

Article

Assessment and Quantification of the Accuracy of Low- and High-Resolution Remote Sensing Data for Shoreline Monitoring

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Abstract: The accuracy of low-resolution remote sensing data for monitoring shoreline evolution is the main issue that researchers have been trying to overcome in recent decades. The drawback of the Landsat satellite archive is its spatial resolution, which is appropriate only for low-scale mapping. The present study investigates the potentialities and limitations of remote sensing data and GIS techniques in shoreline evolution modeling, with a focus on two major aspects: (a) assessing and quantifying the accuracy of low- and high-resolution remote sensing data for shoreline mapping; and (b) calculating the divergence in the forecasting of coastline evolution based on low- and high-resolution datasets. Shorelines derived from diachronic Landsat images are compared with the corresponding shorelines derived from high-spatial-resolution airphotos or Worldview-2 images. The accuracy of each dataset is assessed, and the possibility of forecasting shoreline evolution is investigated. Two sandy beaches, named Kalamaki and Karnari, which are located in Northwestern Peloponnese, Greece, are used as test sites. It is proved that the shorelines derived from the Landsat data present a displacement error of between 6 and 11 m. The specific data are not suitable for the shoreline forecasting procedure and should not be used in related studies, as they yield less accurate results for the two study areas in comparison with the high-resolution data.

Keywords: Landsat; shoreline; erosion; accretion; forecast; accuracy

1. Introduction

The Landsat program began in 1972. Following then, there have been numerous Landsat missions, which were conducted with new sensors that have a better imagery resolution. The most recent, Landsat 8, was launched in 2013. It is the oldest observing satellite imagery program of the planet's surface and is the only source of various types of historical data, which can be extracted in vector format, from almost 50 years ago [1]. Millions of images have been acquired since then, which are now free to access. This historic archive of Landsat data, especially the older one, is very useful for researchers studying coastline evolution, as these images are unique with respect to observing the passing of time. Monitoring shoreline movement has been a favorite subject for the research community in the last twenty years, as due to the climate change, coastal erosion has become a global problem [2], and it is expected to affect economic activities, such as tourism revenues [3]. To study diachronic coastline evolution, researchers have exclusively used the Landsat series [4–33].

Studies that emphasize multitemporal shoreline evolution use all the Landsat series imagery. In a very recent study [34], a total of 621 sets of Landsat images, covering the period between 1984 and 2017 and diverse spectral indexes, were used to automatically extract the shoreline of three different river deltas in Spain. For instance, in [35], such data are used in a study of shoreline and coastal evolution

for a forty-year period in Indonesia. In [14], Thematic Mapper (TM) and 7 Enhanced Thematic Mapper Plus (ETM+) instruments of Landsat satellite are used to assess the influence of a seawall in shoreline behavior over a 25-year period in Egypt. Moreover, in [8], Landsat images are used to study the shoreline evolution in India.

Except for the exclusive usage of Landsat images in multitemporal shoreline evolution studies, there have been researchers that combined Landsat with other satellite or aerial imagery. It is characteristic of most researchers to use a combination of all the types of satellite images that are freely available. In [27], Landsat and Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) images are combined to analyze the shoreline evolution in Ghana. Moreover, in [11], a combination of Landsat and Cartosat-1 and IRS-P6 images is used to evaluate the multitemporal shoreline changes in East India over a 22-year period (1990–2012). Landsat Multispectral Scanner System (MSS)/Landsat ETM, in conjunction with IKONOS images, is used in [36] to map and assess the coastal dynamic in Indonesia. SPOT, Landsat, and CORONA satellite images, in conjunction with aerial data, is used in [37] to monitor the shoreline evolution in Southern Italy. Finally, MSS, TM, and the ETM+ Landsat instrument, in conjunction with SPOT, topographical, and nautical data, are used in [38] to observe the shoreline changes of the Pearl River area in China.

It is well known that in order to study shoreline movements in an accurate way, successive time series of high-resolution images are needed. In a previous study [39], time series of high-resolution airphotos, bathymetric and topographic measurements, and other fluvial and maritime data are combined to assess the morphological evolution of the Guadalfeo River delta (Southern Spain). While shorelines can be derived in a very accurate way through aerial data with a high spatial resolution, the relative cost is very high, especially if a successive procedure is required [40]. Furthermore, as the cost of frequently observing large areas is high, this procedure becomes very expensive, and a study of the accuracy of free-of-charge low-resolution images for the same purpose is urgent.

An archive was created in 1972 using the Landsat satellite instruments, containing historical data on the Earth's surface. This has become an important tool in the study of multitemporal changes of various natural phenomena, such as coastal environments. The only technical problem associated with using this archive is its spatial resolution, which is appropriate only for large-magnitude fluctuations. Thus, the Landsat archive was suitable for studying the evolution of oceanic coasts in general [41–43].

The aim of this study is twofold: (a) to assess and quantify the accuracy of low- and high-resolution remote sensing data for shoreline mapping; and (b) to calculate the divergence in the forecasting of coastline evolution based on low- and high-resolution datasets. Moreover, this paper does not attempt to deal with coastline evolution or consider various qualitative onshore cartographies of shorelines. It is clear that low-resolution data cannot replace high-resolution data for large-scale studies that require a very high accuracy, but they are good enough to present general trends in low-scale studies. After a short presentation of the methodology used for this study, two erosional and sedimentary cases in Kalamaki and Karnari existing in Northwestern Peloponnese, Greece will be illustrated.

2. Study Area

The part of Northwestern Peloponnese, located between Araxos and Rio, was defined as the survey area (Figure 1). The areas are located in the Gulf of Patras and bounded by Cape Araxos to the West and Rio Port to the East. Lithologically, the basin consists of 53.23% limestone, 9.25% chert, 7.13% flysch, and 30.39% Plio-Pleistocene formations (mainly conglomerates of sandstone and marl) [44]. The current structure of the Gulf of Patras presents as an asymmetrical moat, arched in shape, with a curved section to the south. It was gradually formed by the action of pre-existing faults in a NE-NW direction, which were reactivated during the submergence of the Proapoulia zone below the Peloponnese [45]. The Gulf of Patras is a medium-depth marine area (56 m mean depth), which joins the Corinthian Gulf with the Ionian Sea. It is 40–50 km long, 10–20 km wide, with a surface of 535 km² and maximum depth of 138 m. Moreover, the Gulf of Patras receives the water masses of the Evinos, Pirros, and Glafkos rivers, the inflow of which stops completely during the summer period. Windstorms blow

in the area, mainly from the SW or ENE direction [46]. The broader area of the Northern Peloponnese has a warm and moist climate, and the mean annual temperature is 13 °C. The average annual rainfall ranges between 600 mm and 700 mm in the north and south regions, respectively. Rainfall occurs mainly in the period from autumn to spring, while in the remaining months, it is dry [44].

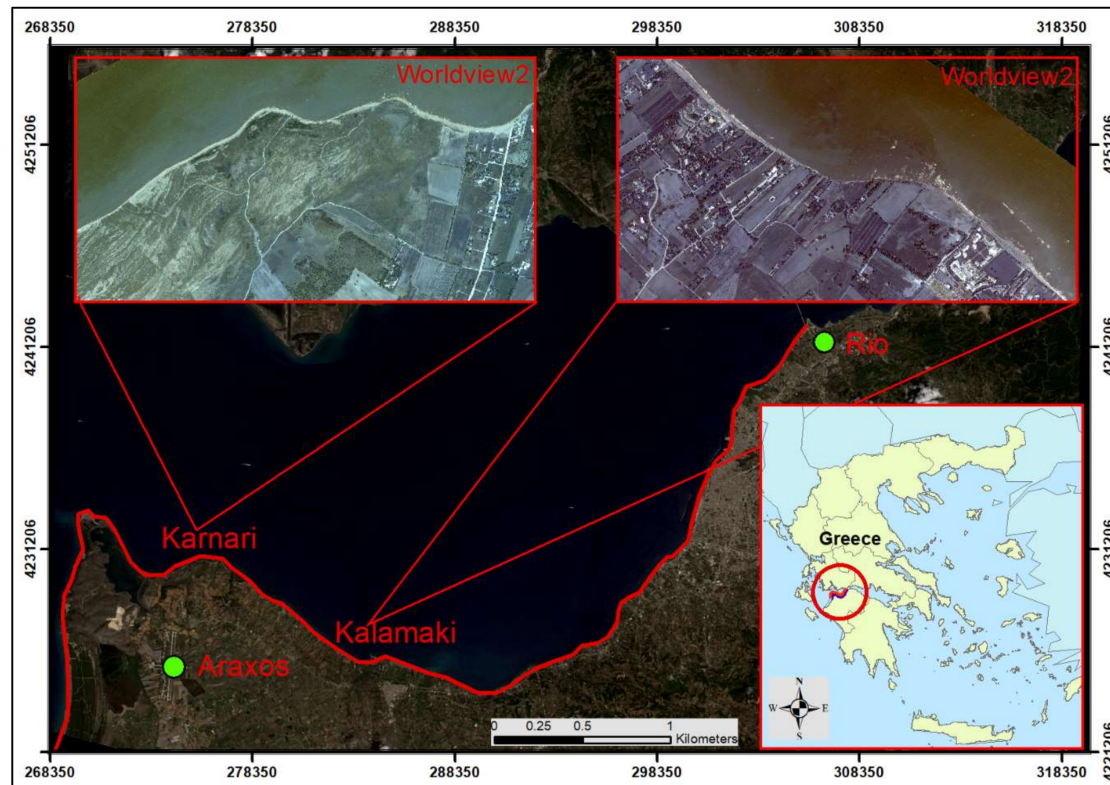


Figure 1. Map for the entire study area and both test sites.

Two sandy beaches, which are part of the study area in Kalamaki and Karnari, located in Northwestern Peloponnese, Greece (Figure 1), were used as test sites to assess and enumerate the accuracy of low- and high-spatial resolution datasets.

3. Materials and Methods

3.1. Materials

In the current study, multitemporal Landsat archival data from 2000, 2001, 2002, 2004, 2005, 2006, 2007, 2008, and 2018 (30 m spatial resolution) on the study area, consisting of images acquired by two Landsat instruments, the Enhanced Thematic Mapper+ and Operational Land Imager, were used. Moreover, high-resolution remote sensing data were acquired through the Ministry of Rural Development and Food, United States Geological Survey (USGS) and Greek Cadastre for 1945, 1973, 1996, and 2008.

The 1973 satellite imagery belongs to the Declassified Satellite Imagery collection that can be reached through the USGS website. The collection has more than 990,000 photographs taken from 1959 through 1980. The images have variable spatial resolution ranging between 2 m and 9 m. The specific image was captured in 1973 and was declassified for the first time after 1995 with spatial resolution 4 m. The image was freely downloaded from USGS through Global Visualization Viewer (GLOVIS) site. Around 45 points were selected from the Greek Cadastre orthophoto to serve as the GCPs. The declassified imagery was orthorectified using Leica Photogrammetry Suite with a Root Mean Square Error (RMSE) equal to 1.06 and a pixel size of 4.00 m. The orthophoto mosaics of 1945, 1996 and 2008 were created for the needs of the Greek Cadastre. The orthomosaic of 1945

and 1996 were developed with photogrammetric techniques from analogue aerial photographs while the respective mosaic of 2008 was created from digital airphotos. The three datasets cover the whole country. The 1945 and the 1996 orthomosaics have a spatial resolution of 1 m while the 2008 orthomosaic has a spatial resolution of 0.5 m. These three data sets are official datasets of the Greek Government and they did not require any further processing. Worldview-2 was a bundle image with eight multispectral bands and a spatial resolution of 0.5 m. The image was acquired on September 18th, 2018 and it was orthorectified using more than 170 ground control points in Leica Photogrammetry Suite using the respective model for worldview-2 data. The total RMSE was lower than 0.5 pixel.

The spatial resolution of these data ranges from 1 to 4 m. Finally, Worldview-2 imagery (0.5 m spatial resolution) from 2018 was used as a control dataset [47]. A shoreline derived from this image was used as a reference for the rest of the vector data.

The data obtained and the sources of their origin are described in Table 1.

Table 1. Datasets used in the current study.

Year	Data Type	Source	Reference System	Number of Photos	Spatial Resolution	Datasets
1945	Orthomosaic	National Greek Cadastre and Mapping Agency	Hellenic Geodetic Reference System of 1987 (Greek Grid)	1	1 m	No further processing
2008	Orthomosaic	National Greek Cadastre and Mapping Agency	Hellenic Geodetic Reference System of 1987 (Greek Grid)	1	1 m	No further processing
1996	Orthomosaic	Ministry of Rural Development and Food	Hellenic Geodetic Reference System of 1987 (Greek Grid)	1	1 m	No further processing
1973	Declassified satellite imagery	USGS	No reference system	1	4 m	Orthorectified using LPS Suite
2000–2008	(Landsat 7 (ETM+))	USGS	Universal Transverse Mercator Zone 34 (EPSG 32634)	1	30 m	Georeferenced to Hellenic Geodetic Reference System of 1987 (Greek Grid)
2018	(Landsat 8/OLI)	USGS	Universal Transverse Mercator Zone 34 (EPSG 32634)	1	30 m	Georeferenced to Hellenic Geodetic Reference System of 1987 (Greek Grid)
2018	Worldview-2	Digital Globe	Universal Transverse Mercator Zone 34 (EPSG 32634)	1	0.50 m	Orthorectified using LPS Suite

3.2. Methods

The remote sensing image selection was mainly based on the availability of historical images and the potential for accurate orthorectification. Furthermore, cloud cover and seasonality were also taken into consideration. Accordingly, all images were retrieved during the summer months (May to September) and in the same tide phase (ebb tide phase) in order to reduce the impact of seasonality and tidal effects.

Using an online platform (<https://www.worldtides.info/>) we calculated the tide height for every day that we dispose a satellite image. As an example, we mention that for 18 September 2018, the day of Worldview-2 image acquisition, the tide height is estimated at almost 0 m. In general, the maximum (positive or negative) height of the tide at the study areas is 0.1 m (10 cm). It is quite negligible and taking into account the relief of the study area, we believe that it does not affect the shoreline extraction.

We used ERDAS IMAGINE 2014 and ArcMap v10.5 to process the data and DSAS v5.0 beta to forecast shoreline movements.

The methodology flowchart adopted for the entire study is given in Figure 2.

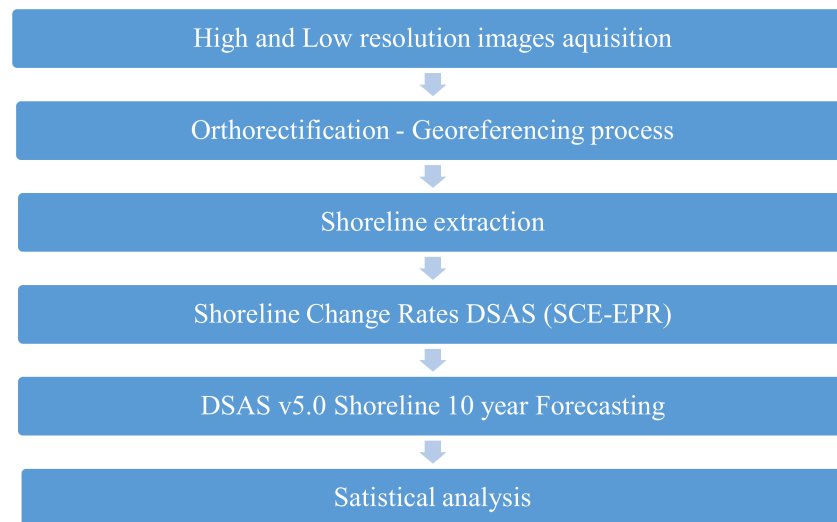


Figure 2. Chart diagram of the study methodology.

3.2.1. Shoreline Digitizing and DSAS Procedure

The first step in low-resolution satellite data processing is to enhance the spatial resolution of Landsat multispectral images. Using the Hyperspherical Color Space (HCS) fusion algorithm, the panchromatic (15 m) and the multispectral (30 m) bands of Landsat were pansharpened, and the new datasets were further processed to extract the shorelines.

Several automatic shoreline extraction techniques, such as the Modified Normalized Difference Water Index (MNDWI) [48] and Normalized Difference Vegetation Index (NDVI) [21,31,49], were tested.

An initial attempt to delineate the shorelines directly via the NDVI and MNDWI indices was unsuccessful (Figure 3a,b). ERDAS Imagine 2014 software was used to compute these indices. We observed various digitizing problems due to the 15-m-per-pixel analysis of the multispectral images, which causes problems in the coastline forecasting procedure, as the automatically extracted shorelines have jagged edges and, in general, are not as linear and smooth as expected (Figure 3d).

On screen, digitizing of the shorelines from remote sensing data is described in many previous studies [14,35,36]. Other studies proposed the automatic classification using the MNDWI [13]. In any case as the main scope of this paper is to assess and quantify the accuracy of low - and high - resolution data and not to accurately determine the position of the coastline, any possible error due to manual or to the automatic shoreline extraction affects the same all the data sets and can be ignored.

After that, we decided to proceed to manual shoreline digitizing from multispectral images with a 15 m spatial resolution (Figure 3c) for all Landsat time series.

High-resolution images from 1945, 1973, 1996, 2008, and 2018, such as the orthomosaic from the National Greek Cadastre and Mapping Agency, USGS declassified satellite image, and orthomosaics from the Ministry of Rural Development and Food and Worldview-2 satellite, were used to vectorize the shorelines using the same procedure (on-screen digitizing) for these years.

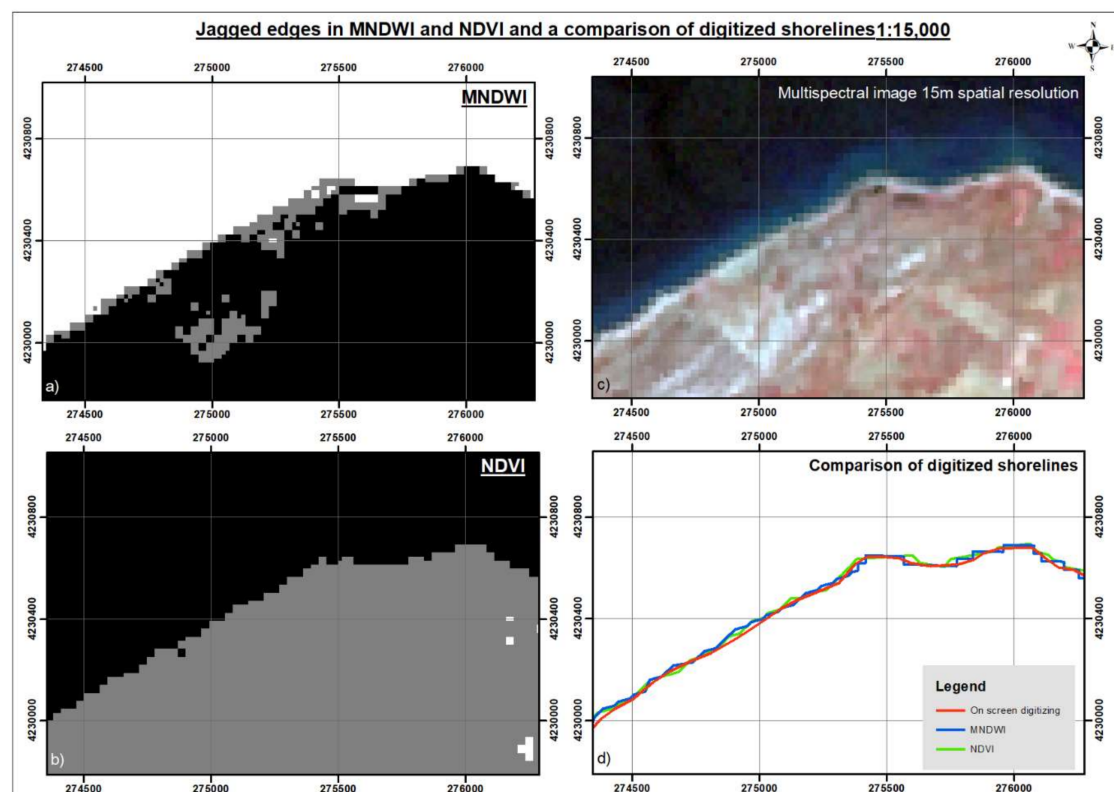


Figure 3. Jagged edges of the Landsat-derived shoreline in comparison to that derived using the on-screen digitizing method (red line). (a) An example of MNDWI index. (b) An example of NDVI index. (c) An example of Landsat multispectral image derived through HCS fusion algorithm. (d) Overlapping of digitized shorelines.

3.2.2. Procedure

After the shoreline digitizing process, two geodatabases were created in the ArcGIS platform, one for low- and one for high-resolution vector data, following the Digital Shoreline Analysis System (DSAS v5.0) requirements.

The low-resolution dataset includes shorelines from 2000, 2001, 2002, 2004, 2005, 2006, 2007, 2008, and 2018. The high-resolution dataset includes the 1945, 1973, 1996, 2008, and 2018 shorelines. The features of each coastline include the date, identity, shape, length, and uncertainty. Furthermore, each geodatabase includes a baseline, which was carefully created landward. Smoothing was required, taking into account the general trend of the under-analysis of shorelines, because as it is well known, its design significantly affects the calculations.

The Digital Shoreline Analysis System is a tool that cooperates with the ArcMap software package and was created by the United States Geological Survey. It is a useful tool that can calculate the changes in shoreline movement due to some various statistical rates [50]. In the current study, the rates that were calculated were the end point rate (EPR) and the shoreline change envelope (SCE). The EPR computes the annual movement rate of a total of points, which occurs from the intersection between the shoreline and many perpendicular lines (named transects) to the baseline, while the SCE computes the biggest distance between the shorelines imported into the geodatabase. Moreover, we evaluated the accuracy of the DSAS forecasting tool by running a 10-year shoreline forecast from low- and high-resolution data. In this study, a baseline was manually created for each test site, while transects were set every 10 m along the coastlines.

Three different tests were performed. Transects every 10, 30 and 50 m were created and used for the measurements. The analysis of the statistics proved that there is not any significant difference to the results. The spatial resolution of the data does not affect the distance of the transects. A denser

transect network every two of five meters means that we expect a different shoreline attitude every two or five meters. The alterations between accretion and erosion in the specific shoreline are not so extreme and dynamic.

A total of 291 and 421 transects were cast from north to south and east to west on the Kalamaki and Karnari beaches, respectively. Finally, the statistical rates of DSAS were automatically calculated from the data derived from each beach.

As discussed in the introduction, this study has two objectives: (a) to assess and quantify the accuracy of low- and high-resolution remote sensing data for shoreline mapping; and (b) to calculate the divergence in the forecasting of coastline evolution based on low- and high-resolution datasets.

To achieve the first goal of the study, shoreline vectors derived from low-resolution Landsat data were compared to the corresponding shorelines derived from high-resolution data. In particular, for the year 2018, the shoreline digitized from the Landsat 8 image was compared to the shoreline digitized from Worldview-2. Furthermore, the shorelines were also digitized from Landsat 7 (ETM+) imagery from 2000, 2001, 2002, 2004, 2005, 2006, 2007, and 2008. Using these vector data, a shoreline forecasted using low-resolution data for 10 years in 2018 was automatically generated using DSAS software. This “forecasted low” shoreline in 2018 was compared (with a high and low scale) to the “actual low” shoreline in 2018, which was digitized from a Landsat (OLI 8/TIRS) multispectral image. Moreover, this shoreline was compared to the “actual high” shoreline, which was extracted from the 2018 Worldview-2 image.

The same procedure has been followed for the high-resolution remote sensing data. Shorelines were manually extracted from the Greek Cadastre, USGS declassified satellite imagery and Ministry of Rural Development and Food for 1945, 1973, 1996, and 2008 (0.50 to 4 m spatial resolution). A shoreline forecasted using high-resolution data in 2018 (“forecasted high”) was developed through DSAS and used for the accuracy tests of the second goal.

To achieve the second goal of the study, the forecast shorelines (low and high) were used to assess the divergence in the forecasting of the coastline position. The 2018 “actual high” manual vectorized shoreline of the Worldview-2 (0.5 m resolution) image was used as a reference for the “forecasted high” shoreline, while the “actual low” manual vectorized shoreline of the Landsat 2018 image was used as a reference for the “forecasted low” shoreline.

A statistical comparison of the forecasted shorelines derived from high- and low-resolution data was conducted using the DSAS v5.0 beta and Microsoft Excel software.

4. Results

Two sandy beaches in Kalamaki and Karnari, located in Northwestern Peloponnese in Greece, were used as test sites in order to estimate and quantify the accuracy of low- and high-resolution data for shoreline mapping and to calculate the divergence in the forecasting of coastline evolution based on low- and high-resolution datasets.

4.1. First Goal Results (Accuracy)

In Figure 4a, on the Kalamaki beach, shown in red, the shoreline extracted from 2018 Worldview-2 is presented and overlaps with the 2018 “forecasted high” shoreline, which is illustrated in green at a 1:5000 scale. In addition, in Figure 4b, the “actual” 2018 shoreline digitized from the Landsat (OLI 8/TIRS) multispectral image, the 2018 “forecasted low” shoreline, and the shoreline extracted from 2018 Worldview-2, shown in blue, green, and red, respectively, are overlapping in the same place and scale. In Figure 5a,b the corresponding presentations, shown in the same colors, are also presented for the Karnari beach at the same scale. There are three areas in Kalamaki beach and two areas in Karnari beach (red cycles) (Figures 4 and 5) where the deviation in the low-resolution data is obvious in high-scale mapping.

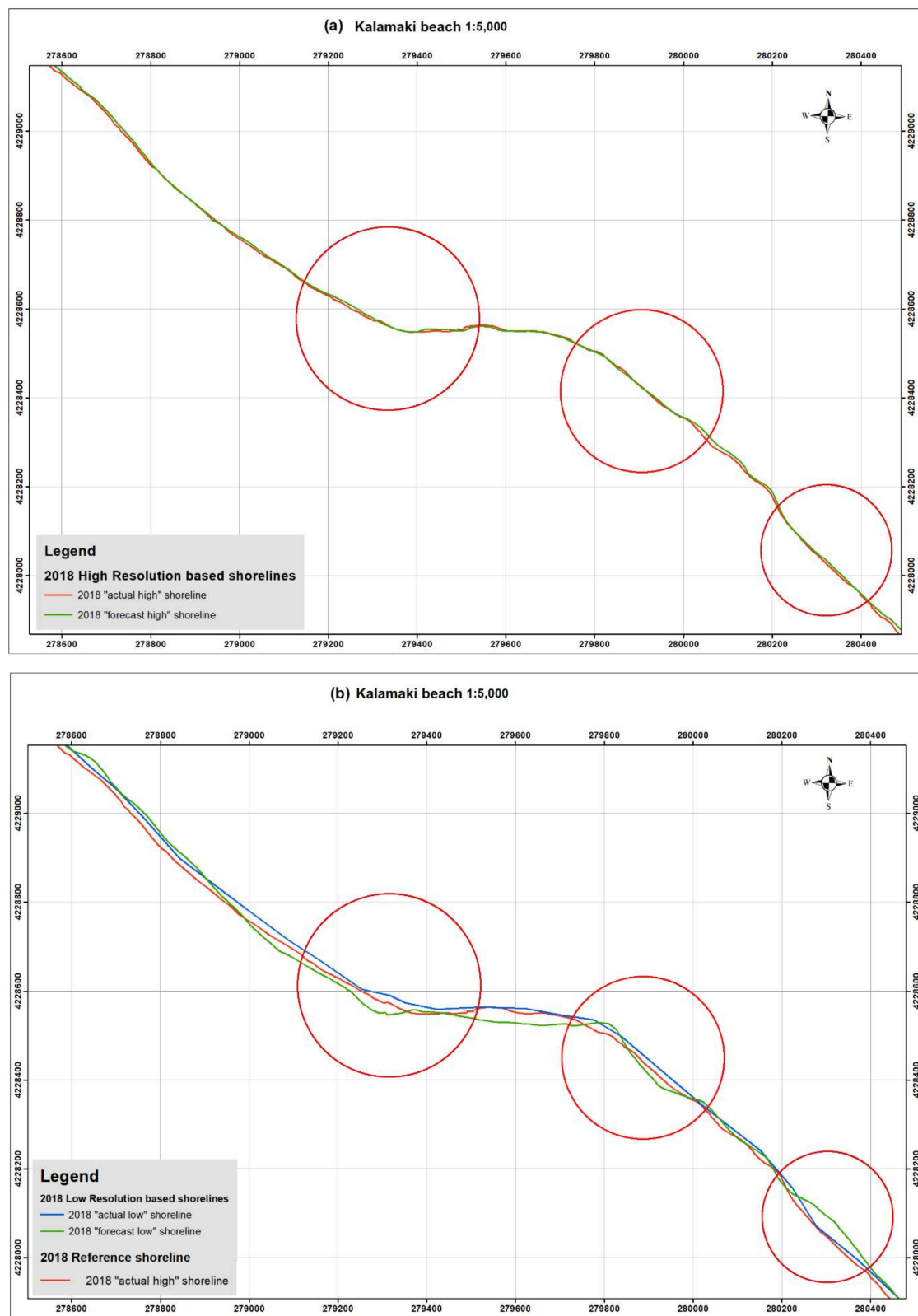


Figure 4. Shorelines of 2018 overlapping at a high scale based on (a) high- and (b) low-resolution images for Kalamaki beach. Red cycles demonstrate areas where the deviation in the low-resolution data is obvious in high-scale mapping.

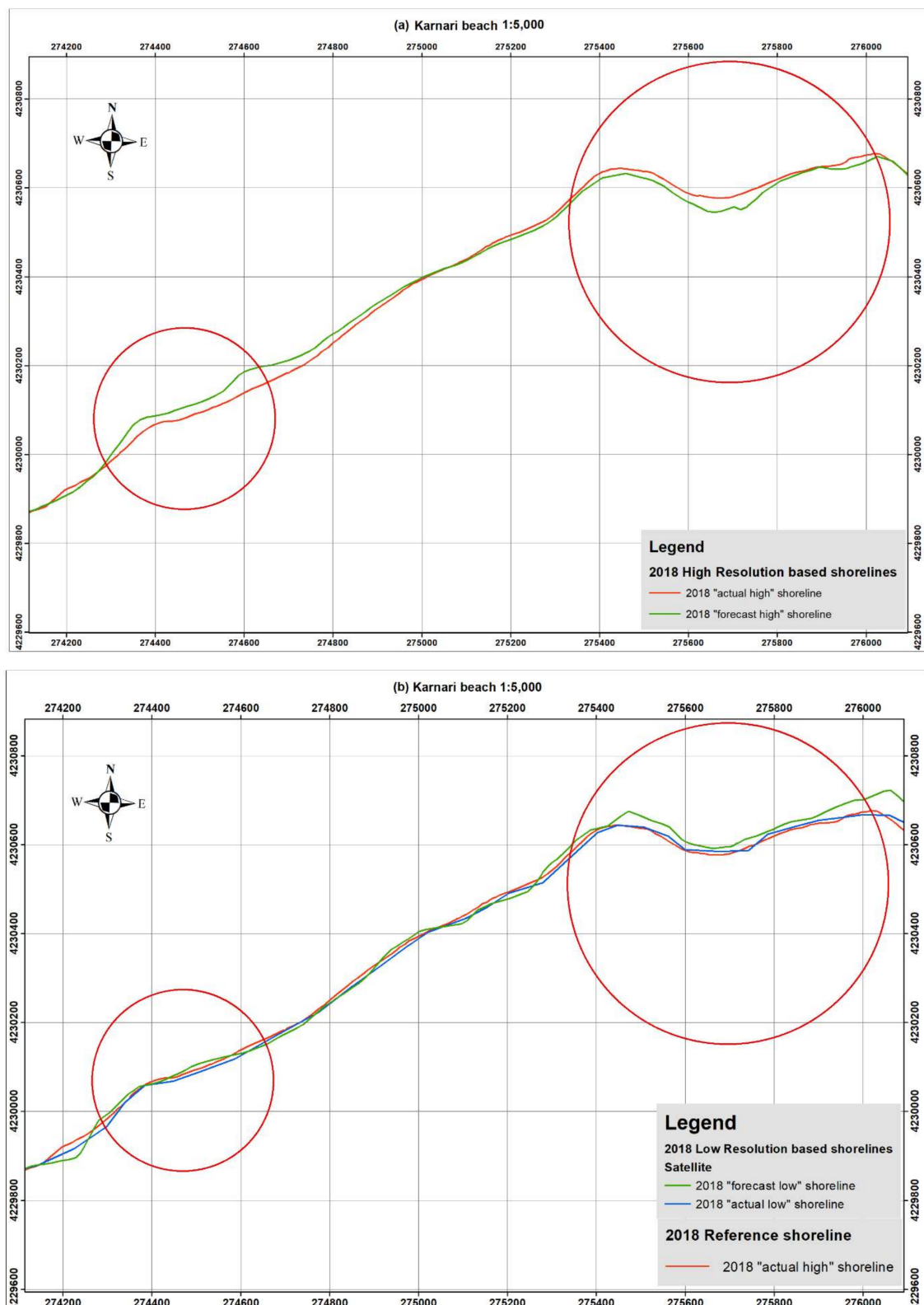


Figure 5. Shorelines of 2018 overlapping at a high scale based on high- and low-resolution images for Karnari beach. Red cycles demonstrate areas where the deviation in the low-resolution data is obvious in high-scale mapping.

Moreover, this deviation also seems to be more intensive in Karnari beach, even in the high-resolution data, in contrast to Kalamaki beach, where there is a good enough fitting for the

shorelines derived from the high-resolution dataset. In addition, this fact raises a new question: whether the forecasting tool has any limitations relating to the accuracy of the results. Furthermore, this discrepancy in one of the two study areas should be explained, so that the process we have applied to assess the accuracy of the data will be acceptable and, at the same time, the parameters that determine the results can be identified. Before the DSAS v5.0 forecasting tool started running, a significant note emerged that the results of this tool are influenced by many factors and may vary between locations, and for this reason, the user should be very careful to ensure that the data are being produced correctly [51].

In order to determine the source of the deviation in the accuracy of the forecasting procedure followed for the two beaches with high-resolution data, we calculated the SCE rates based on 1945–2008 data for both coasts, and we noticed that there was a great difference in the range (Figure 6a,b).

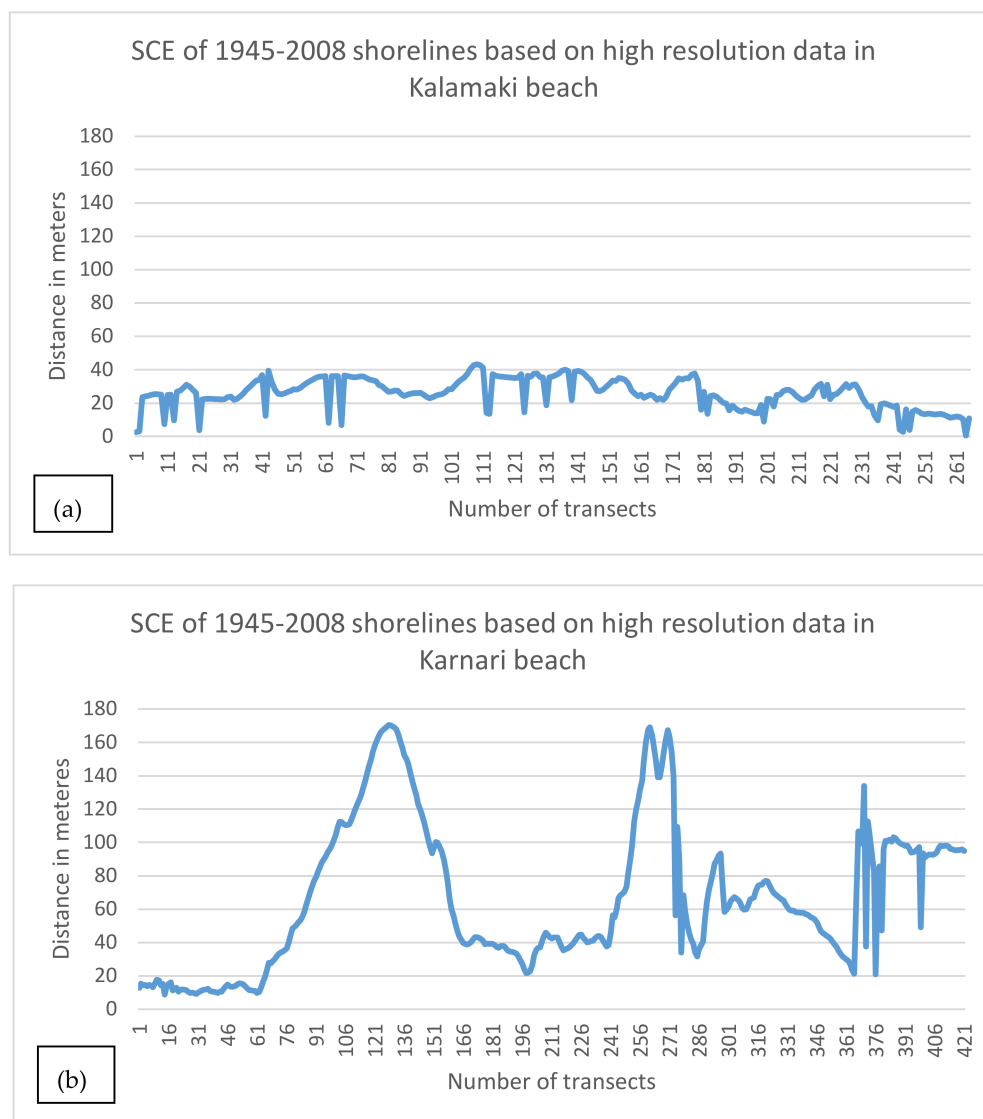


Figure 6. Shoreline change envelope (SCE) rates of 1945–2008 shorelines based on high-resolution data for (a) the Kalamaki and (b) Karnari coasts.

As can be observed in Figure 6a, the distance in meters between the shorelines of 1945 and 2008 from the intersection points of the perpendicular to the baseline transects is limited to a range from 0 to 40 m in Kalamaki beach.

Meanwhile, in Karnari beach, as we can see in Figure 6b, this distance is not limited to a specific range but varies from approximately 10 to 170 m.

In order to demonstrate that the low accuracy of the 2018 “forecasted high” shoreline in Karnari beach is related to the high SCE rates, we project the transects where the SCE rates are over 40 m long (Figure 7 in blue). It is obvious that there is a relationship between the sites in red cycles and the SCE values. Moreover, we concluded that the DSAS forecasting tool provides reliable results, as the SCE rates are as low as possible. In addition, we found that SCE rates above 40 m have a great difference in terms of the results.

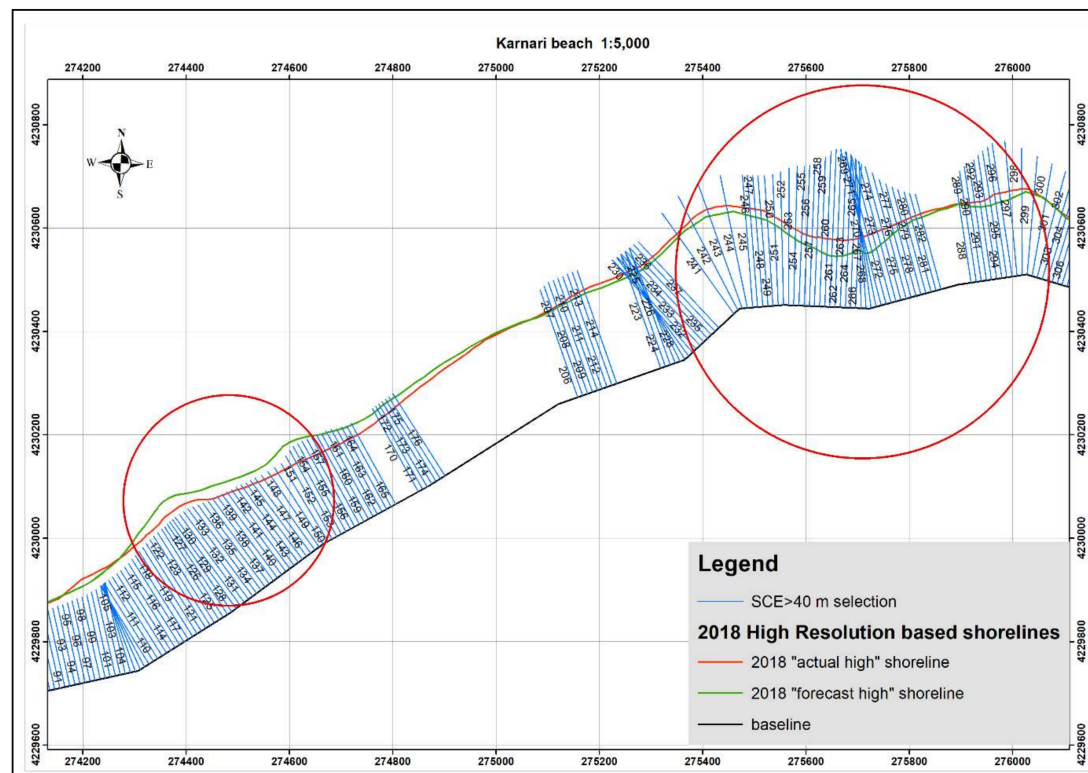


Figure 7. Transects where the SCE rates of the 1945–2008 shorelines based on high-resolution data on the Karnari coast are over 40 m.

On the other hand, if one works at a lower scale, such as 1:25,000 (Figure 8), many of the abovementioned observations would not be noticed.

In Figure 8a, an overlapping of the 2018 “forecasted high” shoreline (green color) with the shoreline extracted from the 2018 Worldview-2 image (red color) is presented for Kalamaki beach at a low scale. Furthermore, in Figure 8b, an overlapping of the 2018 “forecasted low” shoreline (green color) with the shoreline extracted from the 2018 Worldview-2 image and the “actual” 2018 shoreline digitized from the Landsat (OLI 8/TIRS) multispectral image is presented for the same place and scale. In Figure 8c,d, the corresponding presentations, with the same colors, are also presented for Karnari beach at the same scale. From Figure 8, we detected that due to the very good overlapping of the 2018 coastlines derived from the high-resolution data (Figure 8a) for the area of Kalamaki, it is not easy to distinguish any significant deviation, while the same does not apply for the low-resolution data, where a very high deviation is obvious in low-scale mapping. On the other hand, for Karnari beach, this finding is not applicable, because there is not such a good fitting, even with high-resolution data, especially where the rates of SCE are over 40 m, as mentioned above. Thus, we concluded that the high-resolution data provide a very good accuracy for shoreline mapping in places where the distance between the shorelines used is under 40 m or even lower. They produce better results in comparison to the low-resolution data, where the deviation in the respective sites is high and the accuracy is very low.

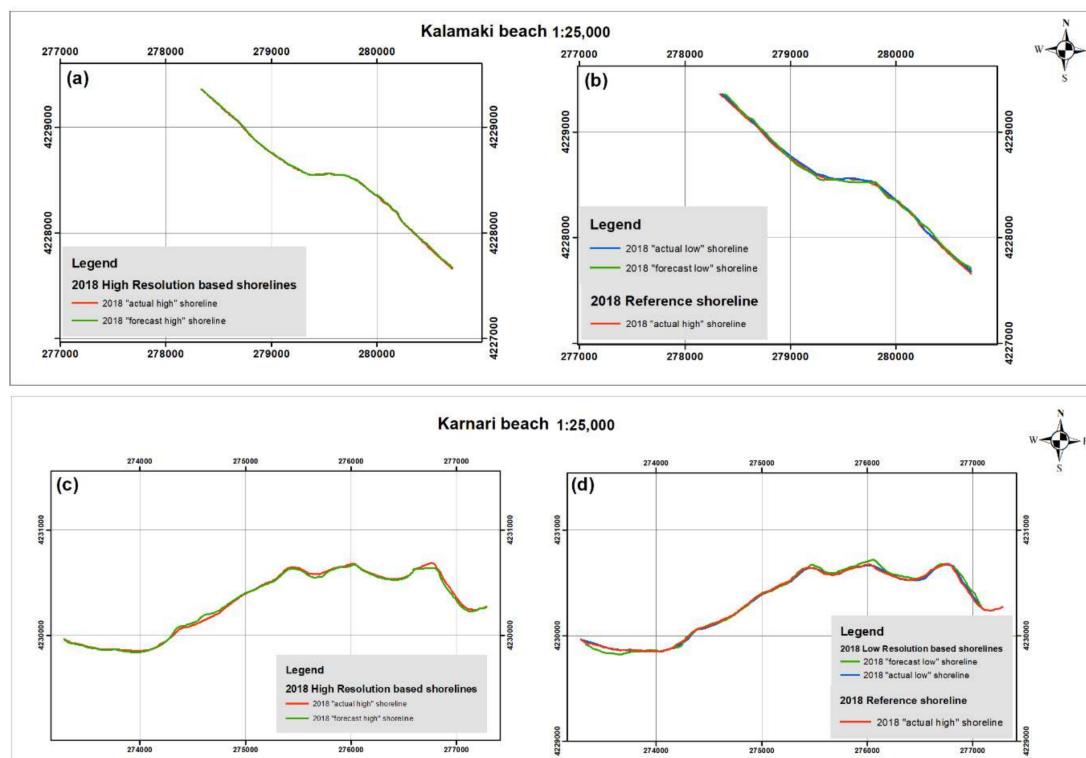


Figure 8. Shorelines of 2018 overlapping at a low scale for (a) Kalamaki and (b) Karnari beaches, based on both high- (a,b) and low-resolution (c,d) images.

Furthermore, except for the graphical comparison described above, we need to enumerate the accuracy of the results. For that purpose, a new geodatabase was created, and the existing 2018 Landsat shoreline and the shorelines based on DSAS v.5.0 2018 forecasting were imported. The same procedure was followed for the shorelines from the high-resolution data. The shoreline change envelope (SCE), which represents the greatest distance among the intersection points between shorelines and transects being produced, was calculated for every pair of 2018 shorelines based on the low- and high-resolution data from the test sites (Figure 9).

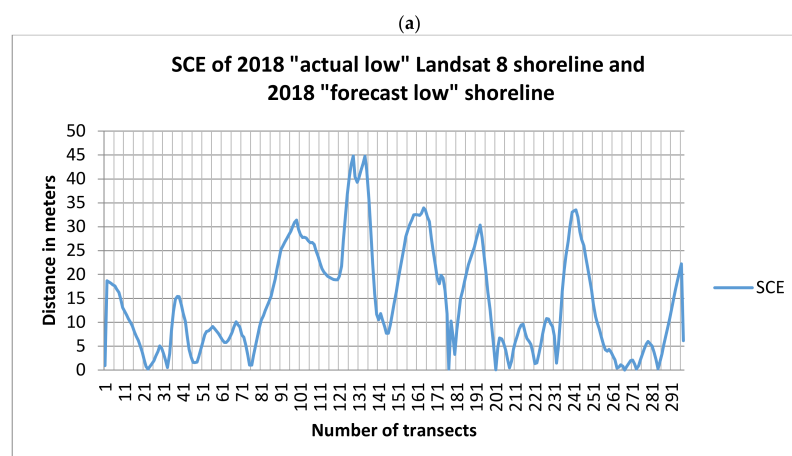


Figure 9. Cont.

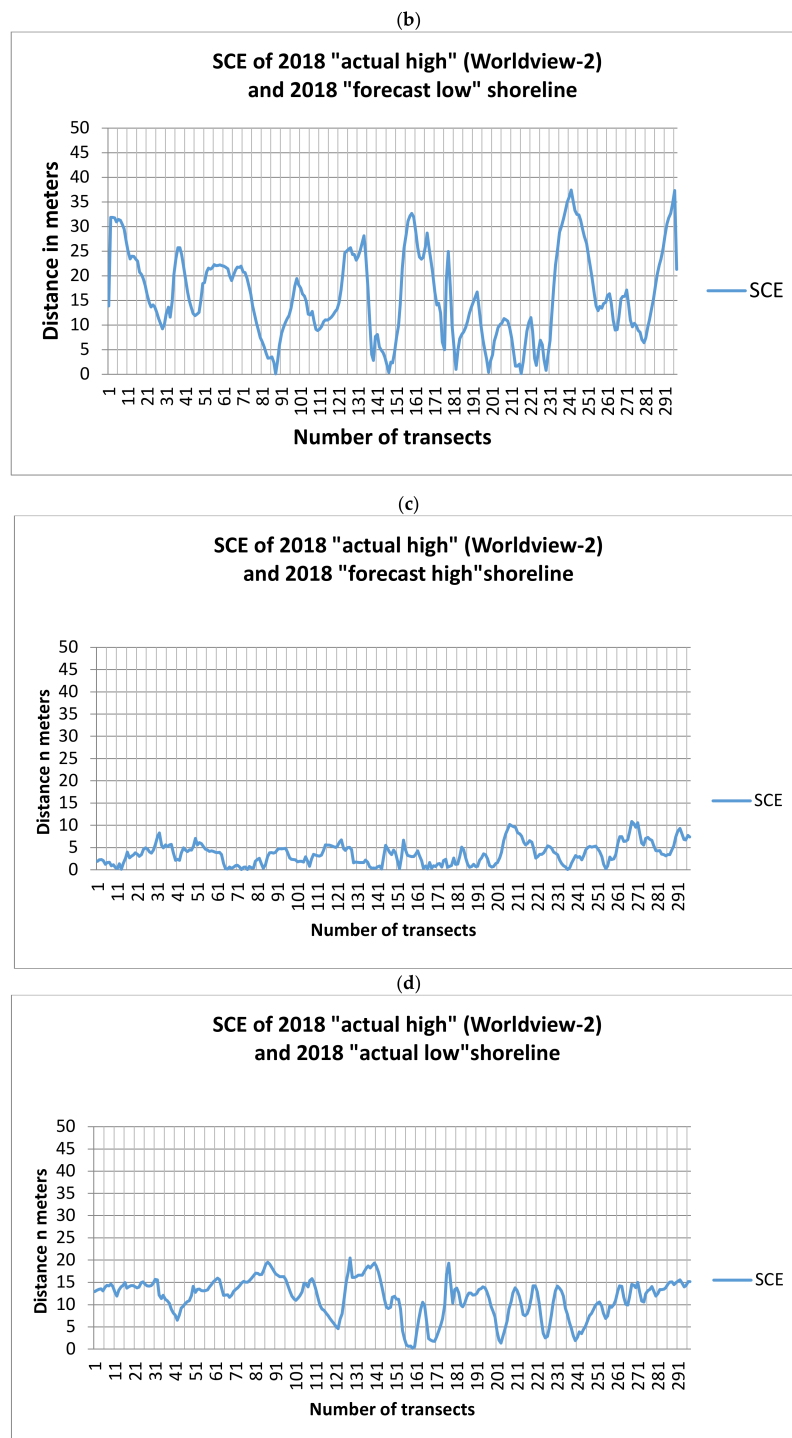


Figure 9. SCE statistical rates from low- and high-resolution vectorized shorelines in 2018 for Kalamaki beach.

Figure 9a presents the SCE rates of the 2018 “actual low” Landsat 8 shoreline and the 2018 “forecasted low” shoreline, while Figure 9b presents the SCE rates of the 2018 “forecasted low” shoreline and the shoreline extracted from 2018 Worldview-2. Finally, Figure 9c shows the SCE rates of the shoreline extracted from the 2018 Worldview-2 “actual high” and 2018 “forecasted high” shoreline, while Figure 9d presents the SCE rates of the 2018 “actual high” and 2018 “actual low” Landsat 8 shorelines. In addition, the corresponding presentations, maintaining the same order, are also presented for Karnari beach in Figure 10a–d.

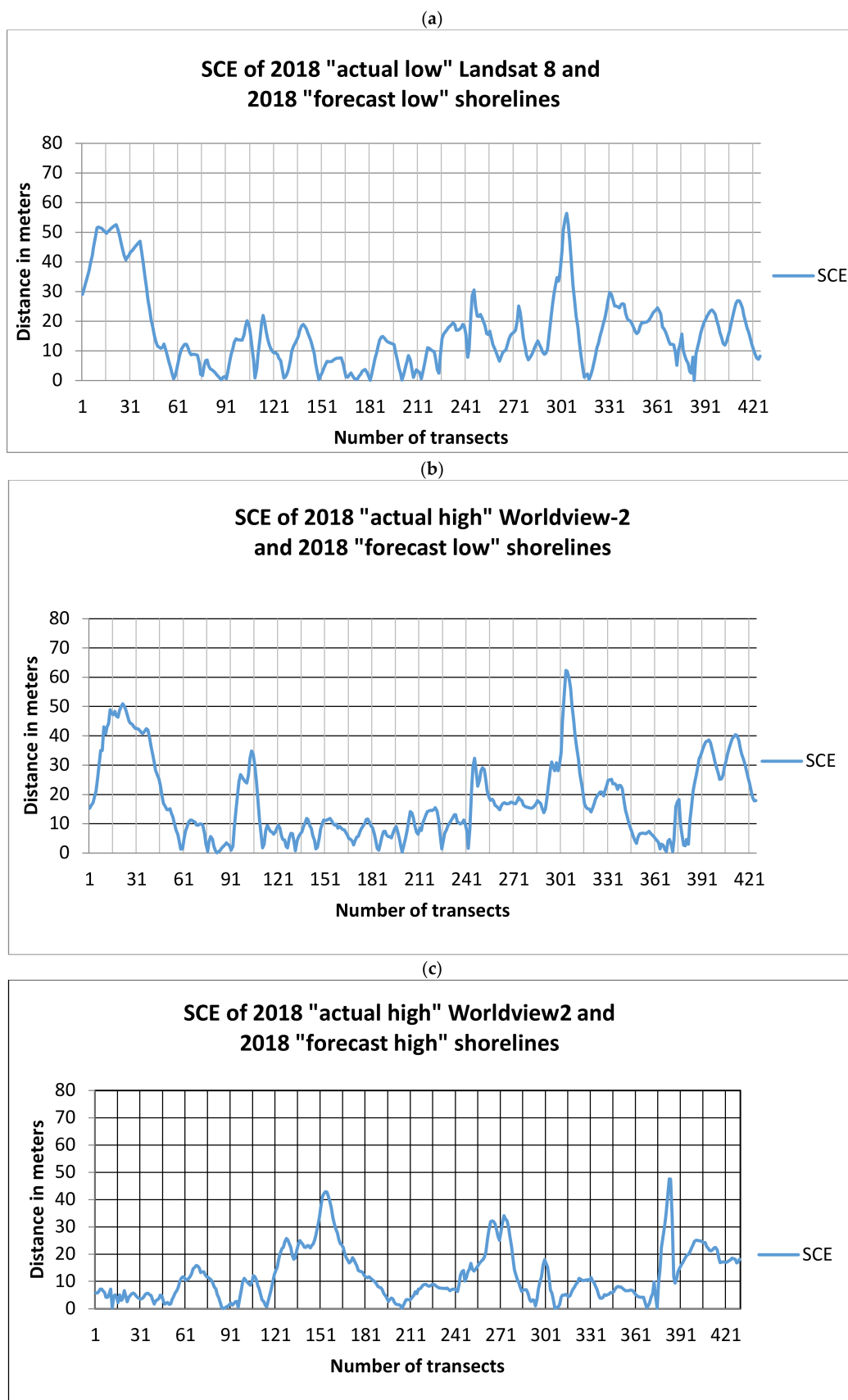


Figure 10. Cont.

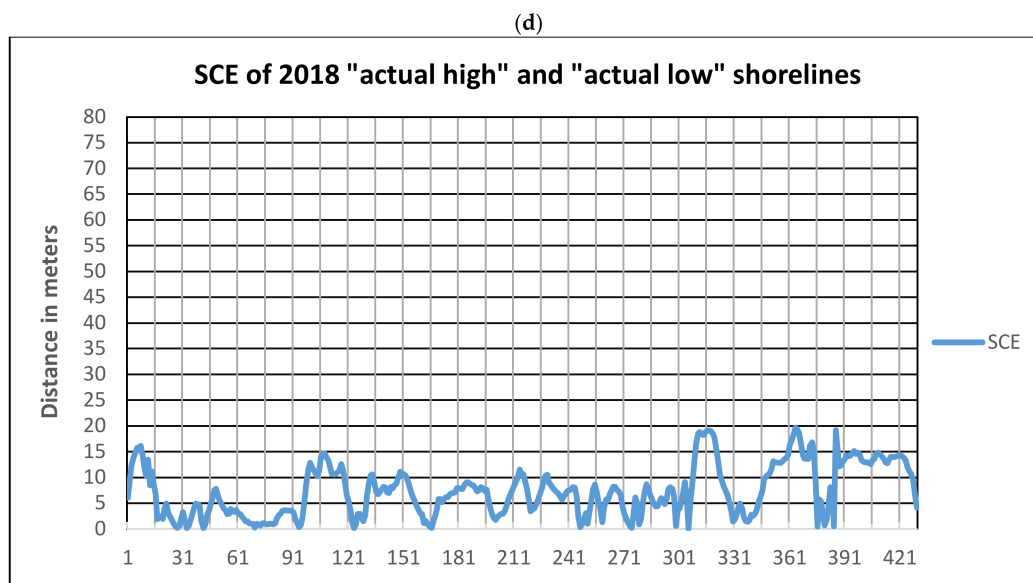


Figure 10. SCE statistical rates from low- and high-resolution vectorized shorelines in 2018 for Karnari beach.

The diagrams for Kalamaki beach show that, using the low-resolution data, there is a high range in the deviation (Figure 9a) between 0 to 44.84 m (Table 2). From transects 1 to 71 and from 256 to 281, the 2018 “forecasted low” shoreline is closer to the “actual low” 2018 shoreline based on the Landsat image (Figure 10a). The mean rate is 14.38 m, while the standard deviation is 11.05 m (Table 2). The mean rate of this distance seems to be increased at 15.94 m, when the “actual high” 2018 shoreline is used for a relative comparison (Figure 9b), with a standard deviation rate of 8.87 m (Table 2). This result is caused by the significant deviation in the spatial resolution of the datasets used. Moreover, the 2018 “forecasted high” shoreline is well matched to the “actual high” 2018 shoreline, with the distance between them being lower than 10 m along the entire coast (Figure 9c). The deviation between them ranges from 0.04 to 10.84 m, and the mean rate is 3.60 m, with a standard deviation at a very low rate of 2.39 m (Table 2). Finally, in Figure 9d, the deviation of the “actual high and low” shorelines ranges from 0.20 to 20.46 m, and the mean rate is 11.61 m, with a standard deviation of 4.28 m (Table 2), which is due to their high difference in their respective spatial resolutions.

Table 2. SCE statistical rates (in meters).

Kalamaki Beach					
2018 Shoreline Overlapping	Figures	Min	Max	Mean	Standard Deviation (σ)
“actual low” and “forecasted low”	Figure 9a	0.00	44.81	14.38	11.05
“actual high” and “forecasted low”	Figure 9b	0.09	37.42	15.94	8.87
“actual high” and “forecasted high”	Figure 9c	0.04	10.84	3.60	2.39
“actual high” and “actual low”	Figure 9d	0.20	20.46	11.61	4.28

The diagrams for Karnari beach (Figure 10) show that, along the entire coast, the distance between the “forecasted low” shoreline and the “actual low” shoreline based on the Landsat 2018 image (Figure 10a) is about 10 m higher compared to when the 2018 “actual high” is used for the comparison (Figure 10b), and the mean rates are 16.17 and 17.47 m, respectively (Table 3). Moreover, the deviation between the 2018 “forecasted high” shoreline and the “actual high” 2018 shoreline (Figure 10c) presents a wide range of rates from 0.03 to 47.63 m, and the mean rate is 12.17 m, with a standard deviation at a very high rate of 9.49 m (Table 3). In addition, in transects 61–91, 121–181, 241–301, and 370–421, there is a significant diversity in the distance rates, varying from 20 to 50 m,

and this reveals the problem pertaining to the accuracy of high-resolution data, mentioned in paragraph 4.1. Finally, in Figure 10d, the deviation of the “actual high and low” shorelines ranges from 0.01 to 19.66 m, and the mean rate is 7.37 m, with a standard deviation of 4.90 m (Table 3), which is due to the high difference in their respective spatial resolutions.

Table 3. SCE statistical rates (in meters).

Karnari Beach					
2018 Shoreline Overlapping	Figures	Min	Max	Mean	Standard Deviation (σ)
“actual low” and “forecasted low”	Figure 10a	0.01	56.35	16.17	12.89
“actual high” and “forecasted low”	Figure 10b	0.08	62.31	17.47	13.47
“actual high” and “forecasted high”	Figure 10c	0.03	47.63	12.17	9.49
“actual high” and “actual low”	Figure 10d	0.01	19.66	7.37	4.90

Summarizing the results mentioned above, we detected that shorelines derived from high-resolution datasets could be used with a great accuracy for shoreline mapping, with some limitations. The high spatial resolution of these data is not enough but must be combined with the lowest possible distance between the coastlines, so that the results are reliable. As the distance between the most distant coastlines increases (in parts of Karnari beach, it was over 40 m), the accuracy of the shoreline evolution results decreases, but if this distance is kept low, the results are better. On the other hand, the low-resolution data do not offer this feature and seem to be useful only at small scales.

4.2. Second Goal Results (Forecasting)

Coastal monitoring studies focus on mapping the diachronic coastline evolution and predicting the trend of shorelines in the future. To achieve the first objective, the use of multitemporal remote sensing data proved quite efficient. To achieve the second goal, new tools are under investigation. A tool for forecasting coastline evolution has been implemented in the fifth version of the DSAS software. This tool can calculate the shoreline movement after 10 or 20 years, based on past shoreline data [51].

The results of this new tool are based on an older similar algorithm, known to the research community as the Kalman filter, which has been used since 1960 to compare the known shoreline position with the position being extracted through a model. The results are used for shoreline forecasting [52].

The “forecasted low” and the “forecasted high” shorelines of 2018, described in the previous paragraphs, are compared to the “actual low” and “actual high” shorelines of 2008.

Furthermore, the EPR rates were computed for the 2008–2018 period from both low- and high-resolution data using the “actual” 2008 and 2018 shorelines and the 2018 “forecasted” shorelines, based on the DSAS v.5.0 beta software forecasting tool, in order to estimate the erosion and accretion in the test areas. The results are presented in Figures 11 and 12 for Kalamaki and Karnari beaches, respectively.

In Figure 11, the ERP rates are computed for Kalamaki beach from both low- and high-resolution data. Figure 11a presents the EPR rates from the 2008 and 2018 “actual high” shorelines in more detail, while Figure 11b also presents the respective EPR rates from the 2008 “actual high” shoreline and the 2018 “forecasted high” shoreline based on high-resolution data in greater detail. The respective EPR rates derived from low-resolution data are presented in Figure 11c,d.

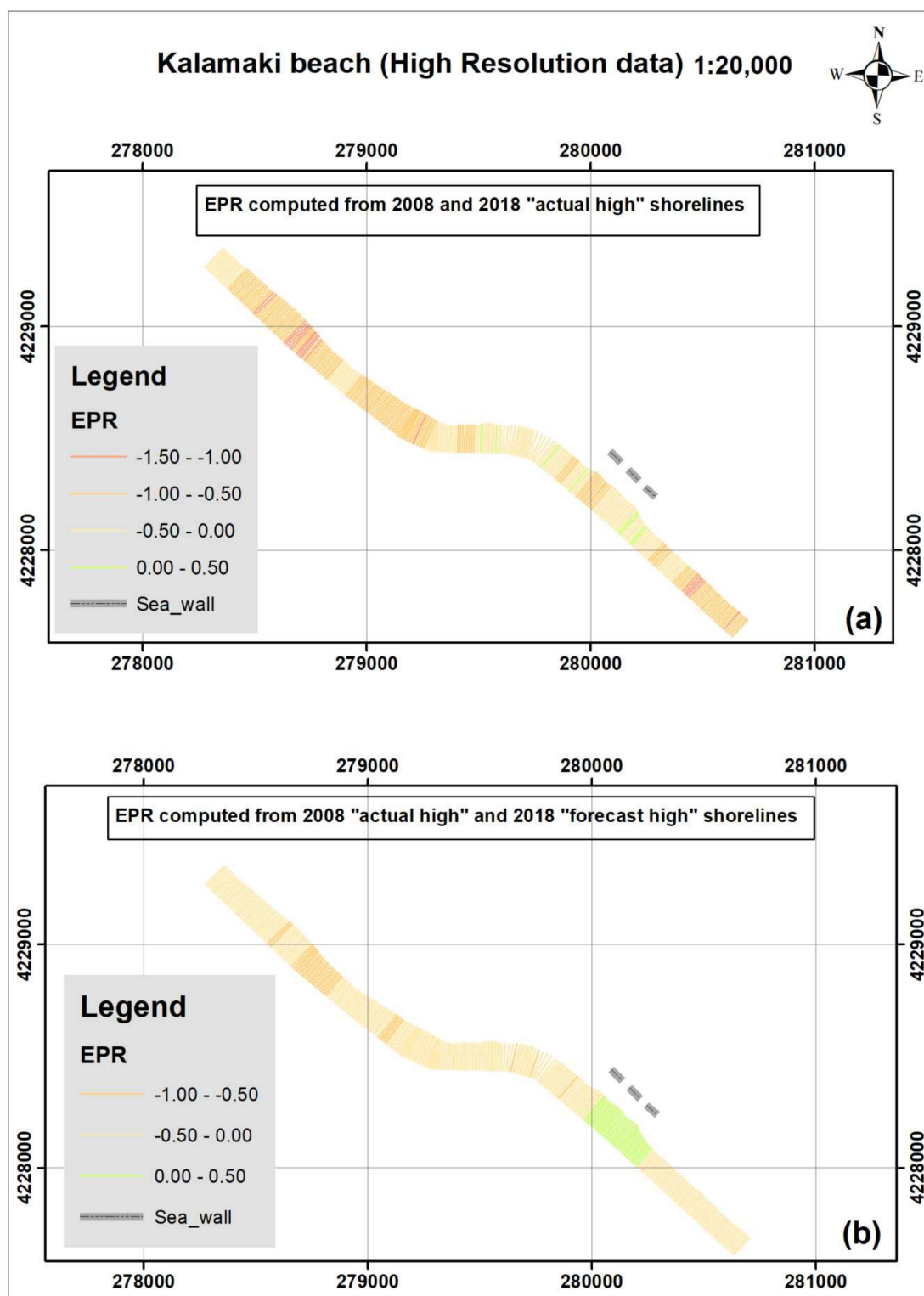


Figure 11. Cont.

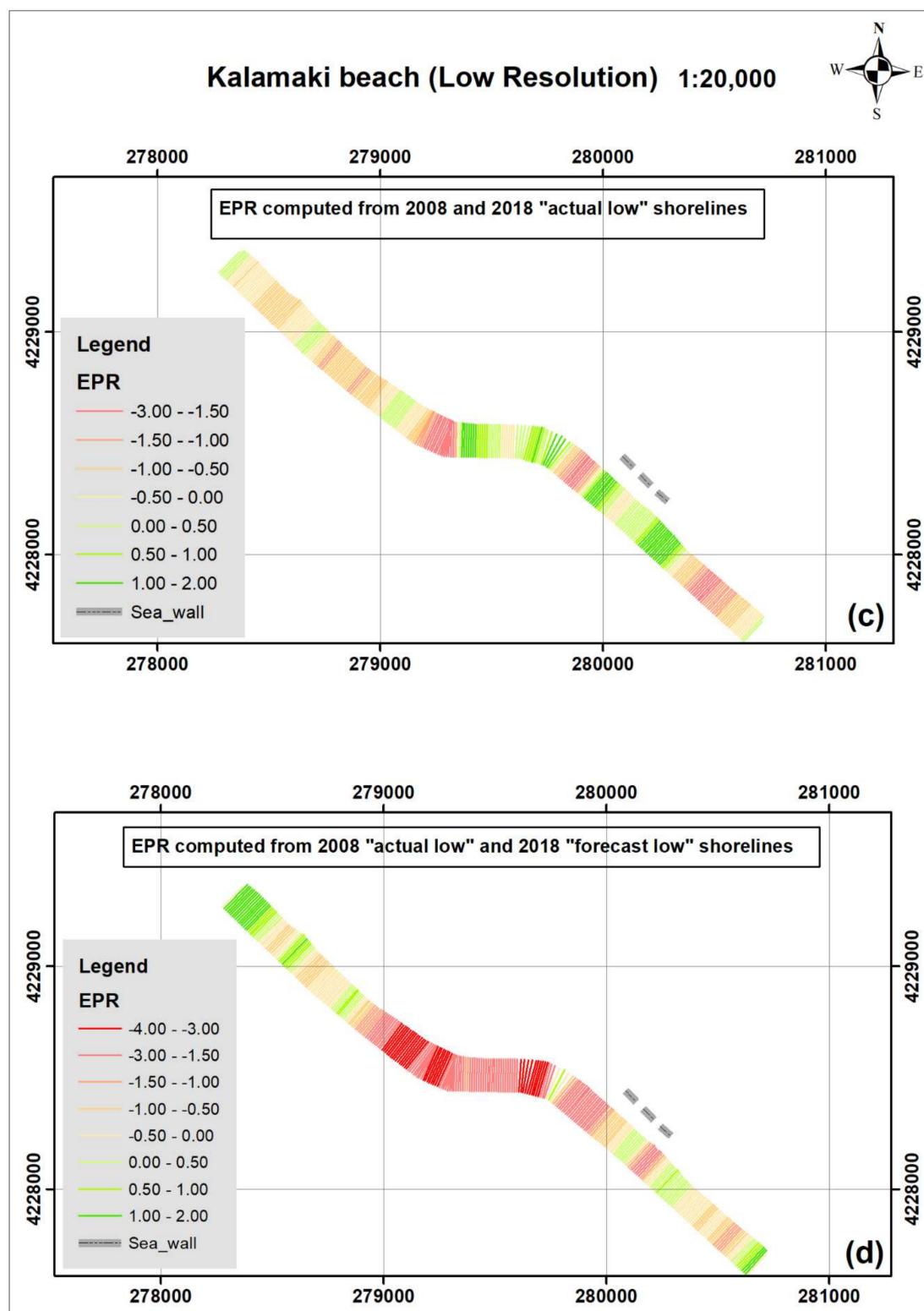


Figure 11. End point rate (EPR) rates were computed for the 2008–2018 period from both low- and high-resolution data using the 2008 and 2018 “actual” shorelines and the 2018 “forecasted” shorelines for Kalamaki beach.

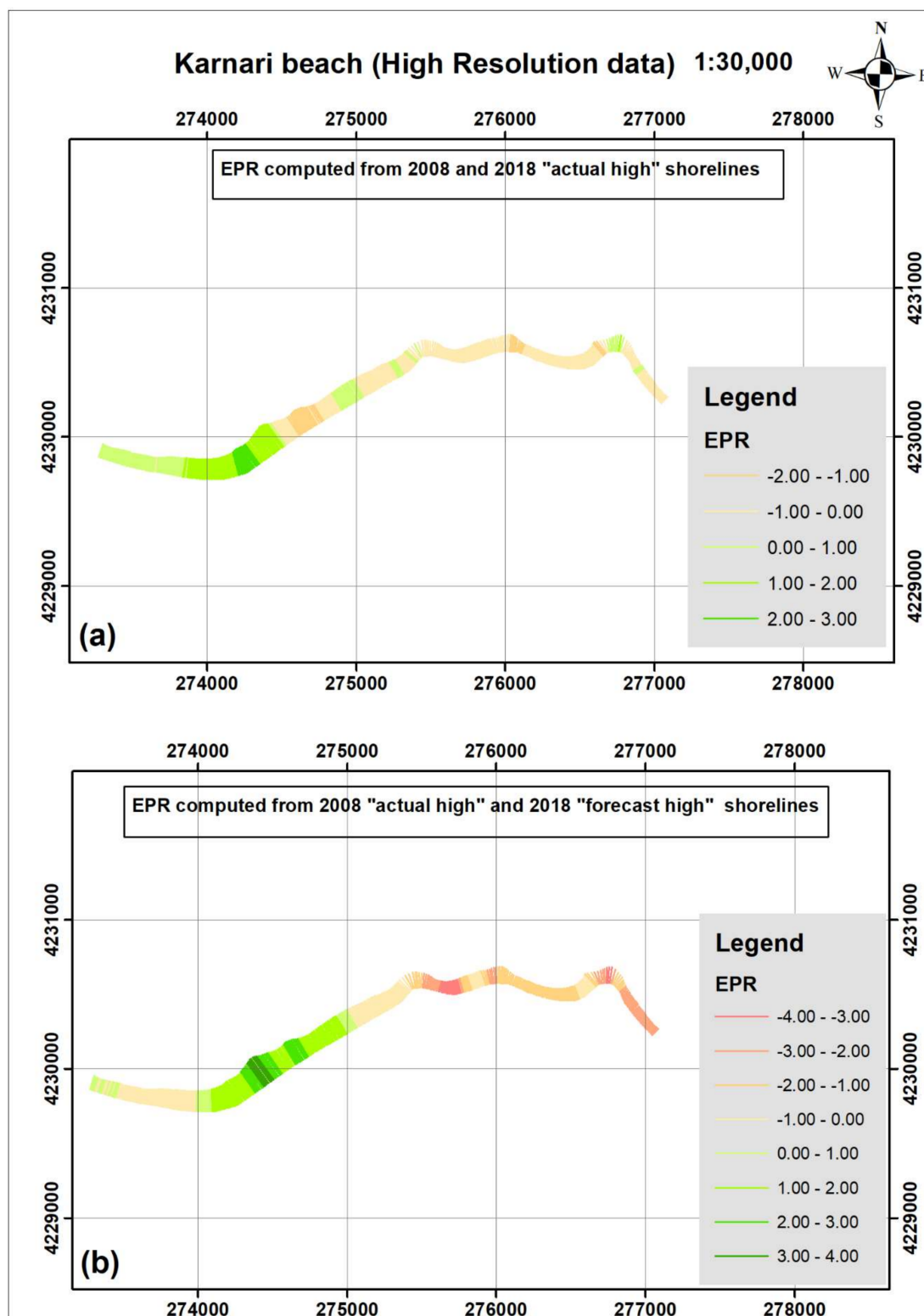


Figure 12. Cont.

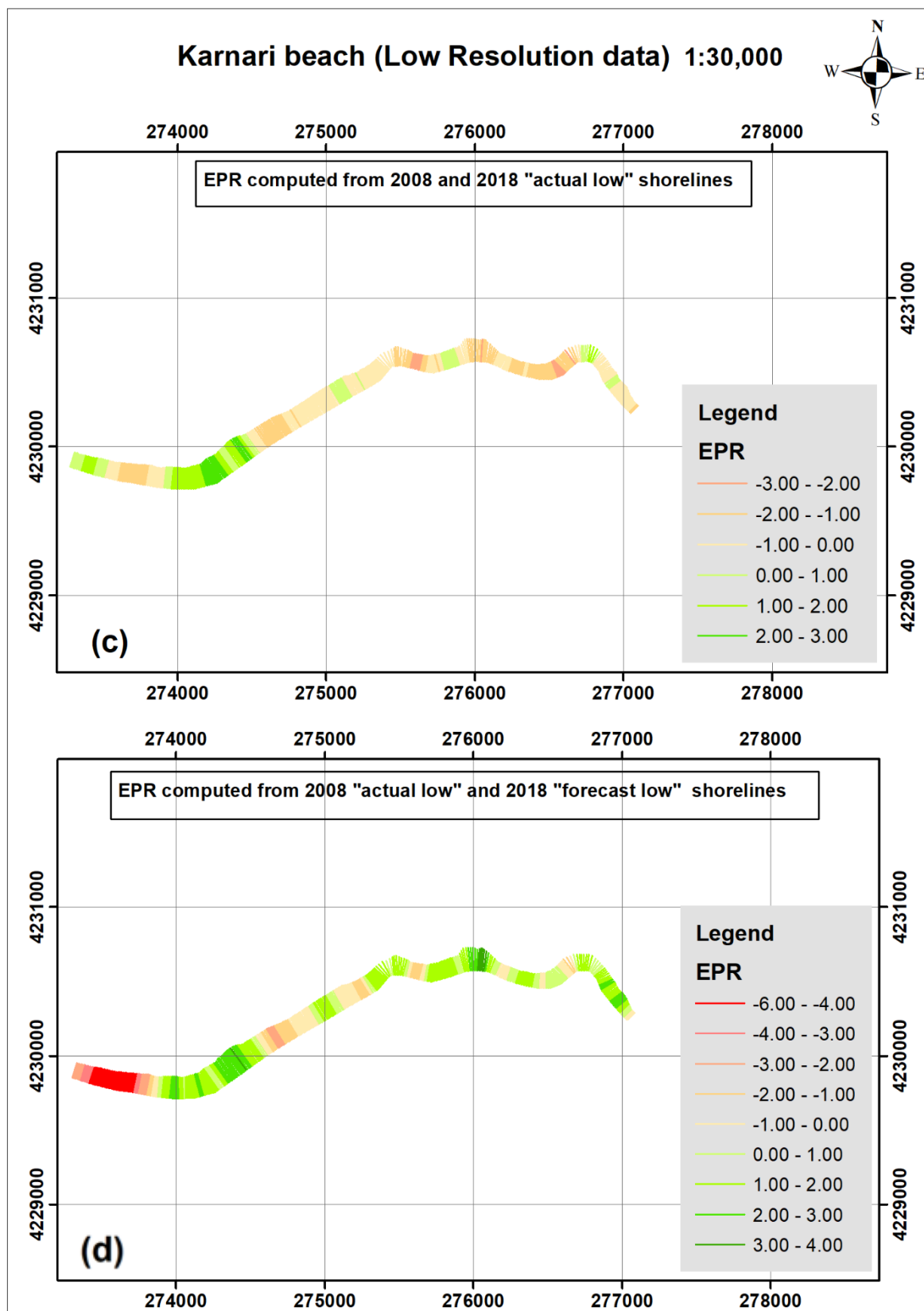


Figure 12. EPR rates computed for the 2008–2018 period from both the low- and high-resolution data using the 2008 and 2018 “actual” shorelines and the 2018 “forecasted” shorelines for Karnari beach.

The results for Kalamaki beach from the “actual high” resolution data (Figure 11a) show that erosion takes place over almost the entire beach. The highest rate of erosion is -1.26 m, while the maximum rate of accretion is just 0.20 m. The average rate is -0.54 m, with a standard deviation of 0.31 m (Table 4). The forecasting model (Figure 11b) seems to agree with the previous state, but there is an accretion trend in front of a local resort, probably due to the artificial sea wall, which is being constructed there to preserve the sand and stabilize the coast. The higher rate of erosion is -0.64 m, while the maximum rate of accretion is 0.51 m. The average rate is -0.25 m, with a standard deviation of 0.23 m (Table 4). As those rates are close to the spatial resolution of the data used, the forecasting model seems to be accurate and reliable too. The forecasting model using the high-resolution data is, in general, in accordance with the results based on “actual” data, as we can observe from Figure 11a,b. On the other hand, in “actual low” analysis and in the relative forecasting model, there is a big difference in the results mentioned above, as illustrated in Figure 11c,d. The relative statistical rates are presented in Table 4.

Table 4. EPR statistical rates (in meters/year).

Kalamaki Beach					
Data Resolution	Figures	Min	Max	Mean	Standard Deviation (σ)
2008 and 2018 “actual high”	Figure 11a	-1.26	0.20	-0.54	0.31
2008 “actual high” and 2018 “forecasted high”	Figure 11b	-0.64	0.51	-0.25	0.23
2008 and 2018 “actual low”	Figure 11c	-3.05	1.84	-0.32	0.95
2008 “actual low” and 2018 “forecasted low”	Figure 11d	-3.73	1.89	-1.00	1.40

In Figure 12, the ERP rates are computed for the Karnari beach from both low- and high-resolution data. Furthermore, in Figure 12a, the EPR rates from the 2008 and 2018 “actual high” shorelines are presented, while in Figure 12b, the respective EPR rates from the 2008 “actual high” shoreline and the 2018 “forecasted high” shoreline based on the high-resolution data are presented. The respective EPR rates derived from the low-resolution data are presented in Figure 12c,d.

The results for Karnari beach from the “actual high” resolution data show that a large area that extends to the northeast is being eroded, while accretion is taking place towards the western part of the beach. The higher rate of erosion is -1.64 m, while the maximum rate of accretion is 3.02 m. The mean rate is 0.00 m, with a standard deviation of 0.90 m (Table 5). The actual and the prediction results based on the high-resolution data are almost in agreement with the previous state, with some local deviations (Figure 12a,b), such as in the northeastern area, where the rates are between -4 to -3 m/yr in the high-resolution forecasting model and between -1 to 0 m/yr in the respective “actual” data.

Table 5. EPR statistical rates (in meters/year).

Karnari Beach					
Data Resolution	Figures	Min	Max	Mean	Standard Deviation (σ)
2008 and 2018 “actual high”	Figure 12	-1.64	3.02	0.00	0.90
2008 “actual high” and 2018 “forecasted high”	Figure 12b	-3.94	3.74	-0.43	1.65
2008 and 2018 “actual low”	Figure 12c	-3.06	2.86	-0.28	1.18
2008 “actual low” and 2018 “forecasted low”	Figure 12d	-6.21	4.10	0.14	2.07

The results based on the low-resolution forecasting model are very different and even generally contradictory, as they show that accretion occurred on almost the entire beach, with mean EPR rates between $+1$ to $+4$ m/yr (Figure 12d). This result does not reflect the real situation, as Figure 12a shows.

Summarizing the results mentioned above for Karnari beach, we concluded that high-resolution data could be used to present the general shoreline evolution trend in an area with a great accuracy. In addition, it is proved that the specific forecasting tool works fine with high-resolution data. Any deviation affects the accuracy and spatial resolution of the data used, which, in turn, affects the forecasting tool parameters. Finally, low-resolution data are not suitable for shoreline forecasting and should not be used for such studies, unlike high-resolution data, which are proved to be much more efficient for forecasting. For the Kalamaki area, the forecasting tool using high-resolution data showed that an erosion of 0.25 m per year is taking place, in contrast to low-resolution data, which revealed an erosion of 1.00 m per year. On the other hand, in the Karnari area, for the period of 2008–2018, the forecasting tool using high-resolution data showed an erosion of 0.43 m per year, while low-resolution data gave an accretion of 0.14 m per year instead.

5. Discussion

We assessed and quantified the accuracy of the data produced by DSAS through low- and high-resolution datasets and estimated the divergence and the trend in the forecasting of shoreline movement from low- and high-resolution datasets. The test sites, Kalamaki and Karnari, located in Northwestern Peloponnesus, were used in a pilot way for the rest of the study area between Araxos and Rio, and the results can be assessed and evaluated, considering the particularities and limitations that have emerged.

Low-resolution data, such as Landsat, have been used in many studies. However, the results were quantified, and an accuracy assessment was performed in very few studies. In [34], the accuracy of different indexes applied to Landsat images was assessed. They compared the automatically extracted shorelines with in situ DGPS measurements and with high-resolution data. According to [53], the freely available images from the Landsat program are georeferenced with a subpixel preciseness (0.44 pixels) resulting in an error of 3.4 m.

The current study proved that the shorelines derived from low-resolution remote sensing data and especially from Landsat imagery present a serious bias that ranges between 6 and 11 m (Tables 2 and 3, Figures 9d and 10d). It is quite crucial to mention that the specific results are in accordance with the corresponding results presented in previous studies. In [10], a very complex methodology is proposed to ameliorate the accuracy of Landsat-derived data. They used a high resolution airphoto mosaic in order to coregister the low-resolution shoreline from the Landsat data to the respective high-resolution shoreline and thus ameliorate the low-resolution shoreline accuracy. They performed a test on 45 Landsat images, and they found a mean error in the shoreline location that ranges from 1.22 to 1.63 m, as well as an RMSE of between 4.69 and 5.47 m. The resulting accuracies may be acceptable; however, the methodology is quite complex and could not be widely used. There is also a necessity for a high-resolution high-accuracy dataset.

The same team in a more recent study controlled the average annual coastline position of many Landsat images and found that there is a mean error of −4.7 m, meaning that the Landsat shorelines are placed seaward in comparison to the corresponding high-precision shorelines [54].

Focusing on the performance of the infrared bands of low-resolution satellites, like Landsat or Sentinel [55], many low resolution images were processed, and it was proved that the derived shorelines present a mean error of 5 m for Landsat 7, and a lower mean error of around 3 m is presented for the Landsat 8 and Sentinel-2 data.

The time series of the Landsat images from 1984 to 2014 [56] were used in order to monitor the coastline evolution in two totally different environments, one Atlantic in Portugal and one Mediterranean in Italy. They mentioned that the maximum accuracy error reached 4.5 and 6.8 m for the Portuguese and Italian case studies, respectively, and they stated that these errors are acceptable, taking into consideration the low resolution of the initial Landsat imagery.

Eight multitemporal Landsat images from 1972 to 2013 [57] were used to monitor the shoreline evolution in Tunisia. The simple overlay of the images and the comparison of markers, like the road

network, proved to be significant discrepancies between the diachronic images. To overcome this accuracy misalignment, they re-registered all the images to a digital topographic map sheet at a scale of 1/25,000.

In another similar study, Landsat diachronic imagery was used to map the coastline evolution for a 29-year period in Australia. The shorelines were produced from the Landsat data, employing the super-resolution border segmentation method. Then, the mean annual shorelines were compared with in situ data. It was proved that the error ranges by around 5.7 m [32].

Similar studies have been performed for high-resolution data (aerial photographs and Quickbird images) over a coastline in Algeria [58]. Discussion on the accuracy of the shorelines based on the accuracy of the orthorectification procedure was reported in a study of the shoreline evolution in Lefkada Island, Greece [59].

The aim of the analysis performed in the current paper was to show that low-resolution data cannot replace high-resolution data at large scale for studies that require a high accuracy; however, these data are feasible for long-term shoreline change monitoring in low scale studies. This study used archival data for the calculation and comparison procedure. It is necessary to further investigate if the combination of (a) many annual low-resolution data, (b) areas with a small length (<1 Km), and (c) areas with a low range in SCE rates could allow for an acceptable forecast of shoreline positions using the procedure described, as in statistics, it is well known that having more data provides better results.

6. Conclusions

In this study, it is shown that shorelines derived from high-resolution datasets can be used for shoreline mapping, with a great accuracy and some limitations. The high spatial resolution of these data must be combined with the lowest possible temporal distance between the diachronic coastlines, so that the results are reliable. As the yearly rate between the coastlines most distant in time increases, the shoreline evolution results become less accurate, but if there were data available for every five to ten years, the results would be more accurate. On the other hand, the low-resolution data do not provide such reliable results. The low-resolution data are feasible for low-scale studies, where accuracy is not a prerequisite, or low-budget studies, where the free availability of data is the main demand.

Furthermore, high-resolution data could be used to present the general shoreline evolution trend in an area, with great accuracy. In any case, the processing of the data may result in small deviations and therefore affect the forecasting results. The low-resolution data are not suitable for the shoreline forecasting procedure and should not be used in such studies, as it was proved that they yielded less accurate results for Kalamaki and completely incorrect results (accretion instead of erosion) for Karnari beach. The software used in the current study (DSAS v5.0 beta) proved to be a reliable tool for shoreline forecasting. The results achieved using this tool are better if the SCE rates of the shorelines used are within a stable low range. It also provides more accurate results when the shorelines are derived from high-resolution datasets. Finally, as the DSAS forecasting method is based on statistical models, it provides better results when the number of the diachronic datasets increases and the period between them decreases.

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