes into account time-based changes. A common error made by scientists is to assume that the instantaneous line represents standardized or average conditions of its occurrence in each area (Boak & Turner, 2005). However, such data may be adjusted in the future by using data on tides in the examined coastal areas (Alicandro et al., 2019). A study by Li et al. (Li, Ma & Di, 2002) claims that in practice the instantaneous shoreline cannot be directly used for mapping a real shoreline, navigation, or quantitative determination of shoreline changes. These authors introduce a concept of a tide coordinated shoreline (TCS), which in practice means that there is a reference shoreline related to the vertical reference system, used for the determination of shoreline changes.

As can be noted, the term coastline is only apparently simple. The terms "coastline" and "shoreline" are often used interchangeably and are defined as the instantaneous boundary between water and land (Braga et al., 2013). Subotowicz (Subotowicz, 2018) defines the shore as a zone of sea-land interaction, where on the part of the sea the factors influencing the land are hydrodynamic, while on the part of the land these are geodynamic and morphodynamic factors. Boak and Turner (Boak & Turner, 2005), to precisely define the shoreline term, identified 45 indicators and divided them into three groups: visual (visible by the operator on the image), tidal (referring to the intersection between the tide data and the digital terrain model or shore profile), digital (identified by automatic algorithms). Toure et al.

(Toure et al., 2019) divided shoreline indicators into seven groups: geomorphological reference lines, vegetation limits, instant tidal levels, instant wetting limits, tidal data, beach contours, storm lines. As mentioned by Boak and Turner (Boak & Turner, 2005) and Toure et al. (Toure et al., 2019), the use of indicators is particularly important when analyzing changes in the shoreline over time. The authors of these publications agree that, depending on the purpose of the work chosen, it is not always possible to use the same indicator.

In coastal engineering and shoreline management, a more technical definition of a shoreline is described. Mangor et al. (Mangor et al., 2017) define the coastline as a technical line marking the boundary between the coast and the shore. In the case of a shoreline, it is the line of intersection between mean high water and shore.

It should also be mentioned that the shoreline is often modified by man. In this case, we can distinguish two types of modification (Walker, 1988): stabilization of the shoreline in the existing position and displacement of the shoreline. The displacement can be seaward and landward and is combined with the stabilization of the structure. Shoreline modifications using artificial structures are often driven by the need to protect vessels entering and leaving ports and to protect shorelines from erosion. Artificial structures can include breakwaters, seawalls, dikes, and many others, which can be adapted to protect a particular type of coastline. Cliff coasts are particularly affected by erosion and require artificial protection.

The recognition and identification of shorelines also depends on the type of shore. In general, there are three categories of shorelines: oceanic, marine, and inland. In nature, there is an even greater variety of shores, such as: mangroves, swamps, freshwater marshes, research planning sheltered tidal flats, sheltered man-made structures, sheltered rocky shores, exposed tidal flats, riprap structures, gravel beaches, mixed sand and gravel beaches, coarse-grained sand beaches, fine-grained sand beaches, exposed rocky platforms, exposed rocky shores (NOAA Office of Response and Restoration, 2021). In addition, dynamic changes in the position of the shoreline should be considered. Such changes may be caused by shore flooding by waves, shoreline ambiguity in wetlands, high tides, extreme weather conditions (typhoons, tsunamis), and the presence of different aquatic and land vegetation. These factors result in a more variable boundary between water and land and in some cases may even cause an unambiguous definition of the shoreline. The results of the analysis carried out in this study allow for the selection of appropriate methods to assess the accuracy of the shoreline extracted from image data.

Material

In this study, the authors used research publications that are based on different types of data and contain different types of coastlines. The analyzed publications were from 2004 and between 2010–2020. In the selected publications, shoreline extraction was performed on the following data: optical satellite (Liu & Jezek, 2004b; Shi et al., 2010; Liu et al., 2011; Yin & He, 2011; Khurshid & Khan, 2012; Pardo-Pascual et al., 2012; Braga et al., 2013; Jiang et al., 2014; Maglione, Parente & Vallario, 2014; Sekovski et al., 2014; Aedla, Dwarakish & Reddy, 2015; Liu et al., 2017; Paravolidakis et al., 2018; Alicandro et al., 2019; Bishop-Taylor et al., 2019; Dai et al., 2019, Zhu et al., 2019), radar satellite (Liu & Jezek, 2004a; Liu & Jezek, 2004b; Liu et al., 2011; Baselice, Ferraioli & Pascazio, 2012; Latini et al., 2012; Braga et al., 2013; Zhang et al., 2013; Ferrentino, Nunziata & Migliaccio, 2017; Lubczonek, 2017; Modava & Akbarizadeh, 2017; Bruno et al., 2019), airborne optical (Bayarm et al., 2015; Paravolidakis et al. 2018), laser scanning data (Liu et al., 2011; Xu, Ye & Xu, 2019), and low altitude optical data (Wilkowski et al., 2017; Templin, Popielarczyk & Kosecki, 2018; Huang, Zhang & Zhao, 2020). The most numerous group of analyzed data was optical satellite data, and radar satellite data was slightly smaller. Table 1 summarizes the analyzed publications by data type and year of publication.

Table 1. Graphical summary showing the analyzed publications in relation with publication year and the data type used

	Optical Satellite	Radar Satellite	Aerial	LiDAR	UAV
2004	1	2	0	0	0
2010	1	0	0	0	0
2011	2	1	0	1	0
2012	2	2	0	0	0
2013	1	1	0	0	0
2014	3	0	0	0	0
2015	1	0	1	0	0
2016	0	0	0	0	0
2017	1	3	0	0	1
2018	1	0	1	0	0
2019	5	1	0	1	1
2020	0	0	0	0	1

Note: The color scale used is shown below:

0	1	2	3	4	5

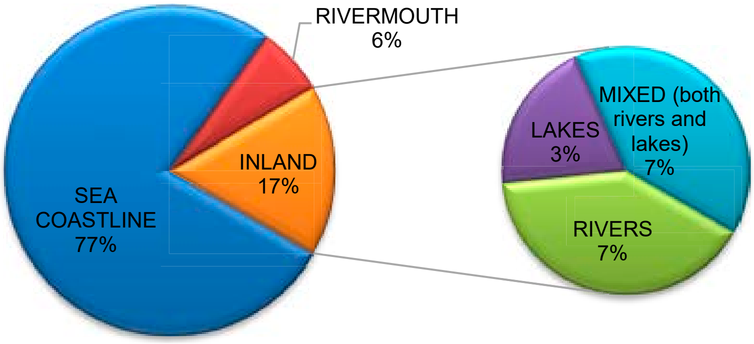

Figure 1. Categorization of the analyzed data by types of shorelines

Figure 1 shows the publications analyzed representing coastline diversity. Data representing the coastline of the sea are the most numerous group (77%). Areas representing river mouths (6%) and inland shorelines i.e., rivers and lakes (17%) were also analyzed.

Accuracy assessment methods

Two aspects of shorelines can be analyzed: visually, by comparing the results obtained by comparing the obtained shoreline extraction results to reference data, and numerical, where certain

Table 2. Type of qualitative assessment

Publication	Digitization	Measurements	Method	Other reference data	None	Other
Liu & Jezek, 2004a	x					
Liu & Jezek, 2004b				x		
Shi et al., 2010			x			
Liu et al., 2011	x					
Yin & He, 2011		x				
Baselice et al., 2012						x
Latini et al., 2012		x	x			
Khurshid & Khan, 2012	x					
Pardo-Pascual et al., 2012	x					
Braga et al., 2013	x	x				
Zhang et al., 2013	x		x			
Jiang et al., 2014	x		x			
Maglione et al., 2014	x					
Sekovski et al., 2014	x			x		
Aedla et al., 2015					x	
Bayram et al., 2015	x					
Ferrentino et al., 2017	x	x	x			
Liu et al., 2017	x		x			
Lubczonek, 2017				x		
Modava & Akbarizadeh, 2017	x		x			
Wilkowski et al., 2017		x				x
Paravolidakis et al., 2018		x				
Templin et al., 2018		x				
Alicandro et al., 2019	x					
Bishop-Taylor et al., 2019	x					
Bruno et al., 2019		x				
Dai et al., 2019				x		
Xu et al., 2019	x		x			
Zhu et al., 2019	x		x			
Huang et al., 2020	x					
Total	18	8	9	4	1	2

indicators and errors will precisely estimate the level of accuracy and reliability of the results and whether they are acceptable and in line with the assumed objectives.

Qualitative analysis

Methods of qualitative verification of the shoreline often utilize a reference line obtained manually by an experienced operator. A similar method is to obtain a verification reference line using data with better spatial resolution than data from the extraction; such a case can be found in Liu et al. (Liu et al., 2017). Another qualitative assessment method is a comparison of one method to another method that usually achieves good results during extraction, as in publications (Paravolidakis et al., 2018), where the results are compared to the results of the method proposed by Liu and Jezek (Liu & Jezek, 2004b). The next qualitative verification method is a comparison of the shoreline with terrain measurements, e.g., obtained by RTK technique. Templin et al. (Templin, Popielarczyk & Kosecki, 2018) found that classic techniques of RTK/GNSS are not always accurate due to the presence of vegetation, marshy areas and trees that hinder the proper identification of the shoreline in the field. Table 2 shows the type of qualitative assessment used in the analyzed publications, and the last row of the table shows the totals representing the popularity of the method.

Quantitative analysis

Quantitative analysis aims to numerically present the accuracy of the information obtained. This is particularly important if shoreline extraction is to be done for a specific purpose including the imposed accuracy standards. The following presents the accuracy indicators found in the examined articles.

Statistical methods were found to be relatively common in literature. One of the most common accuracy metrics for the determined shoreline was the root mean square error (RMSE), i.e., the absolute accuracy of the extracted shorelines compared to the reference shoreline. Other common accuracy measures are mean error and standard deviation. The formulas for the mean error and RMSE are shown below (where e denotes the difference between the reference and the calculated value, expressed in terms of distance):

$$\text{mean} = \frac{1}{n}\sum_{i=1}^{n} e_i \tag{1}$$

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(e_i\right)^2} \tag{2}$$

Zhang et al. (Zhang et al., 2013) used two additional measures in addition to the common statistical indices to assess accuracy, which represents the proximity between the test line and the true coastline. These indicators are P_{GSD} – the percentage of the testline within 1-pixel distance and $D_{90\%}$ – the distance within which 90% of the testlines are included.

When studying shoreline variability over time, transects can be used as a measure of accuracy (lines perpendicular to the baseline), automatically determined by the digital shoreline analysis system (DSAS) program. The transect method was first proposed by Dolan et al. (Dolan, Hayden & Heywood, 1978), to determine the degree of shoreline recession. The extension to ArcGIS referred to as DSAS was developed by Himmelstoss et al. (Himmelstoss et al., 2018) to automate the process of shoreline change calculations.

The accuracy and comparison of classification results are based on accuracy indicators calculated based on a confusion matrix obtained for resultant images of subsequent classifications. The following indicators for classification accuracy assessment were considered (calculated by using the confusion matrix):

1. The overall accuracy (A_{OV}) of classification, is a quotient of the sum of pixels classified correctly and the total number of pixels:

$$A_{OV} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{FN} + \text{FP} + \text{TN}} \tag{3}$$

where:
TP – true positive, hit;
TN – true negative, correct rejection;
FP – false positive, overestimation;
FN – false negative, underestimation.

2. Cohen's kappa coefficient (κ,), equals a maximum of 1 for a situation where there is full consistency between the ground truth image (i.e., a test image and an image after classification). 0 indicates that the conformity obtained corresponds to a level of random conformity (it is not better than the random assignment of pixels), while values between 0.8 and 1 mean very good conformity between the expected and observed values (Pais-Barbosa et al., 2011). The indicator can be considered as a general accuracy measure (all classes) or regarded as an indicator of conditional conformity as it can function as an accuracy measure for each class separately.

$$\kappa = \frac{A_{OV} - P_e}{1 - P_e} \tag{4}$$

where:

$$P_e = \frac{(\mathrm{TP}+\mathrm{FN})(\mathrm{TP}+\mathrm{FP})+(\mathrm{FP}+\mathrm{TN})(\mathrm{FN}+\mathrm{TN})}{(\mathrm{TP}+\mathrm{FN}+\mathrm{FP}+\mathrm{TN})^2} \tag{5}$$

3. The producer's accuracy (A_P), is expressed by the ratio of pixels correctly classified in a given class to the total number of pixels of that class in reference data.

$$A_P = \frac{\mathrm{TP}}{\mathrm{TP}+\mathrm{FN}} \tag{6}$$

4. User accuracy (A_U), is the quotient of pixels correctly classified in the class to the total number of pixels of that class on an image being verified.

$$A_U = \frac{\mathrm{TP}}{\mathrm{TP}+\mathrm{FP}} \tag{7}$$

5. Omission error ($\mathrm{Err_O}$), expresses the ratio of the number of incorrectly classified pixels to the number of pixels of that class obtained from true data (i.e., the sum in the corresponding column).

$$\mathrm{Err_O} = \frac{\mathrm{FN}}{\mathrm{TP}+\mathrm{FN}} \tag{8}$$

6. Commission error ($\mathrm{Err_{CO}}$), is the ratio of pixels incorrectly classified to pixels classified within the examined class.

$$\mathrm{Err_{CO}} = \frac{\mathrm{FP}}{\mathrm{TP}+\mathrm{FP}} \tag{9}$$

7. F-measure ($F1$ Score), is the mean harmonic of producer and user accuracies.

$$F1 = \frac{2A_U A_P}{A_U + A_P} \tag{10}$$

The accuracy assessment based on these indicators is presented in (Khurshid & Khan, 2012; Sekovski et al., 2014; Templin, Popielarczyk & Kosecki, 2018; Zhu et al., 2019).

Metrics based on feature-length rather than pixel-by-pixel comparison are used to assess the accuracy of features such as narrow rivers. Such metrics are used by Jiang et al. (Jiang et al., 2014), which uses the metrics: completeness (CMP), correctness (CRT) and quality (Q) described by formulas (11), (12) and (13), proposed by Wiedemann et al. (Wiedemann et al., 1998).

8. Completeness

$$\mathrm{CMP} = \frac{\text{length of matched reference}}{\text{length of reference}} \approx \frac{\mathrm{TP}}{\mathrm{TP}+\mathrm{FN}} \quad \text{(for low redundancy)} \tag{11}$$

9. Correctness

$$\mathrm{CRT} = \frac{\text{length of matched extraction}}{\text{length of extraction}} \approx \frac{\mathrm{TP}}{\mathrm{TP}+\mathrm{FP}} \tag{12}$$

10. Quality

$$Q = \frac{\text{length of matched extraction}}{\text{length of extraction} + \text{length of unmatched reference}} \approx \frac{\mathrm{TP}}{\mathrm{TP}+\mathrm{FP}+\mathrm{FN}} \tag{13}$$

In Liu et al. (Liu et al., 2017) the accuracy analysis is based on several aspects. One of these aspects is the assessment of pan-sharpening accuracy (i.e., sharpening using a panchromatic image). 10 various algorithms were tested, and to assess and compare them QNR indicators were used (quality with no reference), D_S (spatial distortion) and D_λ (spectral distortion), proposed by Alparone et al. (Alparone et al., 2008).

Accuracy assessment in Maglione et al. (Maglione, Parente & Vallario, 2014) is composed of two stages. The first stage examines the quality of fitness, based on an ERGAS error (*Erreur Relative Globale Adimensionnelle de Synthèse*) that serves to assess the quality of pansharpening of an image (Wald, 2000). A lower value of this indicator means better fitness, so in the case of ideal fitness, the value of this indicator should be 0. Sharpening is also assessed via the coefficient of correlation (ρ) between the original image and the derivative one, proposed in Parente and Santamaria (Parente & Santamaria, 2013).

$$\mathrm{ERGAS} = 100\frac{h}{l}\sqrt{\frac{1}{K}\sum_{k=1}^{K}\left(\frac{\mathrm{RMSE}(k)}{\mu(k)}\right)^2} \tag{14}$$

where:

h/l – ratio between the sizes of pixels Pan and original multispectral images,

$\mathrm{RMSE}(k)$ – root mean square error of k-th band,

$\mu(k)$ – mean from k-th band.

The accuracy was assessed using the formula proposed by Guastaferro et al. (Guastaferro et al., 2011).

This indicator is based on a comparison of surface areas of polygons which are formed by a non-ideal overlay of the reference and extracted lines.

$$I = \frac{S}{L} \tag{15}$$

where:

S – total area of the polygon,

L – length of reference shore (manually vectorized).

Another qualitative assessment method used in Modava and Akbarizadeh (Modava & Akbarizadeh, 2017) and Bruno et al. (Bruno et al., 2019) is the neighborhood pixels method. This method estimates the distance between the extracted edge line and a reference line (e.g., from GPS measurements, manually digitized).

The results of the analysis are presented in Table 3, which presents quantitative indicators occurring in the examined publications.

Table 3. Summary of quantitative indicators occurring in the examined publications

	Aedla et al., 2015	Bayram et al., 2015	Bishop-Taylor et al., 2019	Braga et al., 2013	Bruno et al., 2019	Dai et al., 2019	Ferrentino et al., 2017	Huang et al., 2020	Jiang et al., 2014	Khurshid & Khan, 2012	Latini et al., 2012	Liu & Jezek; 2004a	Liu et al., 2011	Liu et al., 2017	Lubczonek, 2017	Maglione et al., 2014	Modava & Akbarizadeh, 2017	Paravolidakis et al., 2018	Pardo-Pascual et al., 2012	Sekovski et al., 2014	Templin et al., 2018	Wilkowski et al., 2017	Xu et al., 2019	Zhang et al., 2013	Zhu et al., 2019	Total
RMSE			x		x			x				x	x					x	x					x		8
MIN		x						x						x	x											4
MAX		x						x						x	x				x							5
Mean		x			x		x	x			x	x		x	x				x					x		10
ST.DEV		x	x		x		x	x			x				x											7
DSAS	x													x						x						3
A_U									x	x										x			x		x	5
A_P									x	x										x			x		x	5
κ									x											x		x				3
Err_O									x											x						2
Err_{CO}									x											x						2
A_{OV}									x											x		x				3
CMP									x																	1
CRT									x																	1
Q									x																	1
$F1$																									x	1
$D_{90\%}$																								x		1
P_{GSD}																								x		1
H_P						x																				1
D_S														x												1
D_λ														x												1
QNR														x												1
H_D				x																	x					1
V_D																					x					1
ERGAS																x										1
I, ρ																x										1
NP					x												x									2

Note: RMSE – root mean square error, MIN – minimum error, MAX – maximum error, MEAN – mean error, ST.DEV – standard deviation, DSAS – DSAS indicator, A_U – user's accuracy, A_P – producer's accuracy, κ – kappa coefficient, Err_O – omission error, Err_{CO} – commission error, A_{OV} – overall accuracy, CMP – completeness, CRT – correctness, Q – quality, $F1$ – F1 score, $D_{90\%}$ – the distance within which 90% of the testline are included, P_{GSD} – percentage of the testline within 1-pixel distance, H_P – horizontal positioning accuracy, D_S – spatial distortion, D_λ – spectral distortion, QNR – quality with no reference, ERGAS – overall relative synthetic error, I – accuracy indicator , ρ – correlation coefficient, H_D – horizontal differences, V_D – vertical differences, NP – neighborhood pixel.

Summary

Current technologies for image data acquisition are developing rapidly, so it is important to know how to select appropriate methods for assessing the accuracy of mapping topographic objects, including the shoreline. This paper reviews current qualitative and quantitative assessment methods used in shoreline extraction from remotely sensed data. The presented results of the analysis can be used in the processes of assessing the accuracy of geodata in production processes using image processing. Based on the analysis, it was shown that reference materials used or performed quantitative evaluations are not always clearly indicated. Without such analyses, despite the presence of efficient extraction methods, it is difficult to point out the practical use of such methods. Figure 2 summarizes the most important elements of the shoreline extraction accuracy evaluation process in a flowchart form. Three elements can be distinguished in the accuracy evaluation: selection and acquisition of reference data, qualitative evaluation, and quantitative evaluation. This diagram shows the elements of accuracy analysis that should be taken into account during research and in production processes.

The first element is the reference data, as it is used for both quantitative and qualitative assessment, therefore it should have appropriate accuracy. The most suitable choice should be data from national geodetic resources, as these data are compiled according to specific standards and guidelines and have a legal character. If the reference data comes from other sources, it is difficult to unambiguously assess their usefulness in accuracy assessments. For example, reference lines extracted often during the manual digitization of the same materials used for their extraction will not produce absolute accuracies for the extracted shoreline product. "Ground truth" data refers to information collected in the field and permits a pixel-by-pixel analysis of the image. Such reference data, together with a qualitative analysis performed via error matrix indicators, enable the comprehensive evaluation of the obtained data. RTK measurements may also be a reliable source of reference data. However, the dynamic nature of the shoreline should be taken into account and field data should be acquired in the same period as the image data.

The second element for accuracy assessment is a qualitative assessment. It is usually carried out visually by an experienced operator and the quality of the assessment depends mainly on the reference

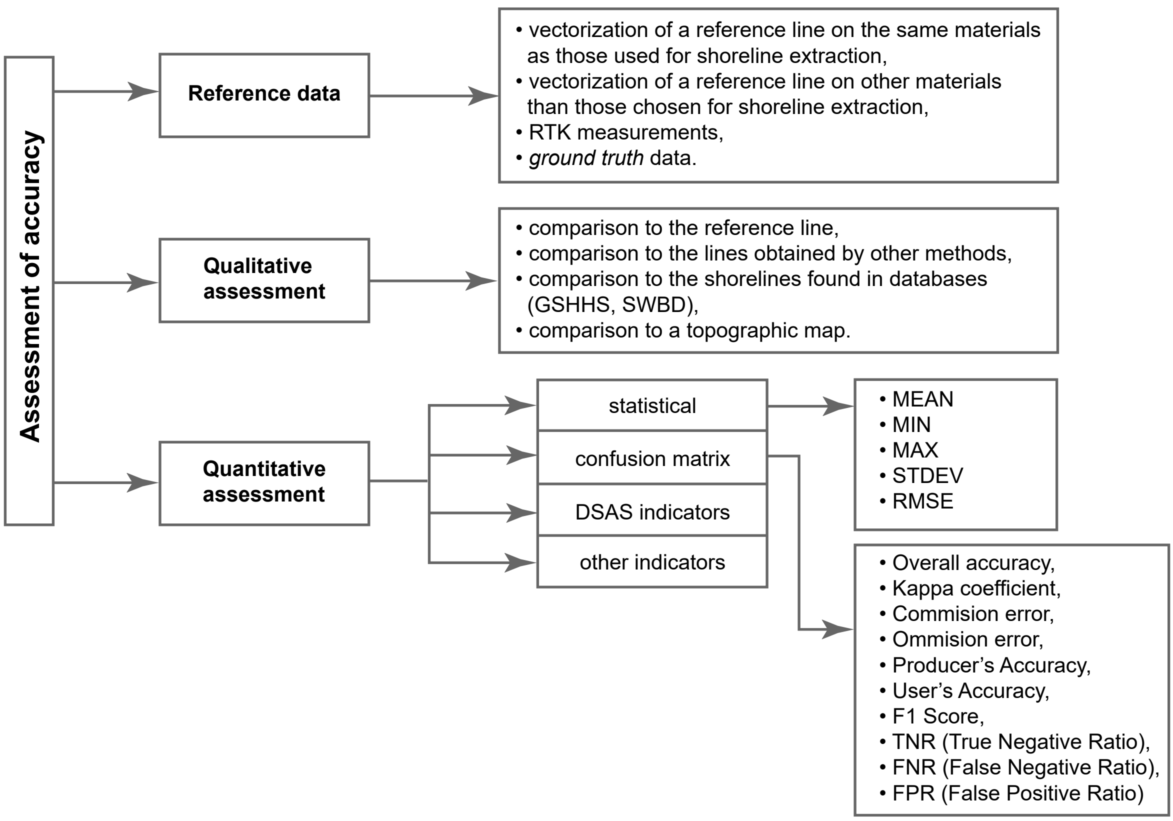

Figure 2. Key steps in evaluating the accuracy of shoreline extraction

materials. Different materials are used for qualitative assessment, such as: manually digitized coastlines extracted on the same image material as the reference data, manually digitized coastlines extracted on material other than that used for coastline extraction, comparison to coastlines derived from national databases or to existing topographic maps. The qualitative analysis carried out indicated that the most frequently used reference data came from manual digitization (70%). Reference data obtained can also be used for quantitative analysis (e.g., calculations of DSAS indicators). GNSS measurements are quite frequently used as reference data (33%) as well as in comparison to another method (30%). It is worth noting that 33% of the reference data undergoes double verification based on more than one type of verification.

The third step in assessing accuracy is a quantitative assessment. The quantitative assessment parameters are grouped into four categories. The first includes statistical indices, the second considers indices based on the confusion matrix, the third indices calculated using the DSAS overlay, and the fourth other methods, such as the neighborhood pixel method. In the analyzed publications the most common statistical indicators are: mean error (33%), RMSE (27%), standard deviation (23%). The most common confusion matrix errors are: user accuracy and producer accuracy (17%). The DSAS indicator is used in 10% of the publications assessed. These indicators are described in detail in the *Quantitative analysis* section.

There are many components to the complexity of conducting a proper shoreline extraction accuracy assessment. The research performed in this study indicates possible methods to assess the accuracy of the extracted shorelines. It should also be emphasized that the choice of reference materials will affect the results obtained. A quantitative analysis, only based on comparisons to the digitized shoreline, will give relative results because reference data are subject to errors. Field measurement was found to be the most accurate reference method. However, taking into account the dynamic nature of the shoreline object and the necessity to take measurements while obtaining image data, obtaining such reference materials may be a difficult task. Without proper verification of the extracted product's accuracy, it is not possible to indicate its specific use. It should also be noted that the tests for shoreline extraction methods from image data may be conducted by people representing various areas of science (e.g., geographers, hydrologists, IT or geoinformatics specialists), who may not be quite familiar with some methods of verification. Considering the diversity of the methods used, it is difficult to determine one possible accuracy assessment method. However, the appropriate selection and careful preparation of reference materials is essential during quantitative analysis calculations.

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