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Performance Comparison of the Cogent Confabulation Classifier with Other Commonly Used Supervised Machine Learning Algorithms for Bathing Water Quality Assessment

Antonia Ivanda, Ljiljana Šerić, Maja Braović and Darko Stipaničev

University of Split, Faculty of Electrical Engineering, Mechanical Engineering and Naval Architecture, Croatia

The purpose of this study was to implement a reliable model for bathing water quality prediction using the Cogent Confabulation classifier and to compare it with other well-known classifiers. This study is a continuation of a previously published work and focuses on the areas of Kaštela Bay and the Brač Channel, located in the Republic of Croatia. The Cogent Confabulation classifier is a thorough and simple method for data classification based on the cogency measure for observed classes. To implement the model, we used data sets constructed of remote sensing data (band values) and *in situ* measurements presenting ground-truth bathing water quality. Satellite data was retrieved from the Sentinel-3 OLCI satellite and it was atmospherically corrected based on the characteristics and specifications of band wavelengths. The results showed that the Random Forest, K-Nearest Neighbour, and Decision Tree classifiers outperformed the Cogent Confabulation classifier. However, results showed that the Cogent Confabulation classifier achieved better results compared to classifiers based on Bayesian theory. Additionally, a qualitative analysis of the four best classifiers was conducted using spatial maps created in the QGIS tool.

ACM CCS (2012) Classification: Computing methodologies → Machine learning → Machine learning algorithms

Computing methodologies → Artificial intelligence → Computer vision → Computer vision problems

Computer systems organization → Architectures → Distributed architectures → Cloud computing

Information systems → Information systems applications → Spatial-temporal systems → Geographic information systems

Information systems → Information systems applications → Decision support systems → Data analytics

Keywords: cogency, confabulation, Sentinel-3, OLCI, machine learning

1. Introduction

Bathing sites in coastal areas are the main places for recreational activity during the summer period for many people. This type of activity provides a number of benefits for human health, both psychological and physical. Many countries generate a lot of income based on this activity and create jobs through coastal tourism. However, microbial contamination of bathing water poses a serious risk to public health, thus jeopardizing the health and economic benefits associated with bathing. Moreover, contamination of bathing water is most often caused by wastewater from sewage, agricultural runoff, or accidental discharge from the city sewage sources [1].

To actively monitor and classify bathing water quality, and provide information to the public for the purpose of protecting human health, the European Union adopted the Bathing Water Directive (BWD) 2006/7/EC [2].

According to the BWD, member states must monitor at least two microbiological parameters of faecal bacteria (*e.g.* Escherichia coli and Intestinal Enterococci). This Directive also complements the EU Water Framework Directive (WFD) and the EU Marine Strategy Framework Directive (MSFD). *In situ* measurements are usually expensive, weather dependent, and time consuming. Additionally, these measurements are not performed every day, so the measured bathing water status may change before the next scheduled measurement. Water quality monitoring by performing *in situ* sampling is an important factor in environmental sustainability, but it should consider other methods and sources of data to achieve timely and yet less expensive information on water quality status.

This work is a continuation of the previously published work [3] and aims to continuously assess the state of bathing water quality for the area of the Kaštela Bay and the Brač Channel. This research used a larger data set than the one in the previous study. In addition, to accurately predict bathing water quality and achieve better data quality, a custom pixel-level atmospheric correction was used for satellite data. For the quantitative analysis and prediction of bathing water quality, the same algorithms as in the previous study were used in order to be able to compare the results. The focus of this paper is on a data-driven model based on the Cogent Confabulation Classifier, which achieved the best results in previous research. The Cogent Confabulation theory was introduced by Robert Hech-Nielsen in 2005 [3], where he proposed a new model of vertebrate cognition – the maximisation of cogency. According to Hech-Nielsen's theory, the confabulation could be cogent if the fundamental theorem of cognition is exploited by using certain restrictions (*e.g.*, proper lexicons and knowledge). It was proposed as a new model of the fundamental mechanism of all aspects of cognition (vision, hearing, planning, movement, *etc.*). In this paper, except quantitatively as was the case in the previously published paper, the results are presented and described qualitatively using spatial maps. As in the previous paper, the aim of this study is to predict bathing water quality based on collected data – *in situ* and remote sensing data.

In situ data on sea bathing water quality in Croatian beaches is measured and publicly released by the Ministry of Environment and Energy of the Republic of Croatia [5].

Remote sensing can be used for environmental monitoring, especially in monitoring bodies of water such as lakes, seas, and oceans [6], because other data collection methods, such as the use of boats and buoys, are expensive, weather-dependent, and difficult to maintain. In addition, remote sensing provides different types of data, such as panchromatic, multispectral, hyperspectral, and Synthetic Aperture Radar (SAR) data, which depend on the characteristics of the sensors installed on the satellite.

The collected remote sensing data used in this study was the Sentinel-3 satellite imagery acquired using the Ocean and Land Colour Instrument (OLCI), which is considered to be the predecessor of the Medium Resolution Imaging Spectroradiometer (MERIS) instrument hosted on Envisat. The OLCI was designed for ocean monitoring and is placed on the Sentinel-3 satellite along with the Sea and Land Surface Temperature Radiometer (SLSTR) instrument. The combination of data from the OLCI and the SLSTR on the same date of the captured image, known as data fusion, enables more accurate predictions of bathing water quality. OLCI provides images with a spatial resolution of 300 m and a temporal resolution of two days (global coverage at the equator) [6]. It has a total of 21 spectral bands ranging from the visible to the near infrared (400 nm to 1020 nm) of the electromagnetic spectrum [7].

With an explained approach the main goal of this study is to see whether the proposed data-driven model can be used to assess the bathing water quality of the beaches of the Republic of Croatia quickly and accurately.

The rest of this paper is organized as follows. First, we outline the application of remote sensing and machine learning methods to assess water quality status. Then the methodology of collecting data and how the Cogent Confabulation classifier can be used to predict bathing water quality is described. Finally, the results of quantitative and qualitative analysis are discussed as proof-of-concept, as well as ideas for future work related to this developed prototype for the classification of bathing water quality.

2. Related Work

2.1. Remote Sensing

Bathing water quality is influenced by numerous optical and non-optical parameters, which are usually monitored through on-site water sampling. Coastal bathing water quality is often assessed based on on-site measurements that analyse the presence of bacteria such as Escherichia Coli, Intestinal Enterococci, Total Coliforms, and Faecal Coliforms [2]. The disadvantage of this approach is that all *in situ* measurements can provide information only for the sampling location. To obtain information on the water quality for the entire coastal bathing area, lakes, or seas, many studies propose water quality prediction models that use remote sensing data together with *in situ* measurements [8]–[11].

The selection of suitable satellite data is based on its characteristics and limitations. Temporal, spatial, spectral, and radiometric resolution are considered the most common criteria for selecting suitable satellite images. In many studies, the focus is usually on the detection of optical parameters such as chlorophyll (Chl-a) [12], [13], coloured dissolved matter (CDOM) [12], [14], total suspended matter (TSM) [12], [15]–[17] or turbidity. These parameters were obtained using different satellite products obtained by MODIS, Sentinel-2, Sentinel-3, Landsat-8, and MERIS satellites. However, in addition to optical parameters, physical parameters such as temperature, total phosphorus (TP) and total nitrogen can be measured [18], [19]. For example, the study [20] described obtaining temperature using Landsat-8 TIRS satellite images, which were then compared using different bacterial parameters to obtain bathing water quality.

Remote sensing can be a valuable source of data as an answer to the limitations of traditional methods where collecting and interpreting information about remote objects can be performed without physical contact with the object.

2.2. Algorithms

There are many examples of using machine learning (ML) methods to retrieve water quality status using remote sensing and *in situ* data. A well-written summary of the most used ML methods is presented in [21]. The authors conducted a study of all the literature published between 2001 and 2021 on the application of ML methods to estimate water quality parameters from satellite data. They concluded that the most common machine learning methods for water quality monitoring (regional and global) are Artificial Neural Networks (ANN), Support Vector Machines (SVM), Random Forest (RF), Decision Tree (DT), Multilayer Perceptron Neural Networks (MLP), Cubist, and Genetic Programming (GP). To the best of the knowledge of the authors of this study, there are no records of articles that use the Cogent Confabulation Classifier to retrieve water quality status.

In [22] and [23], the authors address the segmentation and classification of natural landscape images primarily for the purpose of wildfire smoke detection by using Cogent Confabulation Classifier. Furthermore, the authors in [24] suggest using a two-layered confabulation architecture for artificial creatures to select appropriate behaviours. They implemented an arbiter that decides on the most appropriate behaviour among suggested behaviours from the two confabulation layers. Also, the authors in [25] present an interesting work where they generated user data and matched the probability distribution giving it an additional qualification by using confabulation theory.

Based on these findings, we are motivated to apply this method on Sentinel-3 OLCI satellite imagery to retrieve the status of bathing water quality.

3. Methodology

3.1. Study Area

The study area addressed by this research (Figure 1) includes the Kaštela Bay and the Brač Channel, which are located near the town of Split in the south of the Republic of Croatia in Central-Southern Europe. The Kaštela Bay area is a more closed-off body of water compared to the Brač Channel where the sewage system has not been established properly. Also, this area is known throughout history for environmental contamination with elemental mercury, several heavy metals, and radionuclides mainly caused by the PVC factory Jugovinil [26]. According to this, there are more incidents in the Kaštela Bay, where the bathing water is of inferior quality and below the allowed levels.

The Republic of Croatia is a tourist country, especially in summer periods, when this area is a swimming destination for many tourists. So, examining the bathing water quality of the Adriatic Sea, especially in the summer months when there is a higher tourist activity, is necessary to protect human health and the environment.

3.2. Data Set

The data set used in this paper is a combination of *in situ* and satellite band values. The collected data is related to the summer season between June 1st and October 1st from 2016 to 2021. All of the retrieved data is free and publicly available.

3.2.1. In situ

Firstly, *in situ* data on bathing water quality is collected from the website "Sea bathing water quality in Croatia" [5] published by the Ministry of Environment and Energy, Croatia. The *in situ* data was collected using web scraping implemented in the Python programming language, where the only *in situ* data for the study area is extracted and processed. Each *in situ* measurement has a flag that describes the level of bathing water quality. There are four possible quality flags according to the Bathing Water Directive 2006/7/EC: "poor", "sufficient", "good" and "excellent" quality. More than 95% of the measurements were rated as "excellent" according to the results of the annual assessment of the quality of bathing water in Croatia carried out by the EU Directive for the period 2016-2021. In the absence of data diversity, the *in situ* data set was split into two categories: "good" and "poor". The "good" category represents all measurements rated as "excellent", and the "poor" category represents all other measurement ratings.

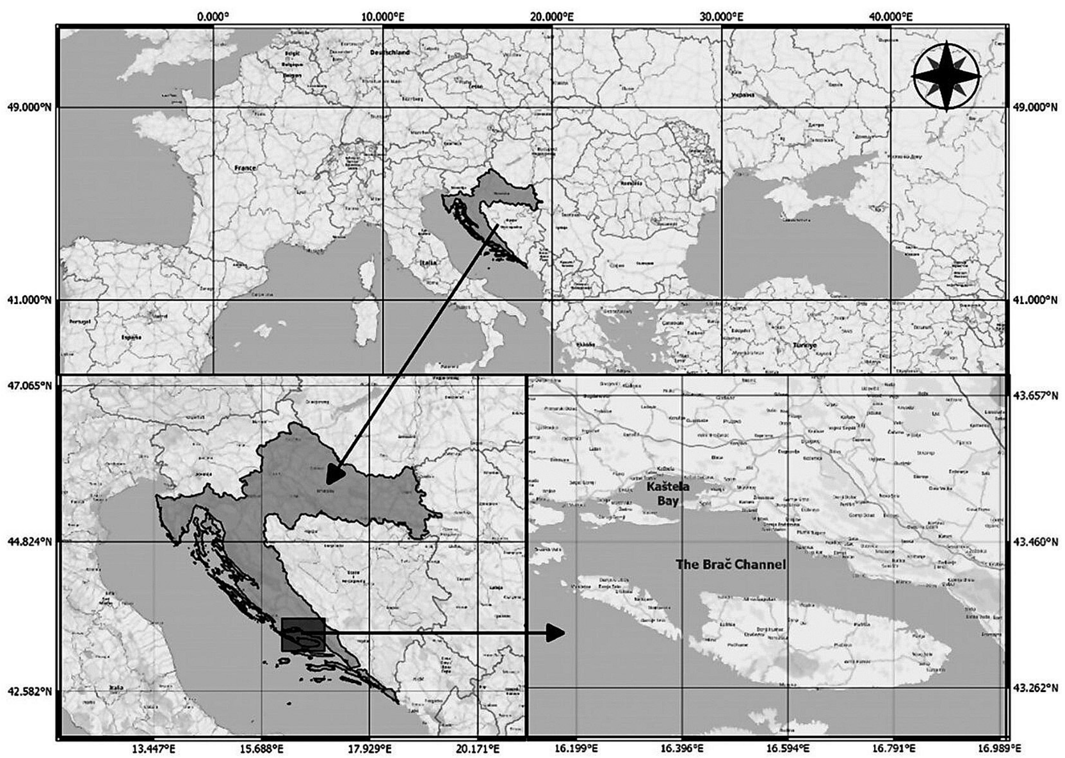

Figure 1. The study area – European context – national context (Republic of Croatia) – the Kaštela Bay and the Brač Channel.

3.2.2. Satellite Imagery

In this paper Sentinel-3 OLCI Level-1B satellite data was used, where all OLCI spectral bands have calibrated, ortho-geolocated, and spatially resampled Top of Atmosphere (TOA) radiances [27].

Satellite imagery georeferenced in the WGS 84 coordinate system (EPSG: 4326) was downloaded by using API from the Sentinel Hub EO Browser [28]. For the period of 1st of June 2016 to 1st of October 2021, we collected satellite scenes where each scene contained 21 spectral bands (B01-B21). Band values were extracted for every performed *in situ* measurement where there was available satellite data.

Some of the most common obstacles in the reliable classification of satellite scenes obtained by optical sensors are clouds and the atmosphere. However, Sentinel-3 does not have a convenient cloud mask. Therefore, in this study, the bands B16, B17, and B21, specific for atmospheric correction and clouds, were used. Satellite data was examined in QGIS and discovered that pixels of these bands that refer to land or clouds have values higher than 0.17. According to this, only those satellite data that have values under this threshold were considered to achieve a more confident data set. In Figure 2a comparison of true color image and bands B16, B17, and B21, on which threshold 0.17 was applied on each pixel, is presented. Satellite imagery describes the scene on the 30th of July 2022 when the scene was affected by clouds. It can be noticed that the land and clouds have black pixels whose values are above 0.17, while pixels related to the sea are white.

Finally, after the applied data correction, the data set is determined as:

Date | Quality rating | Bands B01-B21

The overall data set of 747 measurements was shuffled and divided into two subsets - train and test, where 33% of the data set is used as the test data. In Figure 3 a histogram of the overall data set presented by quality rating density can be seen. As it is mentioned in Section 2.2.1 there have been more than 95% of measurements rated as "excellent", so we downsampled this data set by reducing the size of this major class to get a more balanced data set. The size is reduced by removing measurements when there were more than seven measurements rated as "excellent" on the same date.

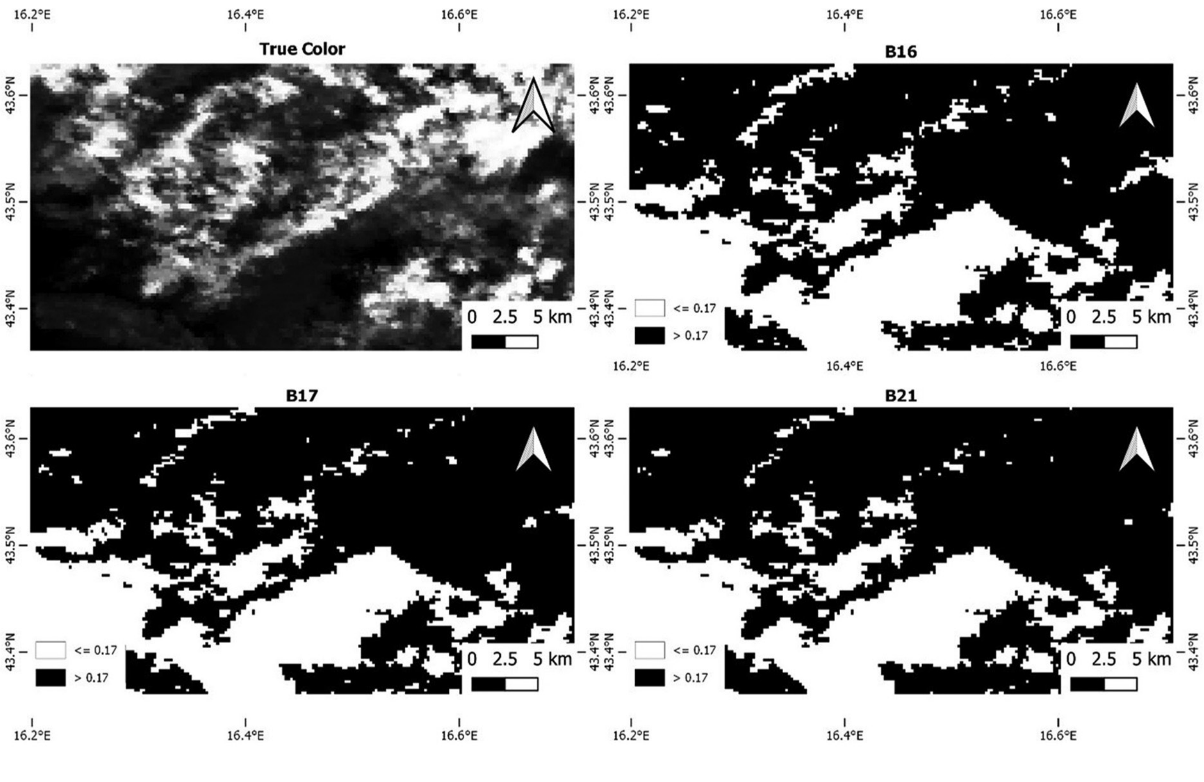

Figure 2. True colour map and B16, B17, B21 masks for the date 30th of July 2022 for the study area.

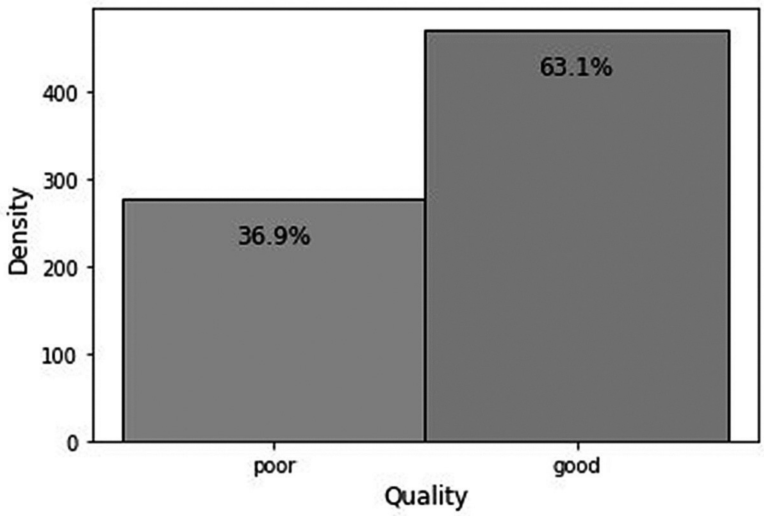

Figure 3. Data distribution based on bathing water quality.

3.3. Cogent Confabulation

Confabulation is the universal basic operation of thought. Hecht-Nielsen described in [29] that the term "confabulation" means "a fast winners-take-all process proposed as the fundamental mechanism of all aspects of cognition (*e.g.* vision, hearing, planning, reasoning, *etc.*)". According to him, "confabulation theory hypothesizes that all aspects of cognition can be explained and implemented by using four fundamental elements: a universal modular system for representing the objects of the mental world, knowledge links, confabulation, and action command origination." Furthermore, the theory proposes that the underlying mathematical process of cognition is the maximization of cogency. Given that, the theory asserts that every decision-making process involved in cognition is a choice of conclusions that give the strongest support that the assumed facts used are true. Cogency is the probability of the assumed facts being true, given an assumption that the event is true. For example, in cogent confabulation theory, the true cogency of each class of water quality is approximated by the confabulation product of the single band's cogencies. These cogencies are determined as facts and formally expressed as $p(b_1, b_2, ..., b_{21|x})$. The theory claims that the decision-making process involved in cognition is the selection of that conclusion which is most supportive of the assumed facts being true. The equation for calculation of the confabulation product referred to as the "winner-take-all" strategy, where winner takes all in competition between the symbols receiving excitation within a module [22][30] is shown in (1):

$$p(b_1, b_2, ..., b_{21}|x) = \\ C * p(b_1|x) * p(b_2|x) * ... * p(b_{21}|x) \tag{1}$$

where:

- $b_1, b_2, ..., b_{21}$ represent band values,
- x stands for the premise of the argument ("good" and "poor"),
- and the factor C is a positive constant, where by using it cogency can be maximised by maximising the *confabulation product* [24].

To calculate the confabulation product, the first measure that was calculated was the cogency of each band for class "good", as well as for class "poor". This was performed on a train data set. Figure 4 illustrates the entire procedure, from selecting and retrieving data from the application domain to calculating the cogency of each band. Once the cogency is retrieved for all bands of both classes of bathing water quality, the calculation of the confabulation product was performed for the test data set. A result of this process is a quantitative analysis where evaluation measures of each applied classifier are calculated, and a qualitative analysis where a map as a spatial visualization of bathing water quality is generated.

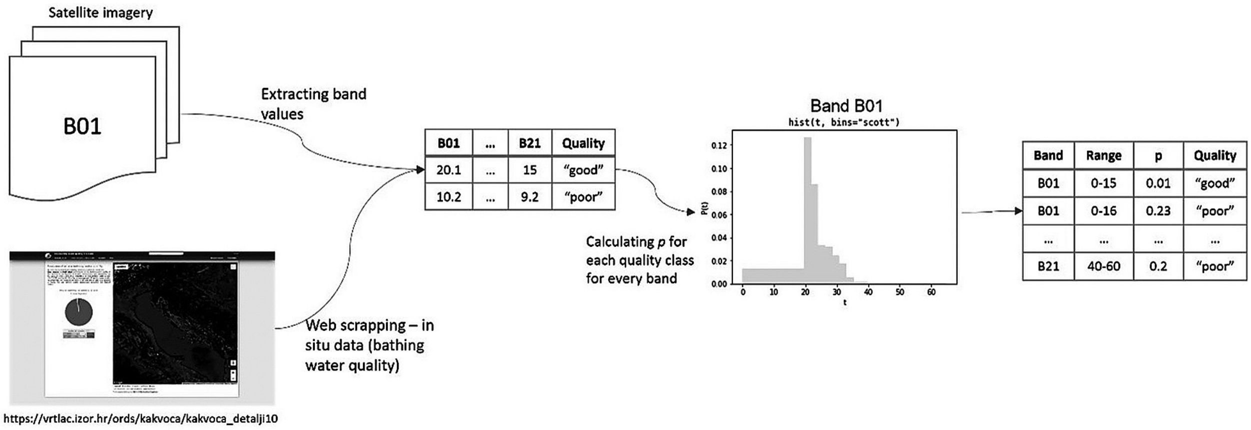

Figure 4. Research methodology – the flow chart presents procedures from data collection to data consolidation, where, for each band, cogency is calculated for two distinctive classes of bathing water quality.

3.4. Evaluation

In this study, the performance of the Cogent Confabulation classifier is compared with other machine learning algorithms that use supervised learning to build the classifier. All algorithms are applied to the same data sets and a short description of each of them is given below:

- *Decision Tree classifier* – a non-parametric supervised learning method that utilises knowledge-based information without making any assumptions about the data [31],
- *K-Nearest Neighbours classifier* – classifies each test sample based on its k-nearest neighbours, which are found by calculating the distance between the test and training samples [32],
- *Multi-Layer Perceptron classifier* – a feed-forward artificial neural network organized in three or more layers (input layer, hidden layer, and output layer) [33],
- *Naive Bayes classifier* is based on Bayes theorem and works on the principle that all the classified features are independent of each other. There are different types of Naive Bayes models, but in this study the following ones were used [34][35]:
  - *Bernoulli* – requires samples to be represented as binary-valued feature vectors,
  - *Complement* – use the statistics from the complement of each class to calculate the weights of the model,
  - *Gaussian* – ensures that the features are following normal Gaussian distribution and supports continuous data,
  - *Multinomial* – consider a feature vector that is used when there is a discrete count,
- *Random Forest classifier* – consists of decision trees, where each tree votes for a particular class, and where more reliable predictions can be produced by combining a large number of decision trees [36].

The above algorithms were implemented using the Python programming language and the free software machine learning library scikit-learn. Python 3.7.15 [37] and scikit-learn library 1.0.2 [38] versions were used to implement these algorithms. To improve the performance of the selected machine learning algorithms, common hyperparameters were tuned to get the best fit for the data set. Hyperparameter tuning was performed by using the Python class GridSearchCV provided by the scikit-learn library on a train data set consisting of 80% of all samples. This class loops through all parameters provided as params_grid with a number of cross-validation folds. The model performance is evaluated on all combinations and the result of the model which performed best in all cross-validation folds is stored in the best_estimator attribute. Table 1 lists parameters for each best estimator found through the grid for both data sets (Case 1 and Case 2), described in the section *Results and Discussion*.

For each trained classifier a confusion matrix that shows the absolute and relative number of TP, TN, FP, and FN values was implemented. The test portion of the data set was classified, and each measurement was assigned to one of the subsets [39]:

- True positive (TP) – the classifier predicts bathing water quality as "good", and the *in situ* measurement shows the same,
- True negative (TN) – the classifier predicts bathing water quality as "poor", and the *in situ* measurement shows the same,
- False positive (FP) – the classifier incorrectly predicts bathing water quality as "poor", while actual *in situ* measurement is "good" quality,

Table 1. List of best parameters for tuning algorithms.

Algorithm	**Best parameters**	
	Best parameters	**Best parameters**
Random Forest	`{'max_features': 'log2', 'n_estimators': 100}`	`{'max_features': 'log2', 'n_estimators': 1000}`
K-Nearest Neighbours	`{'metric': 'manhattan', 'n_neighbors': 3, 'weights': 'distance'}`	`{'metric': 'manhattan', 'n_neighbors': 3, 'weights': 'distance'}`
Decision Tree	`{'criterion': 'entropy', 'max_depth': 9, 'min_samples_leaf': 1, 'min_samples_split': 3}`	`{'criterion': 'gini', 'max_depth': 6, 'min_samples_leaf': 3, 'min_samples_split': 8}`
Gaussian – Naïve Bayes	`{'var_smoothing': 0.01873817422860384}`	`{'var_smoothing': 0.15199110829529336}`
Bernoulli – Naïve Bayes	`{'alpha': 0.01, 'binarize': 10.0, 'class_prior': None, 'fit_prior': True}`	`{'alpha': 10.0, 'binarize': 8.5, 'class_prior': None, 'fit_prior': False}`
Multi-Layer Perceptron	`{'activation': 'tanh', 'alpha': 0.0001, 'hidden_layer_sizes': (10, 30, 10), 'learning_rate': 'adaptive', 'solver': 'adam'}`	`{'activation': 'tanh', 'alpha': 0.0001, 'hidden_layer_sizes': (10, 30, 10), 'learning_rate': 'constant', 'solver': 'adam'}`
Complement – Naïve Bayes	`{'alpha': 10.0, 'class_prior': None, 'fit_prior': True, 'norm': True}`	`{'alpha': 10.0, 'class_prior': None, 'fit_prior': True, 'norm': False}`
Multinomial – Naïve Bayes	`{'alpha': 0.01, 'class_prior': None, 'fit_prior': True}`	`{'alpha': 10.0, 'class_prior': None, 'fit_prior': False}`

- False negative (FN) – the classifier incorrectly predicts bathing water quality as "good", while actual *in situ* measurement is "poor" quality.

The confusion matrix has been shown to be the most appropriate evaluation tool to compare classifiers of rare events on an imbalanced data set. It is extremely useful for determining the following measures to evaluate the performance of the tuned classification model [40]:

- *Precision* – represents the proportion of positive samples (TP) that were correctly classified to the total number of positive predicted samples (TP, FP),

$$Precision = \frac{TP}{TP + FP} \tag{2}$$

- *Recall* – represents the positive correctly classified samples to the total number of positive samples,

$$Recall = \frac{TP}{TP + FN} \tag{3}$$

- *F1-score* – represents the harmonic mean of precision and recall,

$$F1 - score = 2 * \frac{Precision * Recall}{Precision + Recall} \tag{4}$$

- *Balanced Accuracy* – represents the metric that is used to assess the performance of the classification model [41],

$$\begin{matrix} Balanced \\ Accuracy \end{matrix} = \frac{Sensitivity + Specificity}{2} \tag{5}$$

where Sensitivity and Specificity are defined as:

$$Sensitivity = \frac{TP}{TP + FN} \tag{6}$$

$$Specificity = \frac{TN}{TN + FP} \tag{7}$$

4. Results and Discussion

To evaluate the Cogent Confabulation classifier performance, the following metrics were used: precision, recall, F1-score, balanced accuracy, and confusion matrix. For the specified metrics, the *binary* type of averaging is used on the data. The reason the *binary* type of averaging was taken is that ground truth target values (*y_test*) and predicted targets returned by a classifier (*y_pred*) are binary. Thus, in binary classification 0 stands for "poor" and 1 stands for "good" bathing water quality. These metrics are calculated for two different types of data sets:

1. including all Sentinel-3 OLCI bands,
2. including Sentinel-3 OLCI bands (B03, B04, B05, B06, B10, and B11) related to calculation of the Chl-a parameter [7], which is often used as an indicator of water quality.

Furthermore, other machine learning classifiers were considered and compared with the Cogent Confabulation classifier for both data sets. As well, based on the obtained results, a visualization of the quality of bathing water in the study area was made using the QGIS tool.

4.1. Case 1: All Sentinel-3 OLCI Bands

In the first case, all Sentinel-3 OLCI band values were included in the input data set. The main reason for including all wavelengths was to avoid losing any information that can be related to bathing water quality. In Figure 5, the results of the balanced accuracy measure, obtained after applying nine machine learning classifiers on a test data set, are shown in descending order.

According to the measure of balanced accuracy, the Random Forest classifier proved to be the best (96.5%), followed by the K-Nearest Neighbours (94.2%) and Decision Tree (93.5%) classifiers. The Cogent Confabulation classifier has a balanced accuracy of 75.6%, which puts this classifier in fourth place. The first three classifiers are far more complex than the Cogent Confabulation classifier, so they were expected to achieve better results.

Furthermore, it is important to emphasize that the Cogent Confabulation classifier outperforms the Multi-layer perceptron classifier and all Naive Bayes based classifiers. Additionally, the Bayesian and Cogent Confabulation theories are both based on probabilities, but they differ in their approach to determining the probability of an event. These classifiers can be seen as competing methods for representing the formal logic for inductive reasoning. The main difference is that the confidence of an occurred event in Bayesian theory is represented as posterior probability, while in a Cogent Confabulation theory, the confidence of conclusion is represented as cogency.

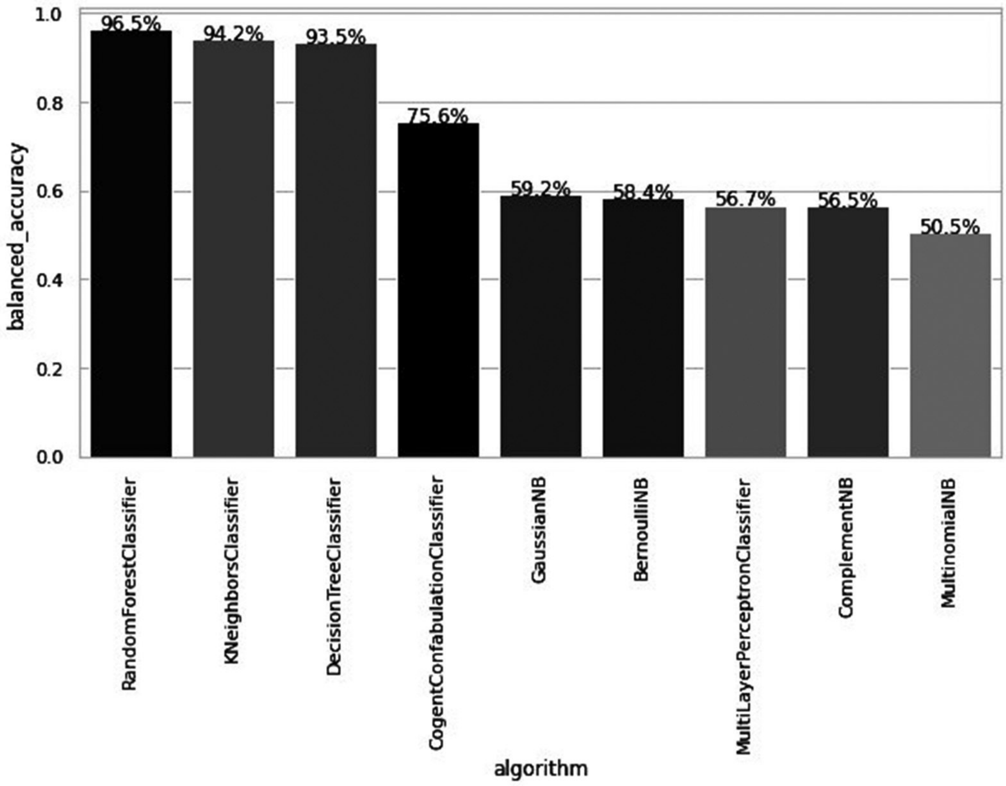

Figure 5. Balanced accuracy results – data set of all bands.

According to these results, the Cogent Confabulation theory is more suitable for determining bathing water quality than the Bayesian theory. Also, it should be noted that all the classifiers based on Bayesian theory in this study had a balanced accuracy below 60%, which is a much lower percentage of balanced accuracy compared to the Cogent Confabulation classifier.

The first four classifiers have achieved a high F1-score, as can be seen in Figure 6. This implies that there is a balance between the precision and recall metrics of these classifiers, which is important because the used data set has an uneven class distribution where the class representing 'good' bathing water quality is in the majority.

By looking closely at each confusion matrix for the first four classifiers represented in Figure 7, it is evident that all these classifiers have predicted true positive (TP) values with a confidence higher than 50%. The Cogent Confabulation classifier shows results that are inferior to those top three classifiers in predicting true negative (TN) values, where it had about 10% fewer predicted TN values. Additionally, it is interesting to note that the Decision Tree classifier had the lowest percentage (1,21%) in predicting false negative (FN) values, while the Random Forest classifier had the lowest percentage (0,4%) in predicting false positive (FP) values. Based on these estimated TP, TN, FP, and FN values we calculated evaluation metrics precision, recall, F1-score, and accuracy.

4.2. Case 2: Selected Sentinel-3 OLCI Bands

Phytoplankton abundance and biomass, usually expressed as chlorophyll-*a* (Chl-a) concentration, both indicate water quality in coastal and estuarine waters. Chl-a can be an effective measure of water trophic status. High concentrations of Chl-a can be the result of high levels of nutrients from fertilizers, septic systems, sewage treatment plants, and urban runoff which is especially characteristic of the Kaštela Bay area. Moreover, excess of this nutrient can cause the algae to grow or bloom in the freshwater of marine water systems and is recognized by the discoloration in the water, often in green, blue-green, green-brown, or red colour.

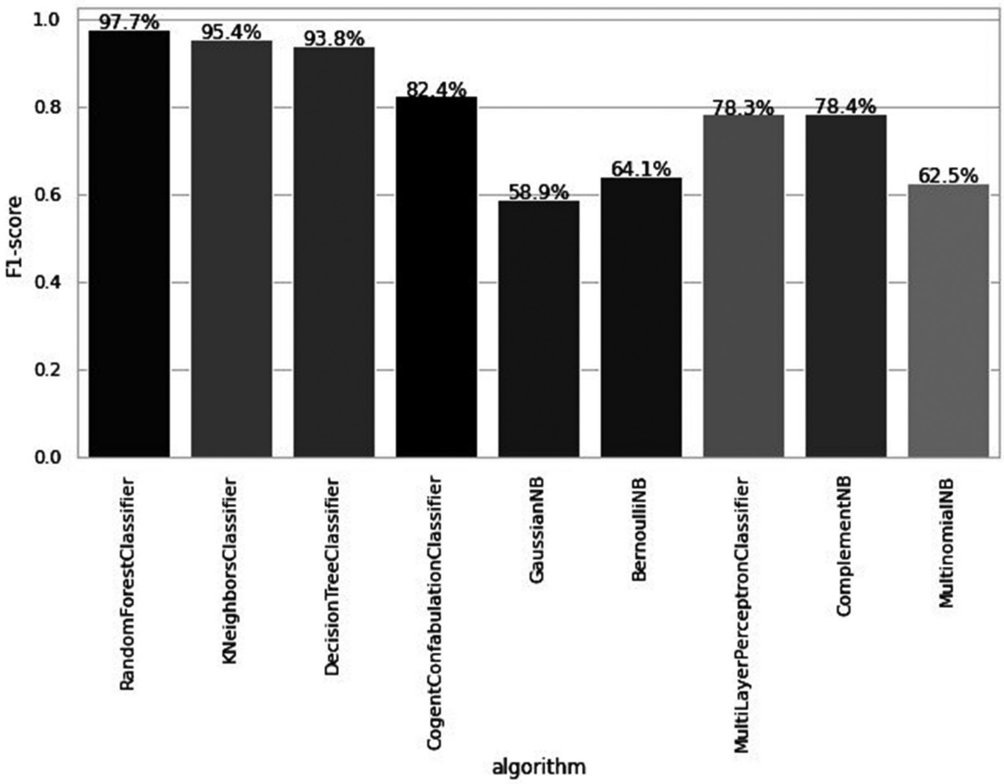

Figure 6. F1-score results – data set of all bands.

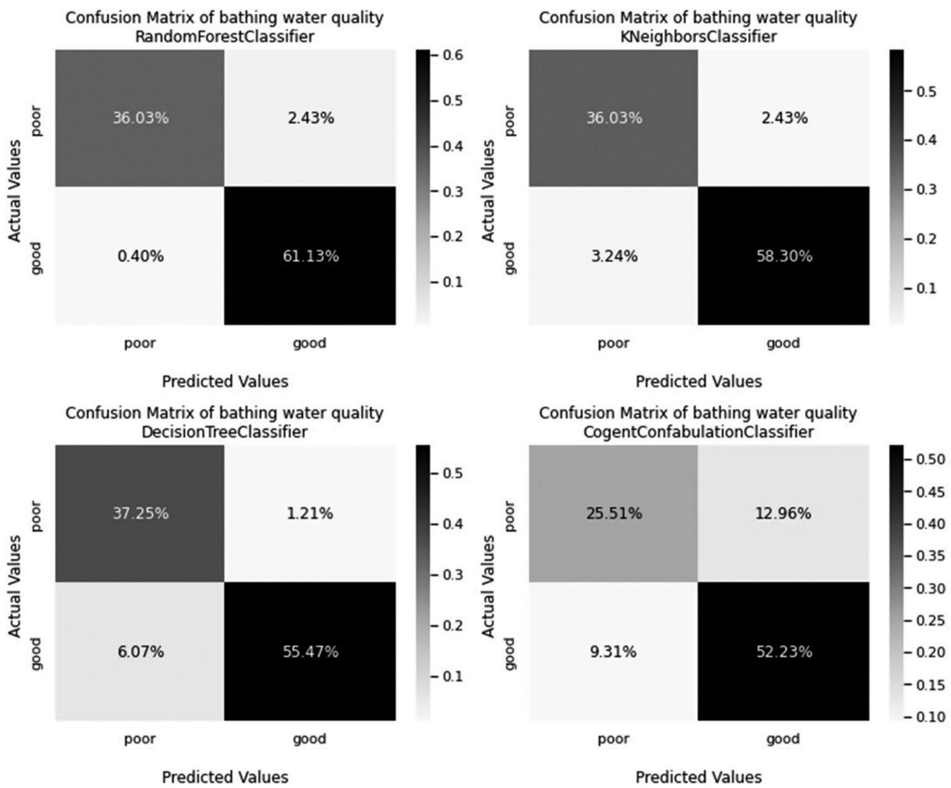

Figure 7. Confusion matrices for the four best classifiers – data set of all bands.

Based on these facts, there was a meaningful reason why to select only the bands B03 (442.5 nm), B04 (490 nm), B05 (510 nm), B06 (560 nm), B10 (681.25 nm), and B11 (708.75 nm) that are characteristic for the detection of chlorophyll. Having fewer features when implementing the machine learning models results in less computation. Also, it speeds up retrieving and reading satellite data where there are now only six images to read instead of 21 as it was when we used all Sentinel-3 OLCI bands.

In Figure 8 results can be seen after applying nine machine learning classifiers to the test data set which includes only the selected bands related to Chl-a. It can be observed that compared to the results of classifiers which included all bands there is a small improvement in accuracy, which can even be said to be negligible. Again, the first four classifiers are Random Forest, Decision Tree, K-Nearest Neighbours, and Cogent Confabulation. This indicates that classifiers that take only six features related to the indicators of water quality can classify well with the same confidence as those including all 21 features. To assess the quality of performed machine learning models we have calculated F1-score for each one and the results can be seen in Figure 9. F1-score is especially important in imbalanced class distribution as is the case in this study and when the FN and FP predictions are crucial as is the case with water quality which impacts human and animal health.

Figure 10 depicts the confusion matrix for the first four classifiers based on balanced accuracy for a data set that includes only the selected Sentinel-3 OLCI bands. It can be noticed that Cogent Confabulation for selected features can better predict TN values by approximately three percent more than it was in the case when all bands were considered. This is especially important because we are more interested in poor bathing water quality and how to detect it as quickly as possible. However, Random Forest, Decision Tree, and K-Nearest Neighbour classifiers still lead the way in predicting bathing water quality, where the percentage of accurately predicted TN values is around 36%. All classifiers based on Bayesian theory are still less reliable in bathing water quality prediction than the Cogent Confabulation classifier.

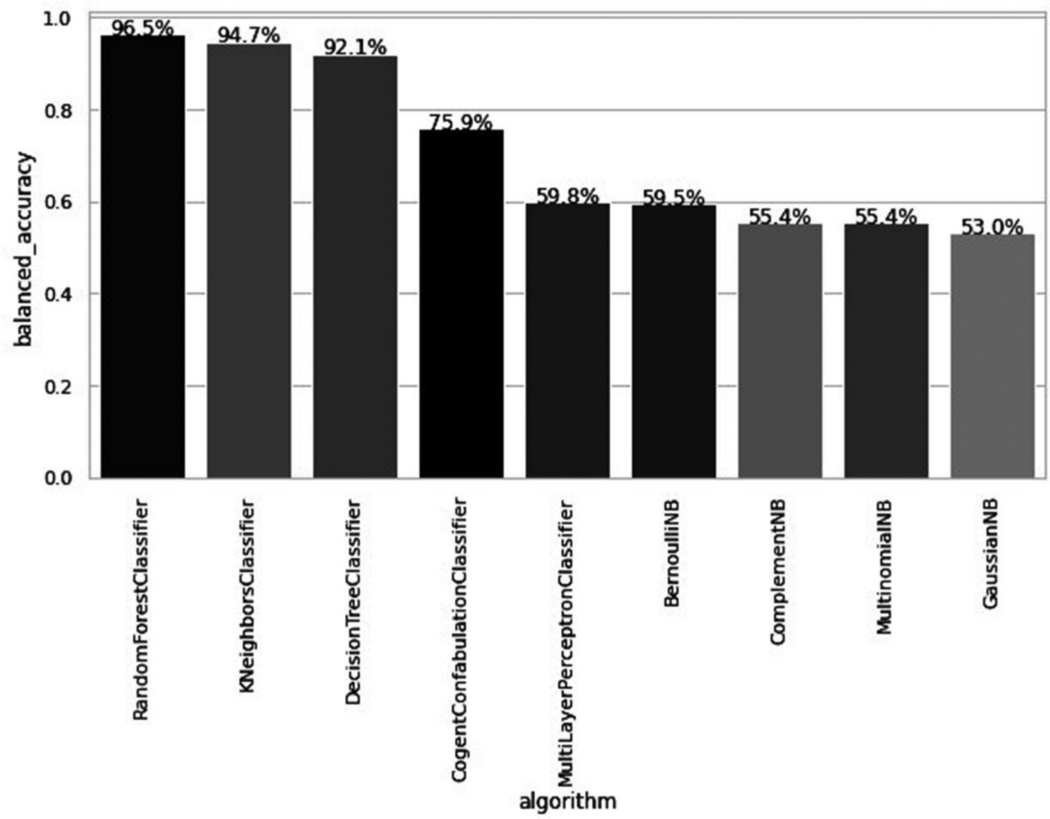

Figure 8. Balanced accuracy results – data set of selected bands.

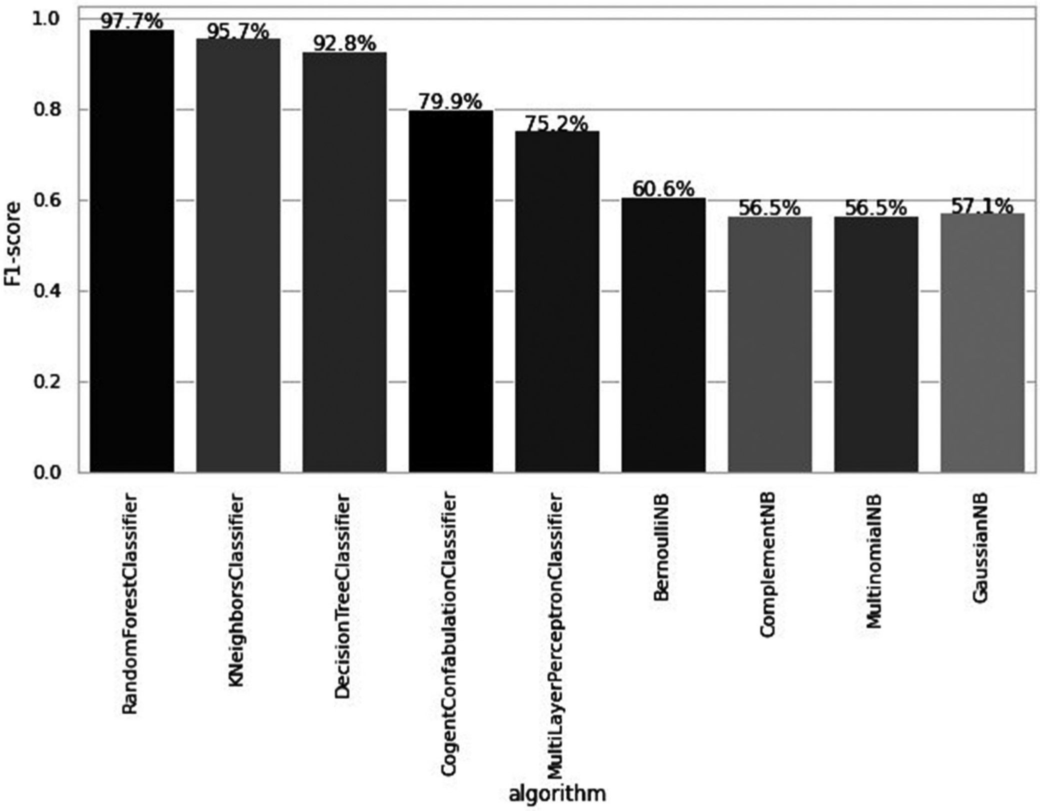

Figure 9. F1-score results – data set of selected bands.

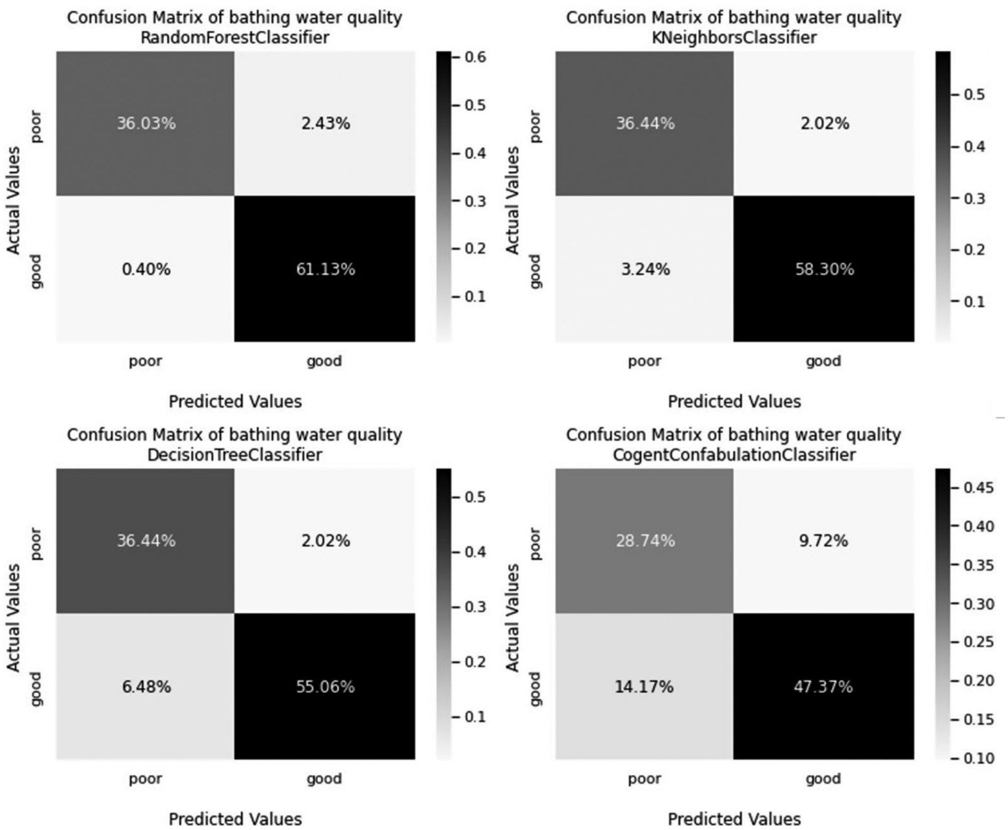

Figure 10. Confusion matrices for the four best classifiers – data set of selected bands.

This article was created as an extension of the study described in [3]. Increasing the data set and including the atmospheric correction led to a better result than the one that was achieved in the mentioned study. The Cogent Confabulation classifier achieved much higher accuracy for both data sets. Furthermore, Random Forest, Decision Tree, and K-Neighbors proved to be exceptionally good classifiers, which, by increasing the data set, achieved better results in predicting the bathing water quality than the Cogent Confabulation classifier. Table 2 and Table 3 show a comparison of the results from the previous study [3] with the new results that classifiers achieved by training on the new data sets. It can be noted that compared to the previous study, all classifiers achieved better and more reliable performance in terms of precision, recall, F1-score, and balanced accuracy metrics.

Table 2. Comparison of evaluation metrics results for all Sentinel-3 OLCI bands (Case 1).

Algorithm		**Precision**	**Recall**	**F1-score**	**Accuracy**
Random Forest Classifier	Old	0.9406	0.9973	0.9584	0.4986
	New	0.9618	0.9934	0.9773	0.9651
K-Nearest Neighbours Classifier	Old	0.9382	0.9151	0.9265	0.4793
	New	0.9600	0.9474	0.9536	0.9421
Decision Tree Classifier	Old	0.9429	0.9507	0.9468	0.5188
	New	0.9786	0.9013	0.9384	0.9349
Cogent Confabulation Classifier	Old	0.9438	0.8740	0.9075	0.5239
	New	0.8012	0.8487	0.8243	0.7559
Gaussian – Naïve Bayes	Old	0.9395	0.9781	0.9584	0.4890
	New	0.7170	0.5000	0.5891	0.5921
Bernoulli – Naïve Bayes	Old	0.9407	1.0	0.9695	0.5
	New	0.6894	0.5987	0.6408	0.5836
Multi-Layer Perceptron Classifier	Old	0.9407	1.0	0.9695	0.5
	New	0.6494	0.9868	0.7833	0.5671
Complement – Naïve Bayes	Old	0.9367	0.5671	0.7065	0.4792
	New	0.6481	0.9934	0.7844	0.5651
Multinomial – Naïve Bayes	Old	0.9407	1.0	0.9695	0.5
	New	0.6194	0.6316	0.6254	0.5053

Table 3. Comparison of evaluation metrics results for selected Sentinel-3 OLCI bands (Case 2).

Algorithm		**Precision**	**Recall**	**F1-score**	**Accuracy**
Random Forest Classifier	Old	0.9407	1.0	0.9695	0.5
	New	0.9618	0.9934	0.9773	0.9651
K-Nearest Neighbours Classifier	Old	0.9463	0.9178	0.9319	0.5459
	New	0.9664	0.9474	0.9568	0.9474
Decision Tree Classifier	Old	0.9387	0.9644	0.9514	0.4822
	New	0.9645	0.8947	0.9283	0.9211
Cogent Confabulation Classifier	Old	0.9472	0.8356	0.8880	0.5482
	New	0.8298	0.7697	0.7986	0.7586
Multi-Layer Perceptron Classifier	Old	0.9407	1.0	0.9695	0.5
	New	0.6754	0.8487	0.7522	0.5980
Bernoulli – Naïve Bayes	Old	0.9407	1.0	0.9695	0.5
	New	0.7143	0.5263	0.6061	0.5947
Complement – Naïve Bayes	Old	0.9405	0.6493	0.7682	0.4986
	New	0.6727	0.4868	0.5649	0.5539
Multinomial – Naïve Bayes	Old	0.9407	1.0	0.9695	0.5
	New	0.6727	0.4868	0.5649	0.5539
Gaussian – Naïve Bayes	Old	0.9401	0.9890	0.9640	0.4945
	New	0.6446	0.5132	0.5714	0.5303

4.3. Qualitative Analysis

The results of the classifier, except quantitatively as was the case in the previous sections, can be presented and described qualitatively using spatial maps. Maps provide a general description and visualization of data, but in most applications, it is necessary to find the spatial relationship between the data. One of the most basic techniques in map analysis is the comparison of two or more maps to establish the spatial relationship of the data. In this qualitative analysis, a map of the actual bathing water quality measurements (Figure 11) and the one generated on the results of the classifier will be compared. As a case study, *in situ* measurements of the bathing water quality sampled on July 6th, 2022, were taken as ground truth values. Also, for the same date, satellite images of the Sentinel-3 OLCI satellite were downloaded. To make a qualitative analysis we took only classifiers trained on selected bands (B03, B04, B05, B06, B10, and B11) related to the detection of Chl-a. For simplicity as in quantitative analysis, the classifiers that showed the best results have been compared, namely: Random Forest (Figure 12), K-Nearest Neighbours (Figure 13), Decision Tree (Figure 14), and Cogent Confabulation (Figure 15).

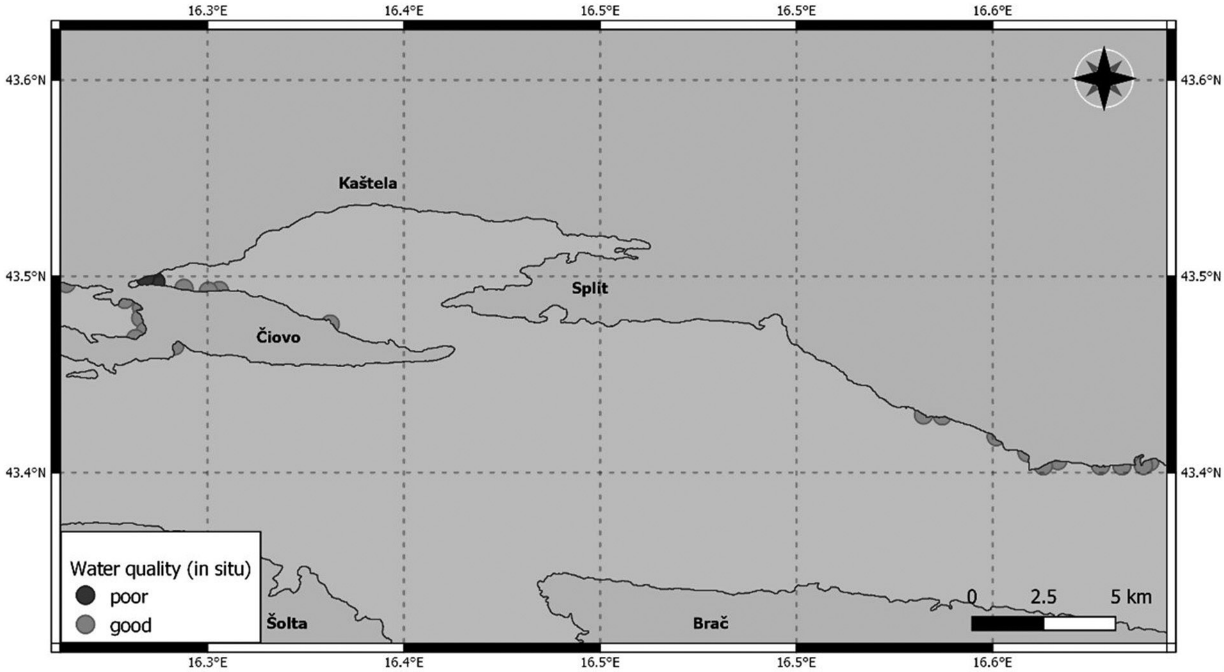

Figure 11. In situ measurements representing bathing water quality for the date 6th of July 2022.

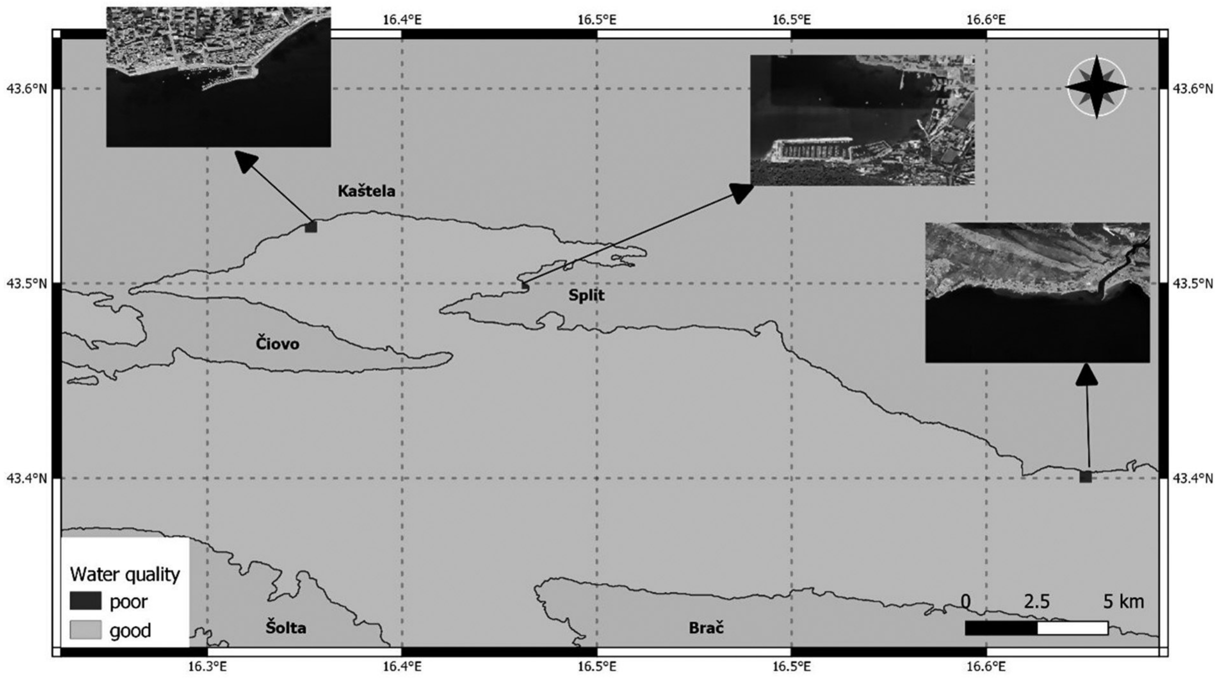

Figure 12. Classification of bathing water quality for the date 6th of July 2022, using Random Forest Classifier.

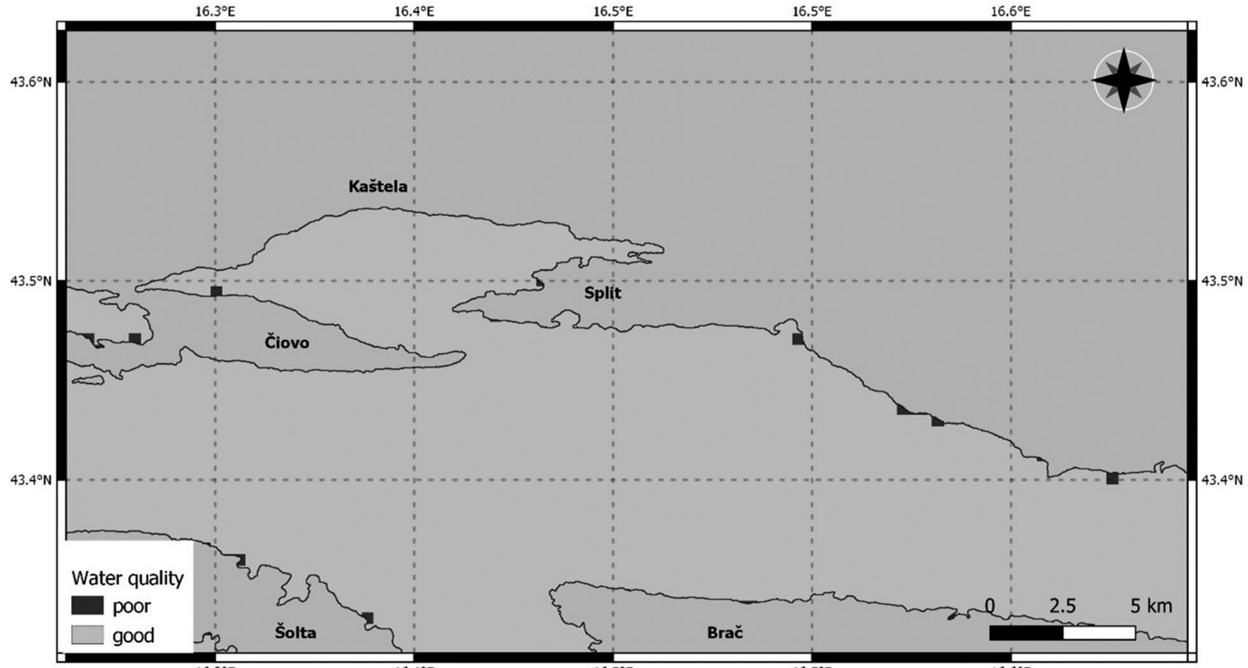

Figure 13. Classification of bathing water quality for the date 6th of July 2022, using K-Nearest Neighbours Classifier.

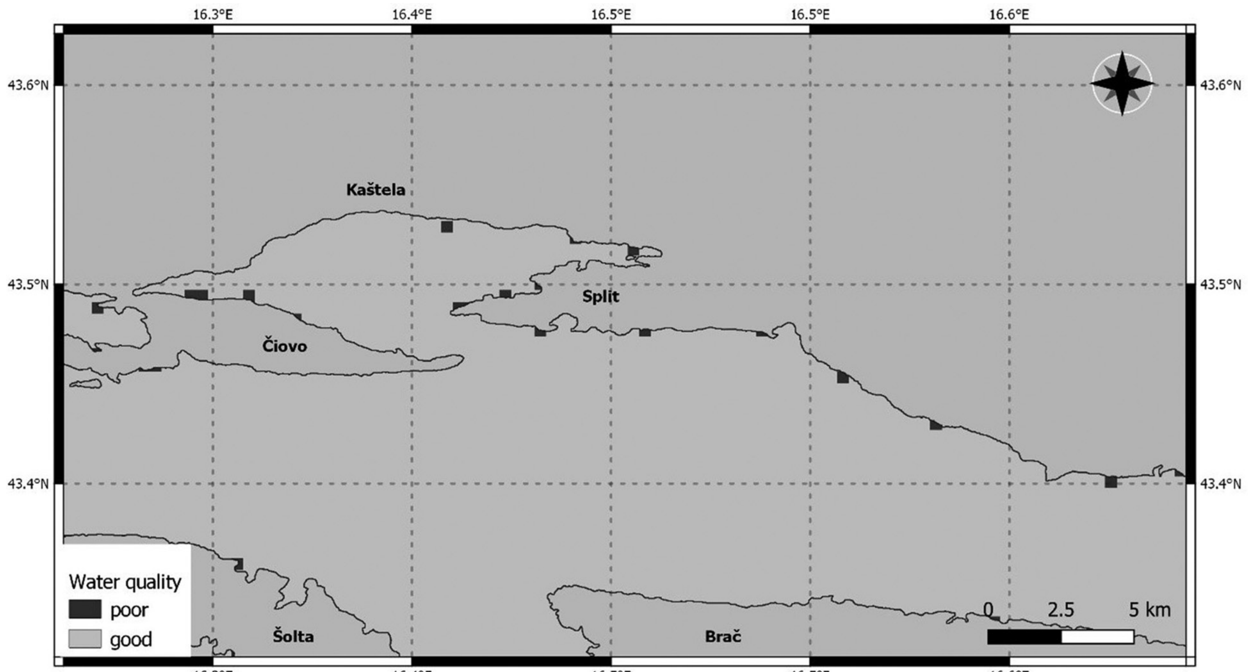

Figure 14. Classification of bathing water quality for the date 6th of July 2022, using Decision Tree Classifier.

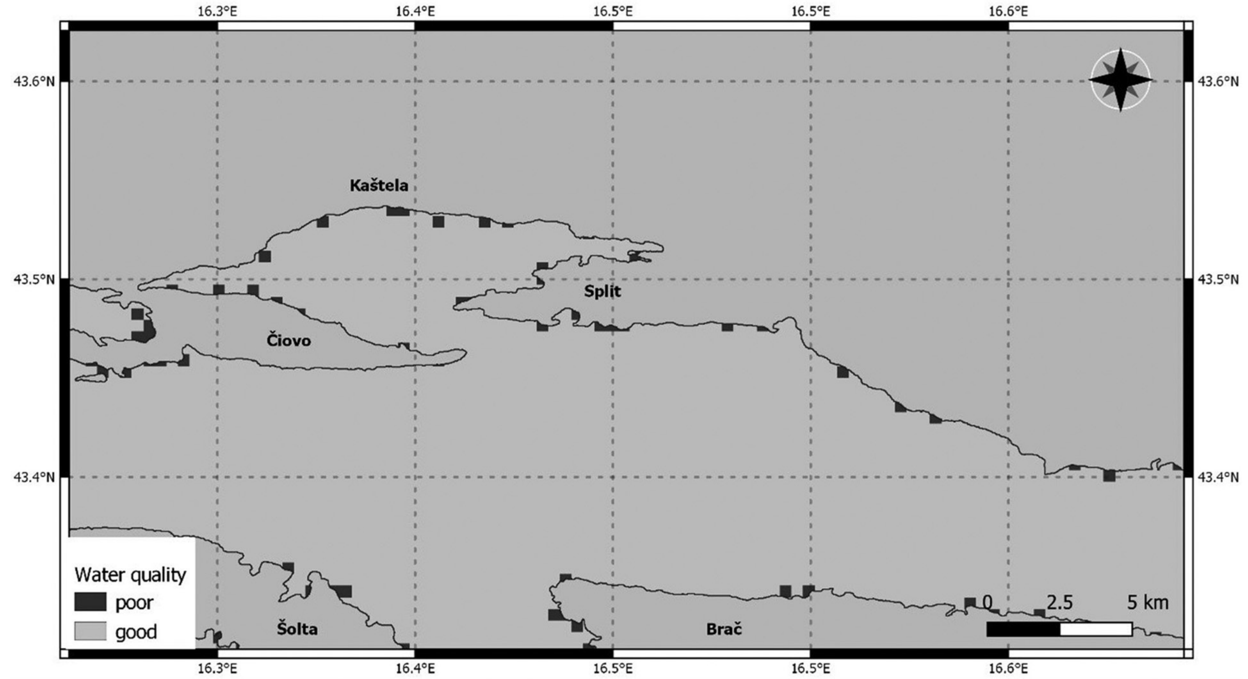

Figure 15. Classification of bathing water quality for the date 6th of July 2022, using Cogent Confabulation Classifier.

In the images obtained by applying the four best classifiers, it can be noticed that the classifiers made a prediction of the "poor" bathing water quality only along the coast. The classifiers made predictions based on the band values for each pixel, and since they were trained with *in situ* measurements only available for the coast, the classifier's predictions will be based on that input. That is why the predictions of the classifier are mostly focused on the coast instead of the open sea, which we consider clean since we have many more sources of pollution on the coast. In Figure 12, satellite images have been added to predicted "poor" classes of several locations predicted by the Random Forest classifier, for which we do not have *in situ* measurements to confirm this. However, if we look at the locations that the classifier singled out as having "poor" bathing water quality, we will notice that it is mainly ports and the coastal area where the rivers flow into the sea (Jadro and Cetina rivers).

The problem with *in situ* measurement is that it refers to only one point, while satellite data together with trained classifiers can provide results for a larger area. Thus, by using satellite imagery bathing water quality can be obtained almost every day (according to Sentinel-3 temporal resolution). Having this in mind, these classifiers may have predicted some contaminants that may have been missed during the sea sampling campaign. Moreover, the generated spatial maps could be a good reference point when sampling the sea so that all potential pollution could be detected in a timely manner.

The empirical results reported herein should be considered in the light of some limitations. First, classifiers are tuned with some hyperparameters, but there could always be another better combination which can lead to a more confident result and avoid overfitting. Second, the data set could be expanded by focusing on a larger study area which will not only include coast *in situ* measurements but also on open sea as well.

5. Conclusion

In this study, a Cogent Confabulation classifier is implemented to predict bathing water quality. This classifier is compared with other machine learning classifiers based on the calculation of different types of performance metrics. Also, results are represented in the form of maps to find spatial relationships between data. The results suggest that the Cogent Confabulation classifier did not outperform Random Forest, K-Nearest Neighbours, and Decision Tree classifiers, but it did outperform four types of Naïve Bayes classifiers for both cases of using different sets of data. Due to an imbalanced data set, binary averaging for all used metrics was performed. Although the performance metrics did not show that the Cogent Confabulation classifier performs better than other used classifiers, this classifier could be considered a promising classifier for solving other similar problems rather than some well-known classifiers which are usually more complex.

In future work, to make this model even more reliable, data fusion should be considered, where different satellite data and data collected by using an unmanned aerial vehicle (UAV) could be combined. Increasing the size of the data set, especially when it contains data from different sources, could give a higher level of detail in images observed at different wavelengths of the electromagnetic spectrum. Having this in mind it is reasonable to believe that this will lead to more sophisticated results for better prediction of bathing water quality.

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Contact addresses:

Antonia Ivanda*
University of Split
Faculty of Electrical Engineering
Mechanical Engineering and Naval Architecture
Croatia
e-mail: asenta00@fesb.hr
* Corresponding author

Ljiljana Šerić
University of Split
Faculty of Electrical Engineering
Mechanical Engineering and Naval Architecture
Croatia
e-mail: ljiljana.seric@fesb.hr

Maja Braović
University of Split
Faculty of Electrical Engineering
Mechanical Engineering and Naval Architecture
Croatia
e-mail: maja.braovic@fesb.hr

Darko Stipaničev
University of Split
Faculty of Electrical Engineering
Mechanical Engineering and Naval Architecture
Croatia
e-mail: darko.stipanicev@fesb.hr

ANTONIA IVANDA is currently a PhD student in Electrical Engineering and Information Technology at the University of Split. In 2019, she completed her MSc at the Faculty of Electrical Engineering, Mechanical Engineering, and Naval Architecture in Split. Her MSc thesis was focused on developing a web system for managing student practices. Her research mainly focuses on the field of computer science, specifically on artificial intelligence for data analysis and prediction of bathing water quality, as well as assessment of autopurification capabilities using a Remote Sensing Data-driven approach. Additionally, Antonia is an expert in using qGIS software for spatial visualization of vector and raster data obtained via satellites.

LJILJANA ŠERIĆ is an associate professor at the Department of electronics and computer science at the Faculty of Electrical Engineering, Mechanical Engineering, and Naval Architecture, University of Split, Croatia. She is a member of the Department for Modelling and Intelligent Systems. She participates in the activities of the Laboratory for Intelligent Systems and Laboratory for Advanced Internet Technologies. She is a collaborator of the Centre for wildfire research. Ljiljana Šerić received her PhD in Computer Science in 2010 at the University of Split. She has worked on scientific, specialistic, and technical projects in the domain of environmental disaster protection and environmental hazard prevention. She participated in projects dealing with wildfires, high winds, and coastal pollution. Her research interests are artificial intelligence, web technologies, and distributed systems.

MAJA BRAOVIĆ received her BSc and MSc degrees in Computer Science from the University of Split, Faculty of Electrical Engineering, Mechanical Engineering, and Naval Architecture, in 2008 and 2010, respectively. She received her PhD degree in Artificial Intelligence from the same Faculty in 2015, where she is also currently an assistant professor. Her main areas of research include artificial intelligence, computational linguistics, natural language processing, computer vision, and image understanding.

DARKO STIPANIČEV is a Professor of Computer Science and Automatic Control at the Faculty of Electrical Engineering, Mechanical Engineering, and Naval Architecture, University of Split. His research interest includes complex systems modelling and control, intelligent systems analyses and design, digital image analyses, advanced Internet technologies, and recently, the application of ICT in environmental protection, particularly wildfire prevention and management, including vision-based wildfire detection system. He is a chair of the Department for Modelling and Intelligent Systems, as well as the chair of the Center for Wildfire Research at FESB. Over the course of his 40-year research career, he has participated in and led numerous projects, with a particular focus on the use of ICT in wildfire protection.