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THE ASSESSMENT OF SCENIC ATTRACTIVENESS ON COASTAL WAYS: A CASE STUDY OF PERSEMBE-BOLAMAN (ORDU-TURKEY)

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Highlights:

- the scenic attractiveness of the coastal way varies according to biophysical characteristics;
- Persembe-Bolaman coastal way has a high scenic attractiveness potential;
- distance to the sea and visible sea area are negatively correlated;
- high positive correlation between visible land area size and slope-elevation diversity.

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Abstract. The biophysical characteristics of the areas that can be seen while travelling on motorways have an impact on the perception of the landscape. Highways provide diverse landscape experiences to travellers according to their natural and cultural qualities. Especially coastal ways that combine with nature and the sea have a high potential for scenic attractiveness. This study aims to analyse the scenic attractiveness of coastal ways using GIS and RS techniques. Persembe-Bolaman coastal way in the Black Sea Region of Turkey was selected as a case study. Three road features and seven viewshed features that are assumed to affect landscape attractiveness on the Persembe-Bolaman coastal road were selected. The data set of these features was categorised into three clusters by k-means clustering, one of the unsupervised learning algorithms. The most attractive cluster in terms of scenic attractiveness was selected by determining the characteristics of the clusters. In conclusion, it was found that the scenic attractiveness was the highest in Cluster-1, which corresponds to 46.3% of the selected route.

Keywords: coastal way, GIS, k-means clustering, remote sensing, scenic attractiveness.

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1. Introduction

Studies in which scenic attractiveness is evaluated as an indicator of the visual connection people establish with the environment are an important part of landscape planning, and management (Chhetri, 2006; Martín et al., 2018; Vukomanovic et al., 2018). These types of studies are often associated with scenic beauty (Bishop, 1996; Schirpke et al., 2013b; Tveit et al., 2018; Li et al., 2020; Tan & Peng, 2020), scenic attractiveness (Chhetri & Arrowsmith, 2003, 2008; Chhetri, 2006; De Vries et al., 2007), visual quality (Bishop et al., 2000; Uzun & Muderrisoglu, 2011; Gungor & Polat, 2018; Jovanovska et al., 2020), visual assessment (Bishop & Miller, 2007; Dupont et al., 2017; Gobster et al., 2019), and visual impact (Möller, 2006; Tsoutsos et al., 2009; Rodrigues et al., 2010). Although there are minor differences between these concepts, research has been carried out on the axis of observer-perception-landscape. The concept of "attractiveness" is used by Chhetri (2006); it is defined as the capacity of the observed landscape area and the various landscape components within it to attract the attention and admiration of the observer due to its biophysical properties. The biophysical features of the perceived landscape include elevation change, slope diversity, vegetation characteristics, proximity to water, and the structures entering the landscape (Schirpke et al., 2013a; Pierskalla et al., 2016; Tessema et al., 2021). Since the visual relations between the natural and cultural components in the visible area change according to the viewing distance, an observer's aesthetic perception changes depending on the point where the landscape is perceived (Kaur, 1981). Additionally, the height of vision, the range of vision, and the presence of natural or artificial elements that prevent vision determine the boundaries of the viewshed area. As can be seen, the interrelationship between aesthetic factors is extremely complex. Therefore, the evaluation of visual quality and scenic attractiveness is not an easy process (Kaur, 1981).

Two basic approaches, subjective and objective, are adopted when it comes to revealing the visual quality of scenic attractiveness. In the subjective approach, scenic attractiveness is associated with the perception of the observer, which is the most important aspect of a person's personality. In this method, observers are asked to evaluate the beauty of the landscape either by scoring each photograph representing the landscape or by choosing from the photographs (Daniel, 2001). Since the perception of landscape will change according to people's age, gender, sociocultural and socioeconomic status, the standard of judgment and expectations, the results obtained do not provide clear results to planners in practice (Chhetri, 2006). For example, studies have found that women have a more positive perspective than men in perceiving landscape and nature (Lindemann-Matthies & Bose, 2007; Svobodova et al., 2012). Women tend to find landscapes with more species diversity and colourful flowers more attractive (Lindemann-Matthies et al., 2010).

There are also differences between the age of individuals and their perception of the landscape. For example, older people see cultivated areas as more advantageous in terms of visual quality than natural areas (Lindemann-Matthies et al., 2010). Besides such differences, the photographs presented to the participants provide very limited data for identifying potential landscapes and often cannot fully represent the landscape studied (Ode et al., 2010; Martín et al., 2016). In the objective approach, the aesthetic and visual value of a landscape is based on biophysical features such as the size of the area visible from the observation point, the diversity of elevation and slope in the viewshed area, the diversity of vegetation, and the proximity to water (Kaur, 1981; Bishop, 1996; Daniel, 2001; Chhetri & Arrowsmith, 2003; Chhetri, 2006; Mooser et al., 2022). In a study conducted in Cerrado National Parks (Brazil), proportional viewshed area, terrain roughness, slope variability, diversity of land cover and drainage density were used as indicators of biophysical properties of the landscape (De Almeida Rodrigues et al., 2018). These variables were calculated based on remote sensing and divided into four clusters according to topographic characteristics. Bishop (1996) compared regression and artificial neural network methods to model-perceived scenic attractiveness. Here, variables such as total visible area, minimum and maximum elevation, area of plantation and forest were determined as predictive variables. There are also studies in which the data obtained using both approaches are used together. For example, in a study of Grampians National Park in Victoria, Australia, the scenic attractiveness was calculated in a GIS by using the variables obtained using the survey method (Chhetri, 2006).

Researchers have developed more accurate, and quantitative methods that allow the physical features of the perceived landscape to be analysed, ultimately providing spatial outputs that are more accurate than those of the real landscape. The first of these is the GIS-based method, through which spatial analysis of landscape attractiveness is performed. GIS strengthens the arguments of researchers regarding in many subjects such as the creation of a spatial database of biophysical variables, the production of various maps, and the modelling of changes in the land (Chhetri & Arrowsmith, 2003). Decision-making processes become easier as more spatially accurate results are obtained with studies in which visual quality, and scenic attractiveness are modelled on a GIS-based approach (Gounaridis & Zaimes, 2012).

It is known that water structures and green areas such as forests in a landscape are effective in increasing the attractiveness of the scenic (Arriaza et al., 2004; Bulut & Yılmaz, 2008; Tempesta, 2010). Conversely, anthropogenic elements have a significant negative impact on scenic attractiveness and visual quality (Purcell, 1992; Real et al., 2000). However, it has been stated that the historical buildings and farmhouses in the landscape mostly increase the visual quality (Tempesta, 2010). Therefore, GIS is an effective tool for spatially marking and analysing the factors that have a negative or positive effect on the scenic attractiveness.

The area where people interact visually with the landscape is the roads (Martín et al., 2018). Road networks are one of the most effective landscape elements that people use to come into contact with the landscape, to see, and perceive natural values (Garré et al., 2009; Sezen & Yılmaz, 2010). Roads are an important environmental element in the areas they pass, and offer landscapes created by natural, and artificial combinations. Roads also form our first impression of the places we visit (Vugule & Turlaja, 2016).

The roads preferred due to their scenic features are defined as "scenic roads." Scenic roads are generally impractical, and uneconomical in terms of transportation, but are preferred only for observing the unique landscapes they offer, and accessing natural areas. For this reason, landscape elements such as landforms, and vegetation, as well as ecological, technical, and aesthetic conditions should be considered together in road network projects realized in regions with high scenic attractiveness potential (Yuan & Cheng, 2017). Additionally, revealing the scenic attractiveness potential for existing alternative roads can contribute to tourism activities in the areas where the roads pass through. Because the attractiveness of the scenic is an important indicator of the potential recreational value that can contribute to the touristic development in a region (Chettri, 2006).

Aware of this fact, countries such as the United States, Germany and Norway have been conducting national studies on the planning and development of scenic roads for many years (Vugule & Turlaja, 2016). The Bronx River Parkway completed in 1922 was the first scenic route designed in the United States (Lew, 1991). With the "National Tourist Routes" project in Norway, aesthetic values came to the fore in road planning (Blumentrath & Tveit, 2014). Every country strives to create road routes where it can reveal its natural and cultural values. The first step in scenic road planning is the inventory collection process. It is an important part of this inventory process to identify areas with high visual quality and scenic attractiveness potential, both on new roads and on existing roads.

This article proposes a GIS, and remote sensing-based methodology to evaluate the attractiveness of scenic within sight of drivers navigating on alternative highways. At this point, two basic features related to the diversity, and quality of the scenic seen were taken as a basis. The first of these is the size of the viewshed, the vegetation in the viewshed areas, the diversity of the land in the viewshed, and the characteristics of settlement patterns, which are defined as "biophysical properties of the visible environment" by Chhetri (2006).

The second is technical features such as the distance of the road to the sea, the difference in elevation on the road, and bend condition of road. Based on these features of ways, the scenic attractiveness of Persembe-Bolaman Coastal Way was analysed within the scope of the study. Each section of the road with a length of 500 m was assigned to one of the 3 clusters determined as the optimal number of clusters by the k-means clustering algorithm. Then, the characteristics of the clusters were determined, and the sections with the highest potential in terms of scenic attractiveness were revealed. The results of the study will serve as a guide for local, and foreign visitors who prioritize the richness of the scenic in choosing this route. Additionally, it will provide important data to the decision-makers in the planning of investments related to the scenic to be made on the route.

2. Study area

This study was conducted on the route known as "Perşembe-Bolaman Coastal Way," which provides transportation between the towns of Persembe, and Fatsa of Ordu-Turkey. The study area is located between 41º 7′ 48′–41º 1′ 12′′ parallels, and 37º 35′ 24′′–37º 49′ 48′′ meridians. The total length of the road, which is located on the Black Sea coast, and between Calis River, and Akcaova River, is approximately 40 km. Within the scope of the study, this route was divided into 80 sections, 79 of which are 500 m long, and one is 661 m long. In Figure 1, the red line represents the coastal road and the lines between the green points represent the sections of the way. The midpoint of each section was defined as the observation point. There are many natural, and cultural values along the route. Some of these are Hoynat Islet, which has the status of a 1st Degree Archaeological Site, is I. Degree Archaeological, and II. Cape Jason, which has the status of a Degree Natural Protected Area, the Jason Church built in the 19th century, is the Timsah Kayasi location with the status of a First-Degree Archaeological Site. There are also numerous beaches and neighbourhood settlements on the route.

The Persembe coastal way was not originally built with the idea of creating a scenic way. While this road was part of the main road route connecting Ordu, and Samsun provinces, after the completion of the Black Sea coastal road project, transit passes started to be carried out on the D010 highway. For this reason, the intensity of active use on the coastal roads has decreased. The length of the Persembe coastal way is 40 km, and it takes 44 minutes to reach the end of the route by private car. When the D010 highway is preferred, this distance decreases to 28.3 km, and it can be covered in approximately 19 minutes due to the high speed of the project compared to the coastal road. Considering this distance, and time difference, the Persembe coastal way is not profitable for transit journeys. However, it can be a scenic route with its various natural, and cultural values, offering rich and satisfying perspectives in terms of scenery, having variable topography.

3. Methods

Many factors affect scenic attractiveness. In studies on the subject, variables such as total visible area, elevation

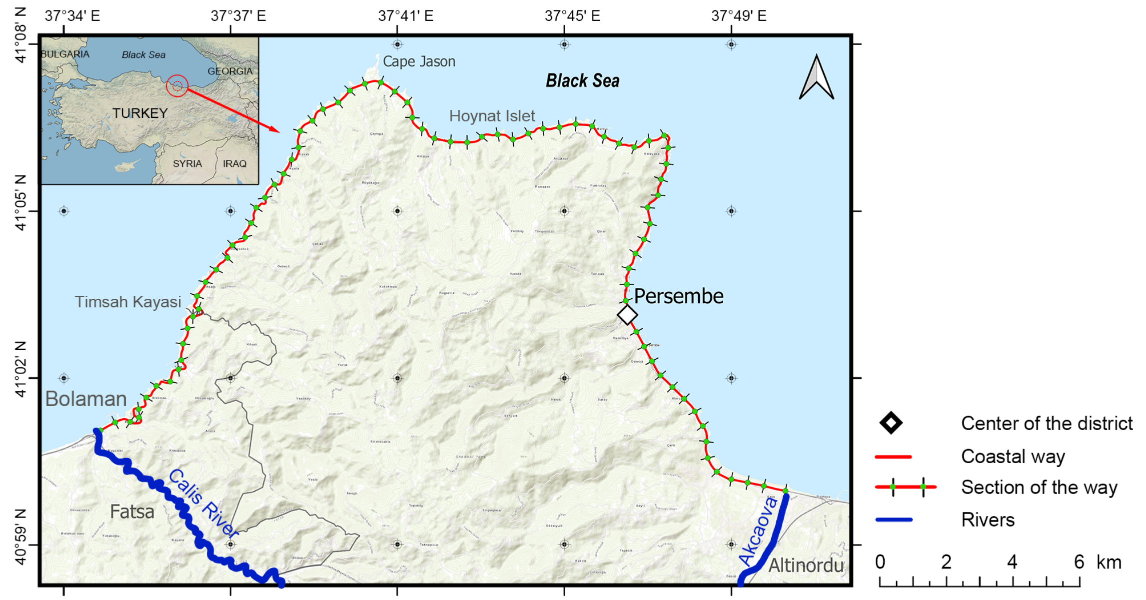

Figure 1. Location map of the study area

difference, slope diversity, vegetation diversity, plantation area, built environment area, and proximity to water have been frequently used (Bishop, 1996; Chhetri & Arrowsmith, 2003; Chhetri 2006; Mooser et al., 2022). Within the scope of this study, three road features, and seven viewshed features were determined that are thought to impact the attractiveness of the landscape that can be seen along a coastal route (Table 1). The criteria for these features were calculated for each section of the road route using GIS, and remote sensing techniques.

Table 1. Properties of road section used to determine scenic attractiveness

Properties	No	Criterion	Abbreviation	Units
Road	1	Average distance to the sea	DistS	m
	2	Bend condition of the road section	BendC	m
	3	Altitude variability on road section	AltVar	m
Viewshed	4	Visible land area from observation point	VisLA	ha
	5	Visible maritime area from observation point	VisMA	ha
	6	Vegetation rate in areas visible from the observation point (at the end of spring)	VegRS	%
	7	Vegetation rate in areas visible from the observation point (in winter)	VegRW	%
	8	Slope diversity in areas visible from the observation point (Shannon Index)	SlopDiv	–
	9	Elevation diversity in areas visible from the observation point (Shannon Index)	ElevDiv	–
	10	Average values of NDBI in areas visible from the observation point	NDBI	–

3.1. Data used

The main data sources used in this study are the images acquired by Sentinel 2A satellite on 4 February 2021 and 20 May 2021 and The Terra Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) Global Digital Elevation Model (GDEM) elevation data version 3 (Table 2). Satellite images were basically used for the calculation of viewshed properties.

ASTER GDEM V003 was generated by processing the ASTER Level 1A archive collected between 1 March 2000 and 30 November 2013. This provides a global digital elevation model (DEM) with a spatial resolution of 1 arc second (U. S. Geological Survey, 2023). DEM data were used for visibility analysis and elevation-slope diversity calculations. The bands 2 (red), 3 (green), 4 (blue), 8 (NIR) and 11 (SWIR) of Sentinel 2A images obtained for two different dates were used to produce true colour image, NDVI, NDBI and vegetation rate calculations.

3.2. Calculating road properties

Three features were identified on the basis of the technical characteristics of the road, and thought to impact the scenic attractiveness. These; mean distance to the sea (DistS), bend condition of the road (BendC), and altitude variability (AltVar). The calculation method of these three features is visually expressed in Figure 2. The closer the road is to the sea, the higher the rate of benefiting from the sea view while driving. The mean distance to the sea was calculated by measuring the Euclidean distance of the midpoint of each segment to the sea boundary. Secondly, the curvature of each section was calculated. The curvature of the road is an effective factor in the attractiveness of the scenic. The presence of bends on the road route creates surprising places as it hides the scenery in the rest of the road. Therefore, it stimulates the curiosity of the observer. It is the case where there is no curve of a straight line drawn between the start, and end points of the section. The curvature of the road is directly proportional to the Euclidean distance of the midpoint of the section from this hypothetical line drawn. Therefore, this distance was measured for each section, and then scored in direct proportion to the distance. Finally, the altitude variability was calculated along each section of the path. The difference between the measured H_{max} and H_{min} for each segment constitutes the altitude variability value. The presence of elevation changes along the way affects the attractiveness of the scenic as it will offer different perspectives to the observers.

3.3. Calculating viewshed properties

The driver's observation height varies according to many factors such as the driver's driving preferences, the type of motor vehicle and the vehicle seat settings (Kapitaniak et al., 2015; Todd et al., 2017). In the United Kingdom, the driver's eye height is considered to be approximately 1.05 m (Hobbs, 2016). In the 1920, 1965, 2000 and 2011

Table 2. Remote sensing data used in the study

Product	Product ID	Bands	Acquisition date	Cloud cover (%)	Zone/path
Sentinel-2	L2A_T37TCF_A020453_20210204T082248	2, 3, 4, 8, 11	4.02.2021	1.1	37TCF
Sentinel-2	L2A_T37TCF_A030863_20210520T082251	2, 3, 4, 8, 11	20.05.2021	0.05	37TCF
ASTER GDEM V003	ASTGTMV003_N41E037_dem	–	–	–	–
ASTER GDEM V003	ASTGTMV003_N40E037_dem	–	–	–	–

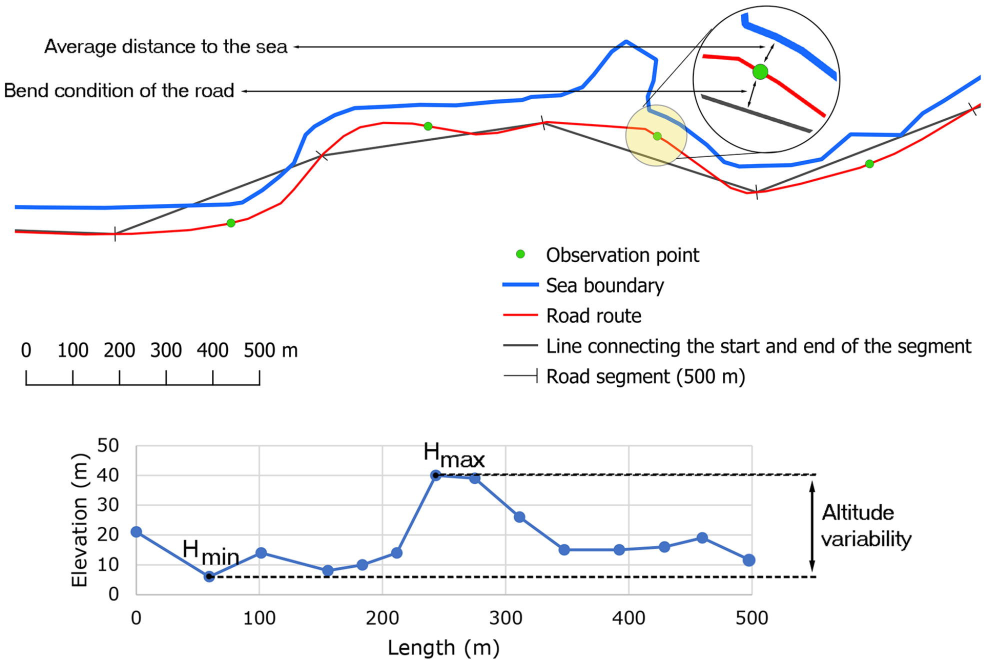

Figure 2. Measurement method of road properties

editions of the AASHTO Greenbook, the driver's eye height was accepted as 1.65 m, 1.15 m, 1.07 m and 1.08 m, respectively (Fambro et al., 1997; The American Association of State Highway and Transportation Officials, 2001, 2011). In this study, this height was assumed to be 1.3 meters as a mean height. One of the most important factors affecting viewing distance is the curvature of the Earth's surface. The average curl per mile is about 8 inches. According to this calculation, the distance at which the farthest point is seen is 3 miles, or approximately 5 km (Healthline, 2022). For this reason, in the study, the visibility range was determined as 5 km, and the observation height as 1.3 meters, and field of view analysis was performed to determine this distance. Viewshed analyses based on the midpoint of each section route were calculated with the "Viewshed" algorithm in QGIS 3.16.6, open-source GIS software (QGIS Development Team, 2013). The yellowish areas, and dark blue areas calculated for observation point 66 are shown in Figure 3.

The land and maritime areas seen from each observation point were calculated and then evaluated according to the criteria given in Table 1. First, the land (VisLA) and sea area (VisMA) sizes that can be seen from the observation point were calculated in hectares. Seeing more space from one observation point means greater potential space for scenic attractiveness. The vegetation ratio for each observation point in the land area was calculated based on NDVI using the formula for late spring (VegRS), and winter (VegRW). The Normalized Difference Vegetation Index (NDVI) is an index that gives information about the den-

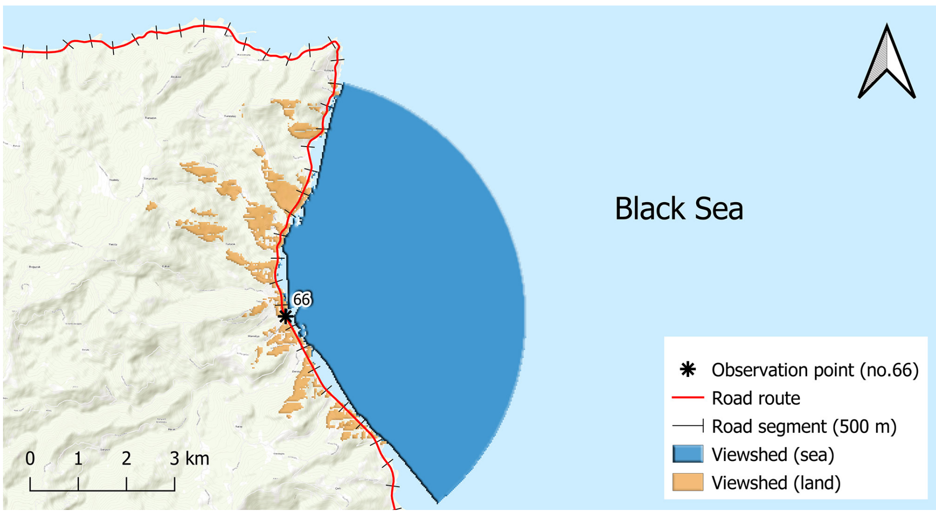

Figure 3. Visible land, and sea areas from the observation point

sity, and health status of vegetation, obtained by proportioning the *NIR* (near-infrared), and *R* (red) spectral bands as in Equation (1). This formula is mainly based on the fact that chlorophyll absorbs the *R* and the mesophyll structure in the leaf reflects *NIR* (Pettorelli et al., 2005). *NDVI* values vary between –1, and +1, with positive values representing areas with vegetation and negative values representing surfaces without vegetation (Fatemi & Narangifard, 2019).

$$NDVI = \left(\rho_{NIR} - \rho_R\right) / \left(\rho_{NIR} + \rho_R\right). \quad (1)$$

The presence of vegetation in the viewshed, the diversity of vegetation, and the colour effect increase the scenic attractiveness. This is because vegetation rates have been added to the viewshed features as an indicator of vegetation density. The vegetation rate (P_v) was calculated with the help of Equation (2), which is an *NDVI*-based equation (Fatemi & Narangifard, 2019). The minimum and maximum *NDVI* values in the formula were derived from the *NDVI* values of all pixels within the boundaries of the study area.

$$P_v = [(NDVI - NDVI_{\min}) / \left(NDVI_{\max} - NDVI_{\min}\right)]^2. \quad (2)$$

The fact that the land in the viewshed has a variable topographic structure increases the diversity of the land. It therefore provides a rich potential in terms of scenic attractiveness. As an indicator of land diversity, slope (SlopDiv), and elevation diversity (ElevDiv) were calculated according to the Shannon index, which is based on information theory (Shannon, 1948). In the Equation (3), p_i is the ratio of the slope or elevation value of each pixel to the total pixel values, and *N* is the number of pixels in the viewshed area where the pixel is visible.

$$Sh = -\sum_{i=1}^{N} p_i \ln\left(p_i\right). \quad (3)$$

Finally, the average of the *NDBI* index, which uses spectral values specific to artificial surfaces, was calculated to include the field of view used in the analysis of the *NDBI* index. *NDBI* is obtained by proportioning the *SWIR* (short wave infrared), and *NIR* (near-infrared) spectral bands as in Equation (4) (Zha et al., 2003). Theoretically, as the *NDBI* value increases, the proportion of artificial areas increases.

$$NDBI = \left(\rho_{SWIR} - \rho_{NIR}\right) / \left(\rho_{SWIR} + \rho_{NIR}\right). \quad (4)$$

3.4. Normalization of the dataset

There are data in different units in the dataset obtained on the road, and viewshed features with the help of GIS. For example, area sizes were calculated in hectares (ha), distances were calculated in meters (m), and vegetation rates were calculated as percentage (%). To eliminate these unit differences between the variables, min-max normalization was applied to each variable in the dataset (Equation (5)). First, the minimum, and maximum values in the column for each variable in the dataset are found, and their differences are taken. It is then divided by the difference obtained by subtracting the minimum value from each value in the data. Thus, the values are scaled between 0, and 1.

$$x' = \frac{x - \min\left(x\right)}{\max\left(x\right) - \min\left(x\right)}. \quad (5)$$

3.5. Correlation analysis

Correlation analyses were applied to understand the relationship between road and viewshed features, which were selected as indicators of scenic attractiveness. Correlation analysis is generally used to analyse the direction and strength of the relationship between two or more variables (Maison et al., 2021). The relationship between variables can be analysed by calculating the Pearson correlation coefficient pairwise. Moreover, Pearson coefficients between all variables can be visualised using a matrix. The coefficient varies between –1 and +1. A value of –1 indicates an excellent negative linear relationship, 0 indicates the absence of a linear relationship and +1 indicates an excellent positive linear relationship (Newman, 2002). Additionally, the significance of the correlation coefficient is usually assessed using *p*-values, with a *p*-value less than 0.05 indicating statistical significance (García-Rubio et al., 2020). The Pearson correlation coefficient provides precious insights about the power and direction of the linear relationship between variables.

3.6. K-means clustering algorithm

The k-means clustering algorithm is the simplest, and most widely used non-hierarchical cluster classification method. It has the advantage of being able to classify data quickly (Son & Cho, 2022). Although k-means is known as an unsupervised learning algorithm, the fact that the number of clusters is determined in advance, and cannot be changed that it is not a completely unsupervised algorithm (Sinaga & Yang, 2020). This algorithm uses distance as the base metric, and k as a pre-defined class. A centroid is created for each cluster. Each data point is assigned to the nearest centroid using Euclidean distances, and the data are clustered according to the closest k-mean value (Hastie et al., 2009). The weakest aspect of the k-means algorithm is that the number of clusters must be determined in advance by the user (Omran et al., 2007; Sinaga & Yang, 2020). Therefore, determining the optimal number of clusters is the most difficult part of using the k-means algorithm in data mining. At this point, different methods are applied (Beddows et al., 2009; Akkucuk, 2011; Sirait & Nababan 2017; Alibuhtto & Mahat, 2020).

The most commonly used methods are "sum of squares," "elbow," "silhouette," "gap statistics." In this study, a practical solution for determining the optimal number of clusters, package for R software titled "NbClust" was used (Charrad et al., 2014; R Core Team, 2020). This package includes 30 different indexes such as "beale," "hubert," "sdindex," "gap", and "silhouette" used in previous studies to calculate the optimal number of clusters. After calculating all indices, the most appropriate number of clusters is determined according to the majority rule (Charrad et al., 2014).During the calculation, the distance parameter in the package was set as "Euclidean distance" and the method parameter was set as "kmeans." Additionally, in this study, k-means clustering analysis was carried out with the package called "Factoextra" developed for the R software language for multivariate data analysis, and visualization (Kassambara & Mundt, 2017). PCA (principal component analysis) plot was used to explain and visualise the variance in the dataset.

3.7. Determination of cluster characteristics

Determination of cluster characteristics is necessary when extracting potential areas for scenic attractiveness. Which of the obtained clusters is rich in scenic attractiveness can be determined according to the cluster characteristics. These mean variables were calculated for the three clusters produced by the k-means clustering algorithm. It is expected that some variable averages will be high, some low based on their effect on scenic attractiveness. Averages at the expected level are selected, and marked. Here, the statistical significance of the difference between the means among the clusters was examined. The difference between the cluster averages was evaluated with the one-way ANOVA analysis performed in Jamovi 1.6.23 software (The Jamovi Project, 2021). Then, the differences between the groups were determined according to the Tukey test, which is one of the post-hoc tests.

4. Results and discussion

In this section, the correlation matrix between road, and viewshed features is given in Figure 4. Then, the results of the k-means clustering analysis based on the features calculated for the 80 sections on the road route are presented as plots, and spatially. Finally, the characteristics of the 3 clusters obtained for the cluster analysis are given as mean values, and the average differences between the clusters are statistically demonstrated. Considering the resulting clusters, and the characteristics of these clusters, the sections with the highest scenic attractiveness potential were determined along the road route.

Figure 4 displays the correlation matrix for the roads and their viewshed characteristics. There is a high negative correlation between vegetation rates in visible areas from the observation point at the end of spring (VegRS) and NDBI (r = –0.97). There is a high positive correlation between the land area size (VisLA) visible from the observation point and the slope diversity (SlopDiv) and elevation diversity (ElevDiv) variables in the visible land area (r = 0.85). It is understood from this that as the visible land area expands, the slope and elevation diversity increase in parallel. This increase is expected, as it will include a wide variety of slope and elevation steps, depending on whether the visible area is large or less. The mean distance to the sea (DistS) of sections of the road and the size of the sea area visible from the observation point (VisMA) are negatively correlated (r = –0.53). Theoretically, as the distance to the sea decreases, the visible sea area increases as the natural or artificial vision barriers in front of the sea will disappear.

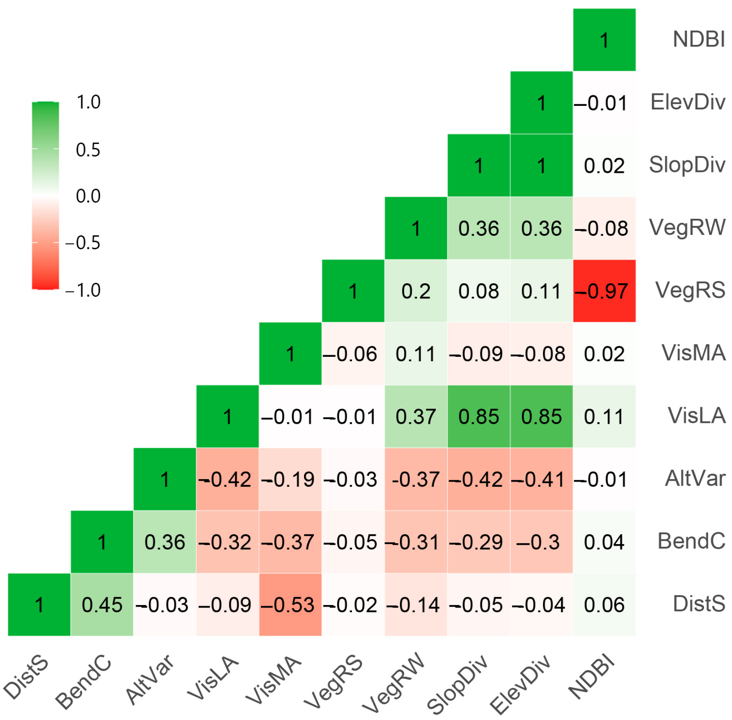

Figure 4. Pearson's correlation between road, and viewshed characteristics

In k-means clustering, the optimum number of clusters according to 11 of the 24 indices was calculated as 3 (Figure 5). As the closest value to this, according to the other 6 indices, the optimal number of clusters is 2. However, since the algorithm of the package works according to the majority rule, the optimal number of clusters was set as 3 as suggested by the indices.

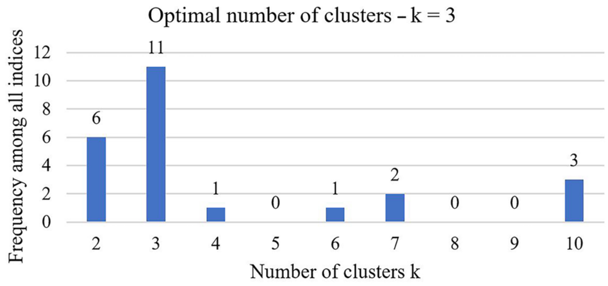

Figure 5. Optimal cluster number by k-means clustering

The results of the k-means clustering analysis performed with the "Factoextra" package in R software are shown in Figure 6 as a PCA plot. In the analysis where the optimal number of clusters is 3, Dim1 explains 35.2% of the variance in the data set and Dim2 explains 20.1%. Therefore, the total variance explanation rate of the analysis is 55.3%. According to k-means clustering, 37 of the 80 sections of the road route are divided into Cluster-1, 10 into Cluster-2 and 33 into Cluster-3. The members of Cluster-1 are sections 1, 7, 18, 30, 34–42, 45–46, 49–52, 58–72 and 78-80. Cluster-2 includes sections numbered 3, 5, 9, 11–13 and 74–77. Cluster-3 includes sections numbered 2, 4, 6, 8, 10, 14–17, 19–29, 31–33, 43, 44, 47–48, 53–57 and 73 (Figure 6).

The distribution of the characteristics of the three clusters obtained because of the cluster analysis is shown in Figure 7, and a comparison of the average values shown in Table 3. It is expected that the average distance to the sea will be low in terms of the road's scenic attractiveness. In terms of this feature, the average is low in Cluster-1, and Cluster-3, and there is no statistical difference between them ($p < 0.05$). Cluster-2 is separated from these two clusters by the average distance to the sea level of the cluster. Theoretically, the high curvature along the road has a positive effect on the attractiveness of the landscape when viewed from a distance. Cluster-2, which has a mean curve of 91.8 m, is distinct from the other two clusters. Again, the change in the vertical distance of the road will allow bumpy rides to be seen on more varied landscapes. In terms of this feature, the average between Cluster-2, and Cluster-3 is higher than that for Cluster-1.

In order to have high scenic attractiveness, some parameter averages are expected to be low (e.g. average

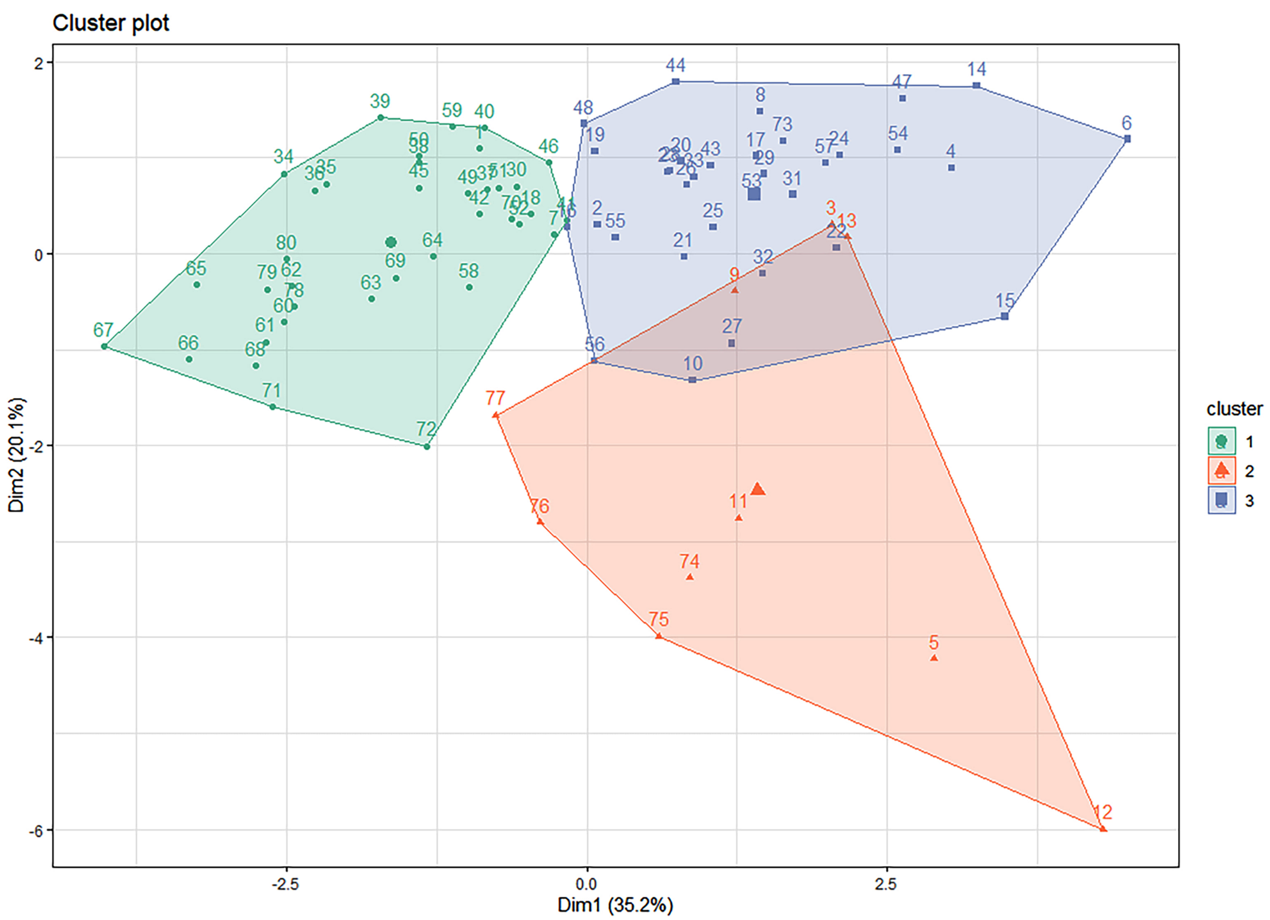

Figure 6. Plot of the cluster analysis (Dim1 and Dim2 explains 35.2% and 20.1% of the variance in the dataset respectively)

distance to the sea) and some are expected to be high (e.g. average of the altitude variability on road sections). In Table 3, the cells marked in green represent the expected mean values for high scenic attractiveness. Features for which there are no differences in cluster means are marked by two or more clusters. When the cluster characteristics are examined, the cluster with the highest scenic attractiveness is Cluster-1. On the map in Figure 8, Cluster-1 is seen in turquoise. In Cluster-1, all parameters, except for the bend condition, and elevation differences, are in the expected quality range of the cluster. For example, it has been stated that components related to the topographic structure, such as elevation, and slope diversity, play a dominant role in determining the level of scenic attractiveness (Chhetri & Arrowsmith, 2008). It is seen that the elevation and slope diversity for the visible areas in Cluster-1 is significantly higher than the other two clusters (Table 3). It is known that water bodies and greenery in a landscape are effective in increasing the attractiveness of the landscape (Arriaza et al., 2004; Bulut & Yılmaz, 2008; Cañas et al., 2009; Tempesta, 2010; Martín et al., 2018). Vegetation, which is stated to have a significant effect on scenic attractiveness, were calculated to include the NDVI-based vegetation in this study. The vegetation rate in the visible areas is significantly higher in Cluster-1 than the other two clusters for the wintertime period (Cluster-1 and Cluster-2). At the end of spring, a higher vegetation rate is observed in Cluster-1, and Cluster-3 compared to Cluster-2.

The cluster with the lowest potential for scenic attractiveness is Cluster-2. Although this cluster, shown in red in Figure 8, has the expected features in terms of bend conditions, and altitude variability, it is weak in terms of all other features. Since 37 of the 80 sections along the route are included in Cluster-1, it can be said that 46.3% of the entire route has a high potential for attractiveness. 41.3% of the road sections are included in Cluster-3. Thus, the scenic attractiveness in these sections is moderate. The sections of Cluster-2, where the potential for scenic attractiveness is the lowest, constitute 12.5% of the entire route. These results reveal the importance of biophysical properties in evaluating scenic attractiveness, and visual landscape quality (Churchward et al., 2013).

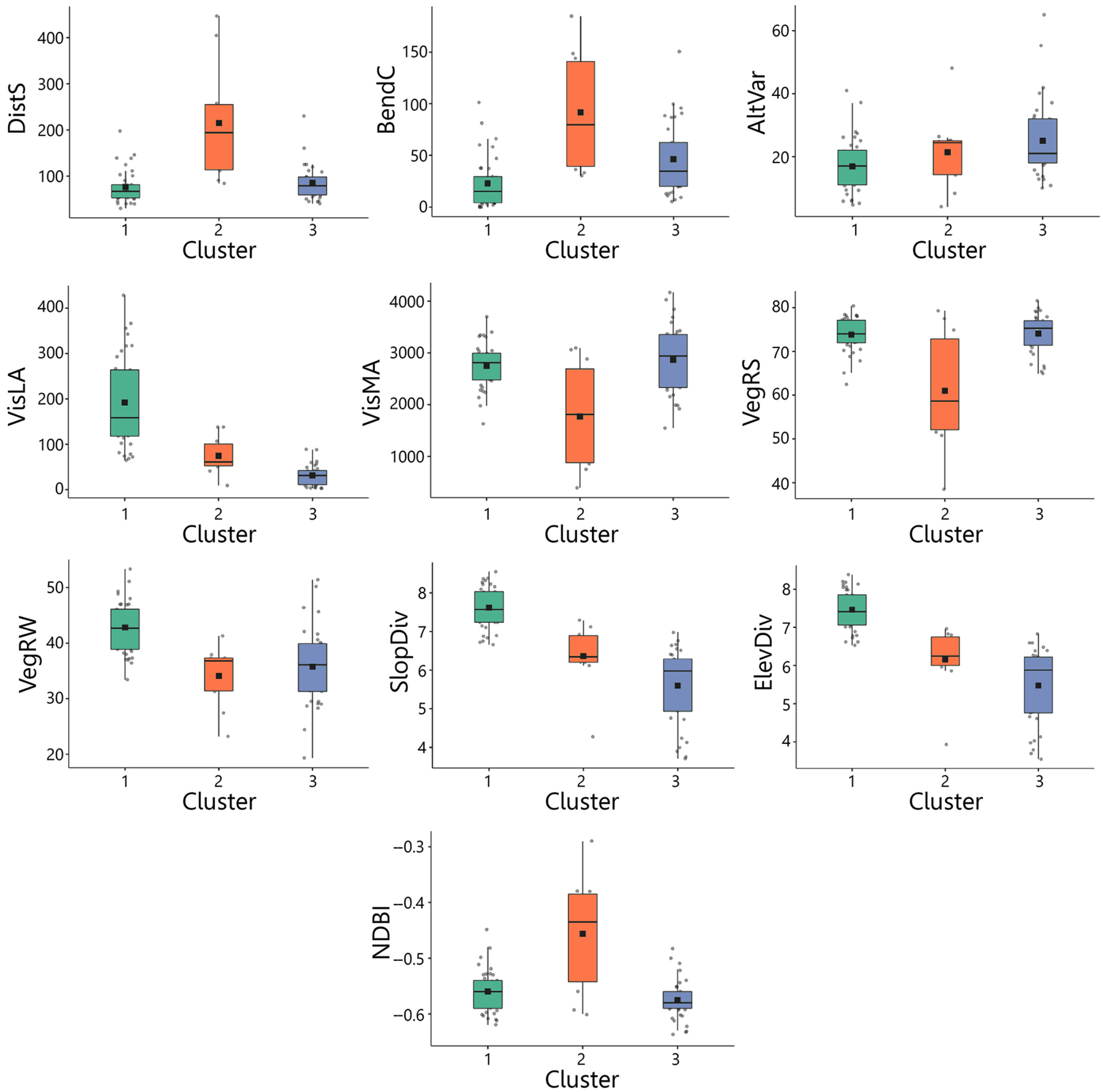

Figure 7. Distribution of road, and viewshed characteristics by cluster

Table 3. Characteristics of the clusters

Characteristics	Cluster no.		
	1	2	3
Average distance to the sea (m)	76.6[b]	215.0[a]	85.2[b]
Average of the bend condition of the road (m)	23.0[c]	91.8[a]	46.3[b]
Average of the altitude variability on road sections ($H_{max} - H_{min}$)	16.9[b]	21.4[a]	25.1[a]
Average of the visible maritime area from observation point (ha)	2747.0[a]	1770.0[b]	2868.0[a]
Average of the visible land area from observation point (ha)	192.0[a]	74.5[b]	31.4[b]
Elevation diversity in areas visible from the observation point (Shannon Index)	7.46[a]	6.16[b]	5.48[c]
Slope diversity in areas visible from the observation point (Shannon Index)	7.62[a]	6.37[b]	5.6[c]
Vegetation rate in areas visible from the observation point (in winter) (%)	42.8[a]	34.1[b]	35.8[b]
Vegetation rate in areas visible from the observation point (at the end of spring) (%)	73.8[a]	61.0[b]	74.1[a]
Average values of NDBI in areas visible from the observation point	–0.560[b]	–0.456[a]	–0.575[b]
The letters show different groups at the p < 0.05 level according to the Tukey test.			

Although the Persembe coastal way offers scenic attractiveness for the most part, it also carries some risks. For example, after heavy rains, landslides occur in some parts of the road and the road is partially closed to traffic. Additionally, as the Persembe coastal way is planned in a curvy structure, it requires extra careful driving. When constructing coastal ways, the ecological and social impacts are often overlooked. Some of these harmful effects of coastal ways are that the transition between natural habitats such as the sea and forests difficult, damages the social relationship between settlements and the sea and makes it difficult to access the coasts. However, as the driving speed is lower on the Persembe coastal way compared to the highways, the sea, coastal and land connections are stronger. There is a need for more comprehensive and multidisciplinary studies on the Persembe coastal way, which is very advantageous in terms of scenic attractiveness, considering its negative environmental and social effects.

This paper proposes a GIS and remote sensing-based methodology for assessing the potential attractiveness of scenery in the field of view of drivers travelling along a coastal route. This methodology assumes that the attractiveness of the landscape is based on the biophysical characteristics of the landscape. Therefore, personal judgements are not taken into account. However, the compatibility of the study results with the user experience needs to be evaluated. Since the proposed methodology is based on the biophysical characteristics of the landscape, sensory-based variables are ignored. Previous studies have shown that landscape perception is influenced by variables such as age, gender and educational status (Lindemann-Matthies & Bose, 2007; Lindemann-Matthies et al., 2010; Svobodova et al., 2012). Therefore, the quantitative results of the study should be compared using relatively more subjective methods such as driver surveys or interviews in the future. If these comparisons are made, the accuracy of the GIS-based method and its compatibility with classical visual quality assessment methods can be tested.

In this study, all parameters were calculated by dividing the road route with a total length of approximately 40 km into 500 m segments. However, the length of each segment may vary depending on the study area. For example, in a route where the natural and cultural elements entering the landscape change at much shorter distances, the length of the segments may need to be shorter. Therefore, in future similar studies, if the road segmentation approach in this study is to be taken as the main criterion, a value should be selected according to the structure of the

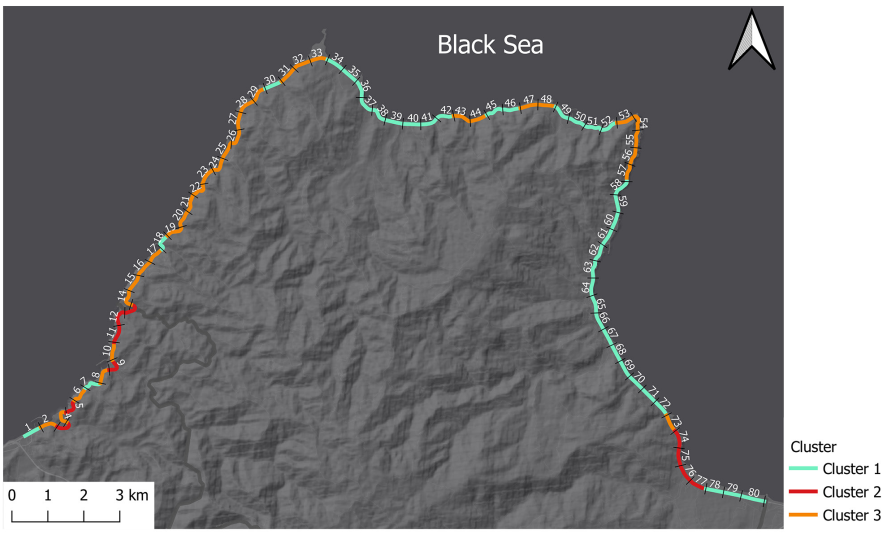

Figure 8. Spatial distribution of road section groups using k-means clustering

route. Also, the variables that are considered to affect the attractiveness of the scenery may vary according to the route and location. Therefore, determining the appropriate segment length and analysing the natural and man-made features affecting the scenic attractiveness of the route will provide higher spatial accuracy results.

5. Conclusions

In conclusion, the Persembe-Bolaman coastal way has a high landscape attractiveness potential with the natural and cultural landscapes it offers to drivers. The sections with the highest scenic attractiveness are located in Cluster-1. The results obtained with this study will fill an important gap in the design processes of the road route. For example, it would be appropriate to locate facilities such as observation decks in sections with scenic attractiveness. Thus, maximum benefit will be obtained from the investment made in terms of scenery.

The conclusions of this study, which includes spatial outputs, are also a guide for local and foreign visitors who emphasise the scenic richness when choosing the Persembe-Bolaman coastal route. In co-operation with local administrations, the findings of such studies can be turned into a handbook and shared with visitors at various points along the route. Sections with high scenic potential can be marked by placing various informative signboards. It also provides important data to decision-makers when it comes to planning future landscape-related investments along the route.

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