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Quantitative Landscape Analysis Using Earth-Observation Data: An Example from Chania, Crete, Greece

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Abstract: Pursuing sustainability in a challenging world and under the influence of numerous natural and anthropogenic drivers of change presents one of the major global concerns. The transition towards a more sustainable development requires a harmonious balance between human well-being and environmental management. The concept of landscape is at the core of such a process. Hence, evaluating the different aspects of the landscape and their components is crucial for policy making, planning and management. In fact, landscape quality assessment has become a special focus of interest, especially with the directives of the European Landscape Convention. This research work aims to analyze the rural landscape of the Chania prefecture, West Crete, Greece, taking into account its multifold dimensions. The analysis was carried out using a series of quantitative spatial indicators. Consecutively, structural (mean patch area, contagion index, edge density and percentage of landscape occupied by a class of the highest share), ecological (density of ecological barriers, Modified Shannon diversity index), visual (share of positive land-cover forms, share of negative land-cover forms, form and color disharmony index, shape disharmony index) and cultural indices (historical monuments index) were estimated and analyzed in a GIS environment. The overall methodology incorporated different land-use/land-cover data (multitemporal Corine data and land use derived from the classification of Earth-observation (EO) data). The historical and current analysis of the landscape within Chania revealed quite high structural and visual values. The ecological dimension is rather stable, with a potential decrease by the year 2045. Additionally, the structural dimension seemed to be sensitive to the spatial resolution of the data source. The spatial extent, at which the landscape is evaluated, seemed to impact the landscape's ecological, visual and cultural values.

Keywords: landscape quality; remote sensing; indicators; GIS

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1. Introduction

The word "landscape" dates back to the 13th century and derives from the Germanic languages. It was first used in Dutch as *landschap* and *lantscap* to refer to a land, region or environment. Later with the introduction of a new type of painting, the meaning of landscape shifted to signify "scenery" [1,2]. In fact, the significance of the term varies among the languages and the translations [1,3]. For instance, in Roman languages, this term refers to a distinct region accentuating its social and historical aspects. However, it is limited to the spatial facet to mean "place" in the modern Greek languages. In other languages, namely Arabic, this word does not exist [3]. Unsurprisingly, the scientific definition and knowledge of the term "landscape" carries much complexity and varies widely in the literature [1,3–6], presenting in some cases contradictory meanings [7]. In fact, several disciplines have been involved in landscape studies such as geography, archaeology, architecture, ecology, anthropology, design, sociology and history [5,7–9]. The history of the different aspects of the landscape as a scientific object underlines its multiple meanings and emphasizes the diversity of its concepts and theories among the disciplines [1,10] and hence the absence of an evident notion [11].

Numerous researchers linked the quality of people's daily lives to the quality of the landscape [12,13]. Yet, a clear and formal definition of landscape quality is lacking in the literature [14]. In this study, landscape quality is interpreted as "the state in which its (landscape's) spatial, functional and visual structure is found at a given time", as elucidated by Sowinska-Swierkosz and Michalik-Sniezek [14].

Nevertheless, several authors highlighted the need for a comprehensive and extensive analysis of the landscape components and their interrelationships [13]. Numerous approaches have been adopted for this aim, which could be regrouped under two mains categories. The first category is fragmented and disengaged expert-based methods, which concentrate on a specific aspect of the landscape and interpret the biophysical characteristics holistically as design parameters. The second category is engaged approaches, also called public perception-based methods, which consider these characteristics as stimuli and evaluating the landscape as a whole while capturing the dynamic and multisensory human experience and appreciation of the landscape [2,15,16]. Other researchers have classified the adopted landscape evaluation methods by using an objective quantitative approach that measures the different components of the landscape, the subjective qualitative approach that deals with the perception of the landscape as a whole [17–19], and a combined approach linking the public preferences to the landscape components [18,19]. In the Greek context, a lack of landscape planning and studies has been underlined. The marginalization and underprioritization of landscape matters have been accentuated with the socioeconomic crisis. Thus, it is imperative to raise awareness and orient training and interventions toward a more focused conscience on landscape [5]. In this context, this study broadly aims to quantify the landscape components over the prefecture of Chania, Crete, Greece, based on spatial indicators derived from Earth-observation data following the general methodology developed by Sowinska-Swierkosz and Michalik-Sniezek [14].

Numerous studies pointed out indicators' ability and effectiveness to analyze the landscape [20] and highlighted the plethora of indicators developed and adopted for this aim [4,12,20,21]. For instance, around 300 potential indices could be used to measure the structural and ecological landscape state, 200 indices to assess the cultural state and more than 200 spectral indicators dealing with the ecological state [20]. Previous studies have attempted to select a manageable set of statistically effective and reliable indicators evaluating the different aspects of landscape quality [12,14]. In practice, the selection of landscape indicators is driven by data availability rather than theory [22,23]. Different data sources could be used for the aim of landscape analysis, namely photos, land-cover maps, satellite images, orthophotos, field observations, census statistics and surveys results [2,12,20,21]. The employment of remote sensing data in landscape quality assessment enables significant savings in terms of both labor and time compared to traditional survey methods [24]. According to Sowinska-Swierkosz and Michalik-Sniezek [14], four aspects of landscape quality could be evaluated using remote sensing data, namely structural, ecological, visual and cultural dimensions.

This study focuses on evaluating the landscape values within the prefecture of Chania based on geospatial data, assessing the evolution of the components of the landscape's dimensions over time, comparing the potential of different land-cover datasets in estimating the landscape indicators and examining the impact of scale in terms of both extent and resolution on the performance of landscape's indices.

2. Materials and Methods

2.1. Study Area

Located in southern Greece and covering an area of 8729 km^2, Crete is the largest Greek island and ranks fifth in size among Mediterranean islands. Crete represents a cardinal point connecting Europe, Africa and Asia [25]. Like most Greek landscapes, the island's topography is mostly mountainous. According to EL-STAT [26], more than 49% of the total extent of Crete is characterized as mountainous terrain, 28.1% is semimountainous and only 22.5% of Cretan lands are plains. The island is one of the biodiversity hot spots thanks to its 1600 native plant species, among which 200 are classified as endemic. Like the flora, Crete is also distinguished by its fauna, namely by its wild goat, wildcat, Cretan badger and endemic invertebrates [27].

As stated in Panagos et al. [28], Crete is dominated by natural grasslands and shrubs, covering 46% of the land. Permanent crops of olives, vines and citrus also cover a critical extent of the island. In addition, 15.2% of Crete is covered by heterogeneous agricultural land. However, forests appear over less than 4% of the total area of Crete.

Due to its geographic location, the island is considered a melting pot of cultures from Europe, Asia and Africa. Historically, the first advanced European civilization, the Minoan civilization, was developed on Cretan land during the Bronze Age. Since then, the island has been influenced by neighboring cultures, namely the Roman, Byzantine, Arab, Venetian and Ottoman cultures [27]. This rich history is evident in the historical monuments and cultural sites located all over the island. Administratively, Crete is divided into four prefectures. The current research focuses on Chania prefecture (Figure 1), located in the western part of the island, covering an area of 2376 km^2 and with a resident population of 156,585 inhabitants, as stated in the census of 2011 [26]. Additionally, this study emphasizes the area of the Keritis watershed located in the central part of Chania prefecture. Keritis is a typical watershed of the broader area in terms of geomorphology, vegetation, extent and land-use/land-cover regime. The region of Chania is well known for its natural landscapes associated with mountains and the seaside [29]. Moreover, the prefecture of Chania is distinguished by the concentration of remarkable historical and cultural heritage sites belonging to different historical eras from the Minoan to the Greek periods [29,30], contributing, hence, to the development of the tertiary sector. In fact, the economy of the prefecture relies heavily on both tourism and agriculture.

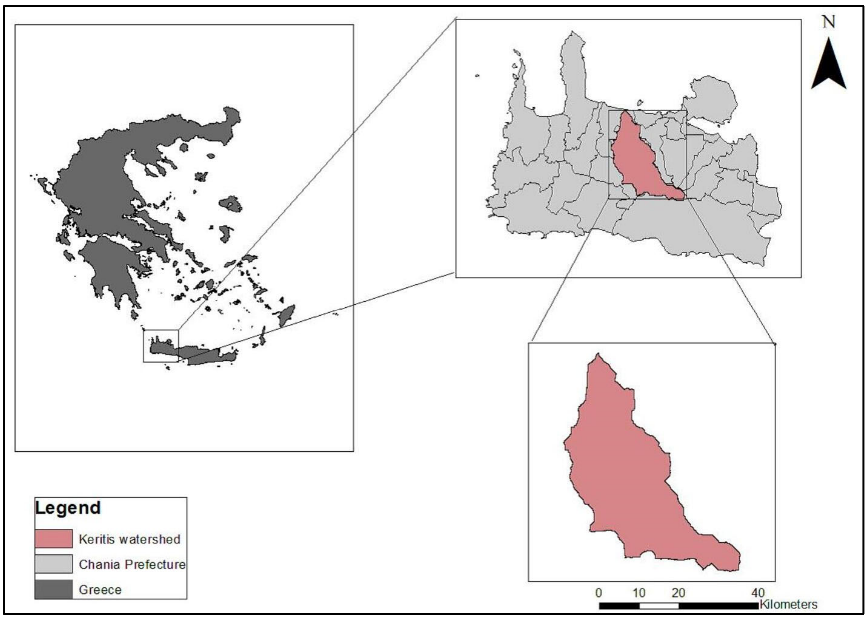


Figure 1. Location of the study area.

2.2. Datasets

2.2.1. Corine Land Cover

The Corine program is part of the European flagship program on Earth observation aiming to standardize data collection on land in Europe to support the development of environmental policy. The Corine Land Cover (CLC) database presents the primary spatial data source on land for the European Environment Agency and includes an inventory of

44 classes. For this research, Corine Land Cover (CLC) status layers for the years 1990, 2006 and 2018 were downloaded from the European Environment Agency (EEA) database in vector format [31]. These datasets were produced with a minimum mapping unit of 25 ha for aerial features and a minimum width of 100 m for linear elements. The acquired vector datasets were clipped to the extent of Chania, then rasterized to a cell size of 30×30 m and transformed to the WGS 84/35N projection system in order to match the properties of the other data used in this study. Concerning the prefecture of Chania, Corine datasets cover 28, 30 and 31 classes for 1990, 2006 and 2018, respectively. For the aim of this study, they were converted to six classes (forest, water bodies, agricultural land, bare land, built-up land and grassland and sparse vegetation) to harmonize the data for further analysis (Table 1).

Table 1. Corresponding LULC classes derived from Corine data source.

Corine Land-Cover Class	Derived Class
Continuous urban fabric	Built-Up Land
Discontinuous urban fabric	
Industrial or commercial units	
Road and rail networks and associated land	
Port areas	
Airports	
Mineral extraction sites	
Dump sites	
Construction sites	
Sport and leisure facilities	
Nonirrigated arable land	Agricultural Land
Permanently irrigated land	
Vineyards	
Fruit trees and berry plantations	
Olive groves	
Pastures	
Complex cultivation patterns	
Land principally occupied by agriculture, with significant areas of natural vegetation	
Broad-leaved forest	Forest
Coniferous forest	
Mixed forest	
Natural grasslands	Grasslands and Sparse Vegetation
Moors and heathland	
Sclerophyllous vegetation	
Transitional woodland–shrub	
Sparsely vegetated areas	
Beaches, dunes, sands	Bare Land
Bare rocks	
Burnt areas	
Water bodies	Water Bodies
Sea and ocean	

2.2.2. Landsat Data

Taking into account the temporal availability of satellite data covering the time period 1990–2021, Landsat satellite images were selected to be adopted for this study. The first Earth-observation optical satellite in the Landsat series was launched in 1972 by the National Aeronautics and Space Administration (NASA). Since then, more satellites have been launched within the Landsat program, providing the most extended continuous Earth-observation data. The latest successful launch and data collection is the Landsat 9 satellite, launched in September 2021. For this study, multitemporal, geo-referenced and radiometrically calibrated Landsat images (path/row 182/35 and 182/36) were downloaded from the United States Geological Survey (USGS) website [32]. Due to the extent of our study area, two image tiles were acquired for each date to cover the total of the prefecture of Chania. The imagery adopted in this study includes Landsat 5 data for 1990, Landsat 7 data for 2006 and Landsat 8 data for 2021. The dates of these images were chosen to be within the same season for the three selected years (1990, 2006 and 2021) to minimize the spectral influence resulting from the seasonal conditions while considering the availability of cloud-free scenes. Clouds did not affect all the pixels within our study area.

2.2.3. PlanetScope Data

The PlanetScope mission operated by Planet was launched to enable a daily capture of Earth's extent with a high spatial resolution ranging between 3.7 and 4.2 m, depending on the satellite orbit altitude, and resampled to 3 m. A PlanetScope classified image for the year 2020 covering the extent of Keritis watershed has been used for this study.

2.2.4. Supplemental Data

Supplemental data of road networks in the Greek grid projection as well as data related to the cultural heritage sites within Chania prefecture were acquired from the digital archives of the Institute for Mediterranean Studies, Foundation for Research and Technology Hellas (FORTH).

2.3. Methods

2.3.1. Image Analysis

Land-Use/Land-Cover Mapping

Land-cover/land-use mapping based on remotely sensed data presents a valuable variable of Earth-observations studies. Digital image classification is defined as the process of categorizing objects or pixels into a particular informational class type. Several classification techniques have been developed over the years due to the advancement of both remotely sensed data acquisition and computer science. These methods fall into three main categories, namely pixel-based, knowledge-based and object-based approaches [33]. In this study, Landsat and PlanetScope images were classified using a supervised pixel-based technique, considering each pixel as a separate entity, and performed using the Resources Data Analysis System ERDAS IMAGINE 2015 software.

Generally, algorithms under pixel-based methods are divided into parametric and nonparametric approaches. The main difference is that parametric classifiers assume a normal distribution of the data, unlike the nonparametric ones that are not based on any statistical assumption [33,34]. A supervised classification using the parametric Maximum Likelihood Classifier (MLC) was performed to map Chania as well as the Keritis land-use/land-cover regime. This classifier is derived from the Bayes theorem algorithm, which assumes a normal distribution of the cells in each class, and hence, each class is defined by its mean vector and covariance matrix [34]. Every pixel is assigned to the class to which it has the highest likelihood of belonging. For each preprocessed Landsat image and for the PlanetScope image, all the pixels were assigned to a particular predefined class among Built-Up Land, Agricultural Land, Forests, Grasslands and Sparse Vegetation, Bare Land and Water Bodies. The spectral signature of each class was determined from training samples acquired from Google Earth historical images.

Prior to their classifications, Landsat images were first preprocessed. Preprocessing of remote sensed data is necessary to remove the noise, prepare the data and improve their capability for further analysis. For this research, the scanline corrector anomaly of Landsat 7 ETM+ was corrected using the Focal Analysis tool in ERDAS IMAGINE. This technique consists of filling the data gap by replacing the missing pixels with useful neighboring ones [35]. The radiometric quality of Landsat Level 1 products in Collection 2 has been updated and improved. Hence, the downloaded images for this study were not subjected to radiometric correction. However, the Level 1 products are provided at top-of-atmosphere radiance. Thus, the atmospheric correction has been performed in order to reduce the influences of atmospheric effects and seasonal disturbances for reliable temporal comparison. In this study, the atmospheric correction was performed using the Dark Pixel Subtraction technique, supposing that the existence of dark pixels in the image have zero reflectance. Hence, the minimum reflectance number is assumed to be atmospheric scattering signals that must be subtracted from the spectral bands [36]. Finally, layer stacking of the visible NIR and SWIR bands was performed. Every two adjacent images (path 182, row 35/36) acquired in the same date were mosaicked and clipped to the extent of the study area.

To assess the accuracy of the produced thematic maps, a total of 300 random pixels, with 50 pixels for each class, was randomly selected from each classified image and verified with the historical imagery in Google Earth for 1990, 2006 and 2021. The classification quality was evaluated by computing the overall accuracy, user's accuracy, producer's accuracy and kappa statistics. The Kappa coefficient evaluates the performance of the classification compared to the arbitrary attribution of values. The Kappa coefficient varies between −1 and 1. The closer the Kappa coefficient is to 1, the better the classification compared to random.

Land-Use/Land-Cover Prediction

Future land -use and land-cover maps for 2030 and 2045 were computed using IDRISI-TerrSet Geospatial Monitoring and Modeling System software for both Corine and Landsat datasets. Markov-Chain and Cellular Automaton (CA-Markov) was integrated for this aim. The Markov chain model is a stochastic process that predicts the probability of LULC change from one time to another. It uses the past LULC change trend at different spatiotemporal scales to estimate the future [37]. According to Li et al. [38], the Markov model succeeds in computing the quantities of the dynamic changes of LULC patterns from the latest date to the predicted date; however, it has some issues concerning the spatial pattern of landscape change. To solve this problem related to the spatial location of the prediction, a combination of the Markov-Chain model and a Cellular Automata model has been implemented in several studies [39]. In fact, the Cellular Automata is a dynamic process model that uses the LULC information of the latest states as well as its neighboring pixels [40]. However, despite the spatial character added to the dynamic prediction, Rocha et al. [41] find that the Cellular Automata faces problems related to both the definition of transition rules and the model structure. Hence, combining Cellular Automata (CA) and the Markov-Chain, integrating the benefits of the two models, provides a robust and more reliable future prediction.

In this study, for each dataset, 1990 and 2006 LULC maps were used as a baseline from which the 2018 map (in the case of Corine data) and the 2021 map (for the Landsat data) were predicted. The background value was set to 0 and the proportional error value was set to 0.15 in order to produce the future prediction with an accuracy of 85%. After validating these simulated maps with the existing ones, future LULC for 2030 and 2045 were computed using the same defined parameters. The LULC map for 2030 was produced using the 2006 and 2018 maps as baselines in the case of the Corine data source and the 2006 and 2021 maps in the case of classified Landsat images. The maps of 2045 were estimated based on 2018 and the estimated 2030 map for Corine and 2021 and 2030 maps for the Landsat dataset.

2.3.2. Landscape Quality Analysis

Considering the literature analysis, the availability and the characteristics of the Earth-observation data, a set of 11 landscape quality indicators, covering its structural, ecological, visual and cultural dimensions, have been selected. Among them, 10 indices were derived from the LULC state and hence analyzed for Corine, Landsat and PlanetScope data sources. The specific indicators adopted and measured for this study were selected based on their effectiveness and considering the availability of data.

Structural Dimension

Knowledge of landscape patterns enables a better understanding of the landscape functions [42] and a better evaluation of the efficiency and sufficiency of management and planning decisions [43]. Numerous landscape indices have been developed to analyze and quantify landscape structure in terms of composition (e.g., richness, evenness) and configuration (e.g., shape, core area, contagion). They could be determined for three spatial levels, namely patch, class and total landscape, and they are easily computed using tools such as FRAGSTATS [44,45]. Landscape metrics, given their simplicity, have been widely applied to assess both landscape functions and land-use/land-cover patterns and changes [42]. Other indices have also been tested in quantifying landscape pattern and structure [46,47].

The structural characteristics of the landscapes of Chania and Keritis were evaluated for the different datasets and for the different studied years using four landscape metrics computed with FRAGSTAT software (version 4.2.1). Landscape metrics are an efficient tool for quantifying landscape structure and complexity. Generally, landscape metrics are algorithms enabling the description and measurement of the spatial composition and configuration of the landscape.

- Mean patch area (MPA): MPA presents one of the simplest indicators of the landscape, enabling the evaluation of the degree of fragmentation within the studied landscape. MPA was analyzed at the landscape level:

$$\mathrm{AREA}_{\mathrm{MN}} = \text{mean}\ (\mathrm{AREA}\ [\mathrm{patch}_{\mathrm{ij}}]) \tag{1}$$

  where AREA [patchij] is the area of each patch in hectares.
- Edge Density (ED): ED can be used to evaluate the aptness of the analyzed landscape for wildlife, mainly its suitability as a habitat for edge species. ED was determined at the landscape level in order to describe its configuration:

$$\mathrm{ED} = \frac{E}{A} \times 10000 \tag{2}$$

  where E is the total landscape edge in meters and A is the total landscape area in square meters.
- Percentage of landscape occupied by a class of the highest share (PLAND): The percentage of the landscape belonging to each class was calculated at the class level, as shown in Equation (3). The PLAND index as given in Sowinska-Swierkosz and Michalik-Sniezek (2020) corresponds to the highest computed percentage:

$$\mathrm{PLAND} = \frac{\sum_{j=1}^{n} aij}{A} \times 100 \tag{3}$$

  where aij is the area of each patch and A is the total landscape area.
- Contagion index (CONTAG): This index evaluates the overall clumpiness of the landscape by assessing both dispersion and interspersion within the analyzed area. An increase in value of this index refers to a landscape characterized by contiguous and fewer large patches. On the other hand, a decrease in the CONTAG index indicates

an increase in the subdivision and interspersion of patches. CONTAG was measured at the landscape level in order to evaluate its aggregation:

$$\text{CONTAG} = 1 + \frac{\sum_{q=1}^{na} pq \times ln(pq)}{2 \times ln(t)} \tag{4}$$

where *pq* is the adjacency table for all classes divided by the sum of that table and *t* is the number of classes in the landscape.

Ecological Dimension

The ecological dimension of the landscape is a complex system encompassing the interrelated natural and environmental features as well as the anthropogenic disturbance related to human activity, such as noise and pollution [43]. The use of ecological indicators simplifies the understanding of the ecosystem components and functions as well as their evolution. Thus, they have been helpful for several studies dealing with ecological planning, assessment and monitoring [48]. Three sets of ecological indices have been found in the literature, namely geo-morphometric indices, spectral variability-based indices and landscape metrics [14]. In addition, numerous authors' remote sensing-based ecological indicators have been developed and tested to assess the ecological state of the landscape [43,49–52].

Two indicators were selected to assess the ecological state of the landscape in both Chania and Keritis:

- Density of ecological barriers (ECOLBAR): Several studies highlighted the ecological impact of the transportation infrastructure on wildlife mortality, habitat fragmentation and destruction, soil erosion, hydrological network and microclimate change [53,54]. In this research, the effect of the road network on the ecological quality of the landscape has been evaluated using the ECOLBAR index based on the methodology of Sowinska-Swierkosz and Michalik-Sniezek [14], as given in Equation (5). Only paved roads crossing natural and seminatural land-cover forms have been examined as ecological barriers [22]. As natural and seminatural land-cover forms, the classes of Forests, Grasslands, Sparse Vegetation and Water Bodies were considered:

$$\text{ECOLBAR} = \frac{(Lroad + Lrail)}{Area} \tag{5}$$

where *Lroad* and *Lrail* are lengths of rail and road networks in km and *Area* is the total area of the landscape in km^2.
- Modified Shannon diversity index (MSDI): This index was calculated based on the methodology of Sowińska-Świerkos [43], consisting of relating the normalized Shannon diversity index, considering the abundance and evenness of the land-cover forms, to their ecological significance, as given in Equation (6):

$$\text{MSDI} = \frac{-\sum_{i=1}^{s} Pi \times \ln(Pi) \times I1}{\ln(s)} \tag{6}$$

where *Pi* is the percentage of a given class, *S* is the total number of LULC classes and *I1* is the land-cover quality score. The latest was determined as specified in Table 2.

Table 2. LUCL quality score.

Land-Cover Forms as Defined by Sowińska-Świerkos [26]	Land-Cover/Land-Use Forms Used in This Research	Land-Cover Quality Score (I1)
Natural land-cover forms: areas where the vegetation is in balance with the abiotic and biotic forces of its biotope	Forests	1
Seminatural land-cover forms: areas where the vegetation is not planted by humans and does not need human intervention to be maintained; however, human actions influence it	Grasslands and Sparse Vegetation	0.75

Table 2. *Cont.*

Land-Cover Forms as Defined by Sowińska-Świerkos [26]	Land-Cover/Land-Use Forms Used in This Research	Land-Cover Quality Score (I1)
Anthropogenic land cover Type 1: areas where the natural vegetation has been removed or modified and replaced with other types of vegetation	Agricultural Land	0.5
Anthropogenic land cover Type 2: Complex settlements	Built Up	0
Areas without vegetation	Bare Land	0
	Water Bodies	0

Visual Dimension

Despite the value of this aspect, visual indicators are poorly developed compared to structural and ecological indices [18,23]. Nevertheless, several approaches have been developed to evaluate the aesthetic perception of the landscape, namely expert-based theories, perceptual and experimental theories and humanistic theories [13].

The literature highlights two contradictory paradigms: an objective model assuming that the aesthetic value occurs on the landscape properties and a subjective one considering the aesthetical value as an evocation through "the eye of the beholder" [15]. A wide range of indices has been reviewed and identified in the literature. Yet, the visual quality has been reduced in other studies to the concept of naturalness. Thus, the visual value of the landscape increases with the absence of visible human impact [55]. Other authors designed their visual quality indices in order to evaluate the landscape's visual state [55,56]. Some demonstrated their effectiveness in other contexts after careful adjustments, taking into account the landscape's differences and specificity [16].

For this study, a set of four indicators has been selected to evaluate the quality of the landscape's visual aspect.

- Share of positive land-cover forms (PLCF) and negative land-cover forms (NLCF) were calculated to assess the landscape's aesthetic quality over Chania and Keritis. The classification of the LULC forms based on their impact on the visual quality was performed based on Sowinska-Swierkosz and Michalik-Sniezek [20] and is clarified in Table 3.

Table 3. Impact on perceiving visual quality of LULC classes.

LULC Classes Adopted in This Study	Impact on Visual Quality
Forests	Positive
Grasslands and Sparse Vegetation	Positive
Agricultural Land	Neutral
Built-Up Land	Negative
Bare Land	Neutral
Water Bodies	Positive

- Form and color disharmony index (FCDHI): Form and color disharmony are assumed to be related to the anthropogenic elements (man-made objects) and thus to the anthropogenic land-cover forms. The integrity of natural objects is considered harmonious in terms of color and form [57]. Sowinska-Swierkosz developed this index to evaluate the harmony in terms of colors and forms of anthropogenic objects. It was calculated as given by Sowinska-Swierkosz and Michalik-Sniezek [14]:

$$\text{FCDHI} = 0.5 \times \left(2 - \frac{1}{\sqrt{(1 + log2(N))}}\right) \tag{7}$$

where N is the share of land-cover forms visually perceived as negative (Table 4). If $N < 1$, then FCDHI = 0.

Table 4. Percentages of area coverage of land-use/land-cover classes.

Year	1990	2006	2021
Forest	7.37%	6.73%	5.88%
Water bodies	0.05%	0.03%	0.02%
Agricultural land	31.39%	32.08%	32.50%
Bare land	7.02%	6.57%	6.58%
Built-up land	1.42%	2.31%	2.53%
Grassland and sparse vegetation	52.74%	52.27%	52.49%

- Shape disharmony index (SDHI): This index, elaborated by Sowinska-Swierkosz [57], combines both the ecological and aesthetic values of the landscape in order to evaluate the harmony degree of its shape:

$$\mathrm{SDHI} = \frac{|1 - [\left(\frac{Sn \times FRACn^2}{100\%}\right) + \left(\frac{Ssn \times FRACsn}{100\%}\right)]|}{3} \quad (8)$$

where *Sn* is the share of natural LULC forms (%), *Ssn* is the share of seminatural LULC (%), *FRACn* is the fractal dimension index computed using FRAGSTAT for natural land-cover forms and *FRACsn* is the fractal dimension index computed using FRAGSTAT for seminatural forms.

The shape of the different patches forming the land-cover forms is reflected by the FRAC index with FRAC = 1 in the case of simple shapes (squares for example) and FRAC = 2 in the case of irregular shapes.

Cultural Dimension

The landscape's historical-cultural aspect covers tangible and intangible values [14,58,59]. The concept of cultural heritage focuses on heritage in terms of buildings and architecture, territory and culture and historical value. However, most of the published indicators in this field deal with the quality of the built heritage [60].

Sowińska-Świerkosz [59] and Volpiano [60] reviewed the published indicators dealing with the historical-cultural components. The literature shows numerous qualitative and quantitative indicators applied for the characterization, transferability, enhancement and assessment of the cultural dimension. Yet, this facet is considered marginalized due to the underdevelopment of operational standards and international cultural indices [60].

For this study, the Historical Monuments index (PROTAP) was used to evaluate the cultural heritage values within the regions of Chania and Keritis based on the methodology of Sowinska-Swierkosz and Michalik-Sniezek [14].

$$\mathrm{PROTAP} = \frac{Nmonuments}{Area} \quad (9)$$

where *Nmonuments* is the number of cultural monuments and *Area* is the total area of the analyzed landscape (km^2).

2.3.3. Statistical Analysis

A statistical analysis using Student's *t*-test at the 95% confidence interval (p = 0.05) was conducted to investigate whether there are statistically significant differences among the measured landscape indicators' values between the two data sources.

3. Results and Discussion

3.1. Image Analysis

3.1.1. Land-Use/Land-Cover Mapping from Landsat Data

Supervised classification using visible, NIR and SWIR band combinations of the three Landsat imageries for 1990, 2006 and 2021 was carried out using the Maximum Likelihood algorithm. These images were classified into six land-use/land-cover classes, namely forest, water bodies, agricultural land, bare land, built-up land and grassland and sparse vegetation. The outcomes of the classification are given in Figure 2 and Table 4.

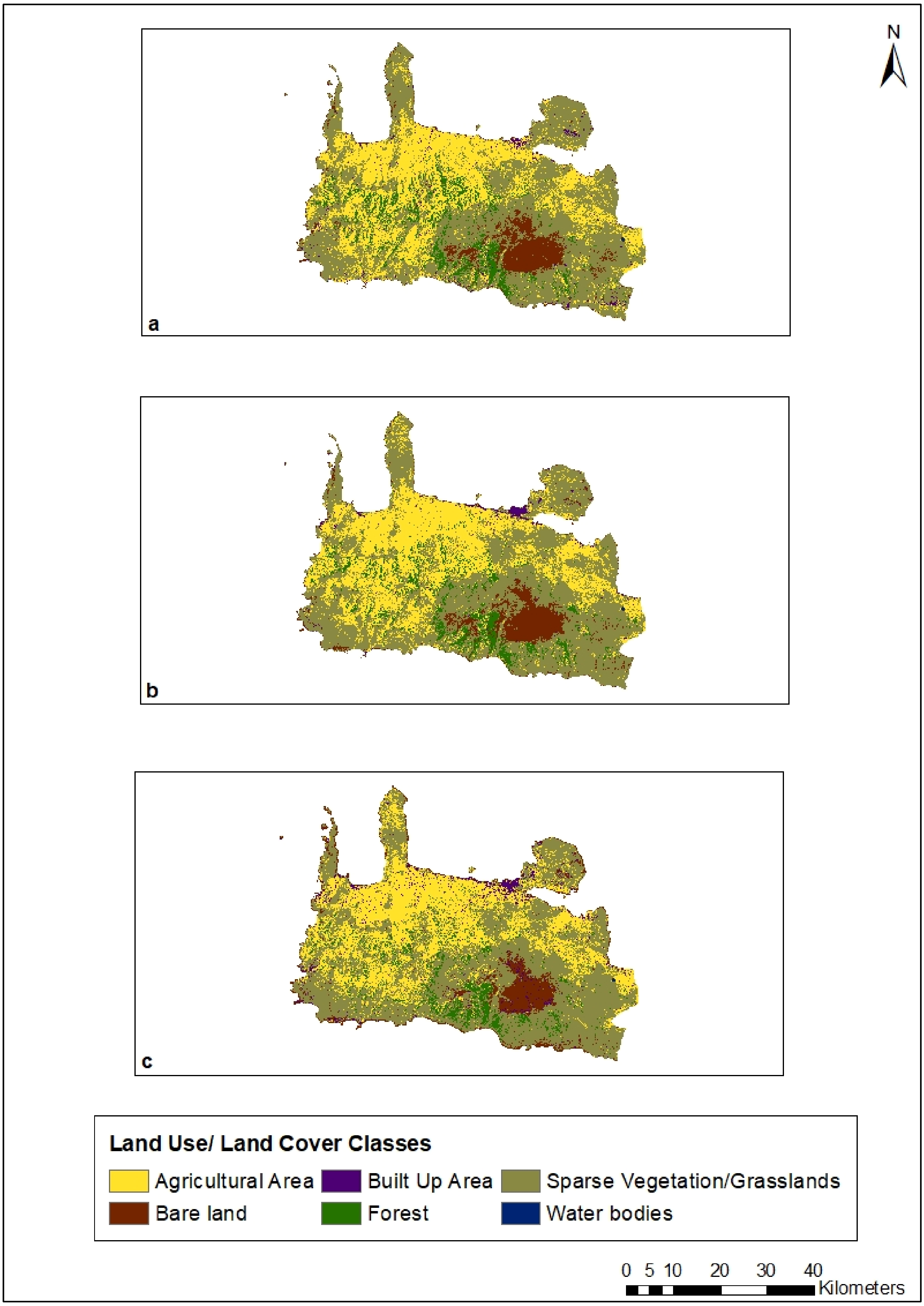


Figure 2. Land-use/land-cover maps of Chania derived from Landsat data for (**a**) 1990, (**b**) 2006 and (**c**) 2021.

The results showed that the dominant land-use/land-cover types in 1990, 2006 and 2021 were grassland and sparse vegetation, with around 52% of the total extent of the prefecture followed by agricultural land with more than 30% of the total area. These findings align with the general characteristics of land use/land cover in Crete as stated in Panagos et al. [30]. Additionally, the results revealed a gradual decline in forest coverage by nearly 1.5% from 1990 to 2021. On the other hand, the agricultural lands and the built-up areas each experienced a 1.1% increase in percentage cover for the same period. Minimal changes (less than 0.5%) were recorded for water bodies and bare land classes for the same study period. Viewed as a time series, the outcomes did not reveal a critical spatiotemporal change in the land-use/land-cover pattern regime of the region under study in the last three decades. Similarly, the findings of Polykretis et al. [61] showed a low level of land-cover change within the island of Crete between 1990 and 2019. To conclude, these outcomes follow the predominant trend of the land-use/land-cover dynamic in Crete, where the magnitude of change is manifested in terms of intensity rather than in the change of the class type [28].

This study generated land-use/land-cover maps based only on satellite data imagery to identify the ground features. The validation of the three produced maps for 1990, 2006 and 2021 was done by producing error matrices. For each map, 300 random points equally distributed among the six categories have been validated using Google Earth imagery corresponding to the closest possible image to the captured Landsat data. The results showed an acceptable level of accuracy for use in the next stages of this research, exceeding 75% for the three produced maps. The lowest achieved accuracy was recorded for 1990 in terms of both overall (76%) and kappa statistics (0.71). This was mainly due to the low resolution of Google Earth imagery used as reference data for this time period. The quality of the reference satellite data improved the classification accuracy for the 2006 and 2021 produced maps, reaching 84% and 85.33%, respectively.

3.1.2. Land-Use/Land-Cover Mapping from PlanetScope Data

The classification of the PlanetScope image has been produced using the Maximum Likelihood Classifier algorithm. Six classes (forest, water bodies, agricultural land, bare land, built-up land and grassland and sparse vegetation) have been identified within the region of the Keritis river basin. The outcome of the image classification revealed that land use/land cover within the Keritis watershed is dominated by agricultural lands, grasslands and forest, covering, respectively, 32.85, 32.79 and 32.63% of the total area of the region. Additionally, the results showed a satisfying accuracy of the classification procedure with an overall accuracy of 0.879 and a kappa accuracy of 0.823.

3.1.3. Land-Use/Land-Cover Prediction

Based on the classified Landsat images and the Corine data, the future land-use/land-cover maps, at the mid and long term, were generated using the combined Markov and Cellular Automata (CA-Markov) model (Figure 3). The area of coverage of each class by percentage for the years 2030 and 2045 are illustrated in Table 5. The results showed a difference in the coverage area between the generated maps derived from the two datasets.

Table 5. Predicted coverage areas of land-use/land-cover classes.

Dataset	**Prediction from Landsat**		**Prediction from Corine**	
Year	**2030**	**2045**	**2030**	**2045**
Forest	5.56%	4.97%	7.95%	7.75%
Water bodies	0.01%	0.01%	0.29%	0.24%
Agricultural land	32.74%	33.31%	32.96%	34.02%
Bare land	6.47%	6.35%	1.35%	0.69%
Built-up land	3.10%	3.92%	2.79%	3.10%
Grassland and sparse vegetation	52.11%	51.44%	54.65%	54.18%

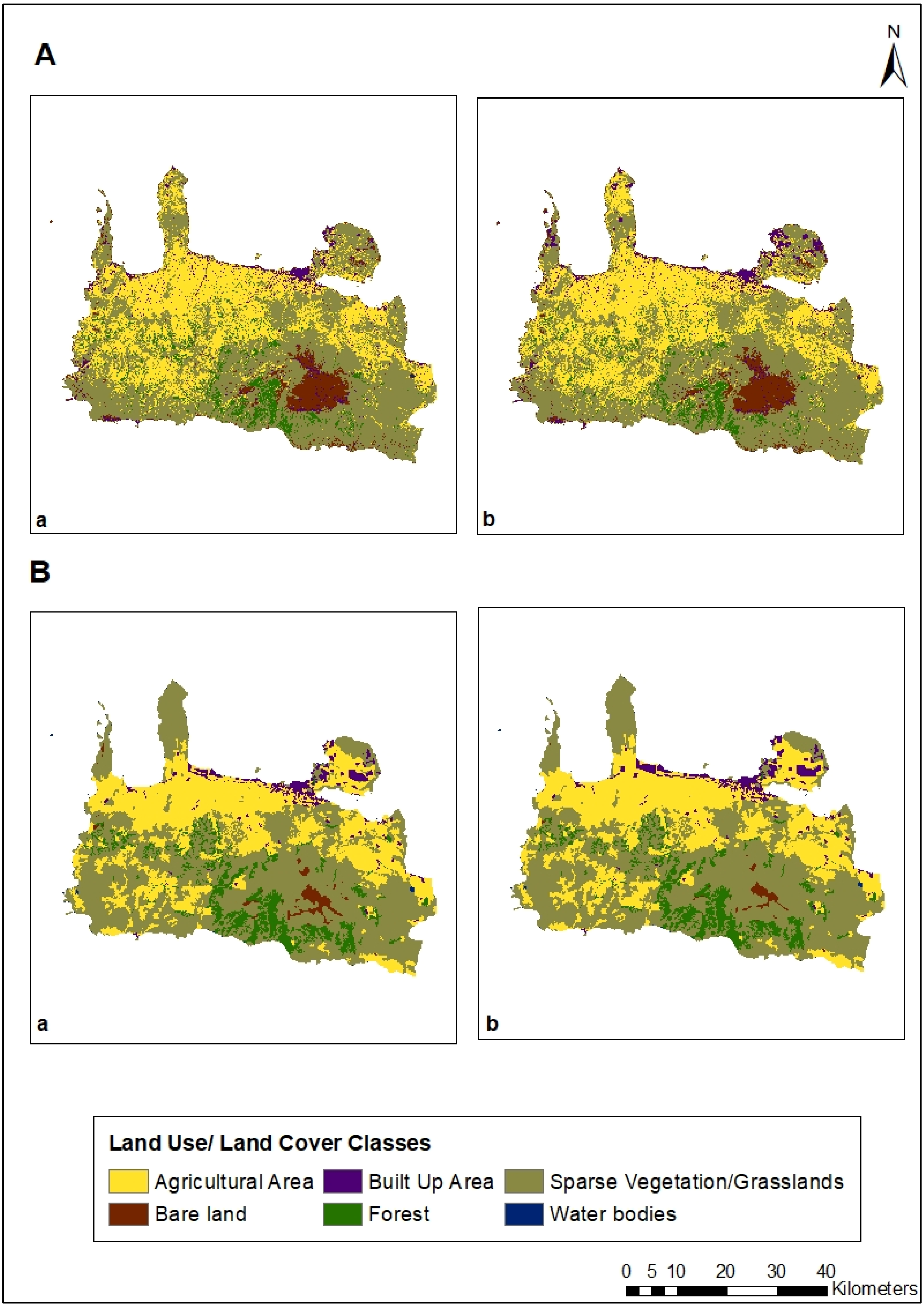


Figure 3. Land-use/land-cover prediction derived from (**A**) Landsat data and (**B**) Corine data for (a) 2030 and (b) 2045.

The grassland and sparse vegetation class would continue to dominate more than half of the total extent of Chania. Moreover, the outcomes showed a continued loss in forest areas, quantified by 0.9% in the case of Landsat-based predictions and by 0.2% in the case of Corine-based predictions. Additionally, the outcomes revealed a continued increase in the agricultural and built-up lands for both datasets. The results derived from Landsat classified images demonstrated that the speed of urbanization would slightly increase with a susceptible extension in built-up areas by 1.4% in the next 24 years (from 2021 to 2045) compared to 1.1% in 21 years (from 1990 to 2021). This could result from the gradual increase in both population and tourism activities. However, the outcomes of the predictions based on Corine maps show a decline in the speed of urbanization from 0.94% (from 1990 to 2018) to 0.57% (from 2018 to 2045). Similarly, the predicted increase in the coverage of the agricultural area varied between the two datasets; it is two times more important for Corine-based than Landsat-based maps. Generally, no dramatic change would be observed in the trend characterizing the temporal evolution of the land use/land cover within the prefecture of Chania in the horizon of 2045.

It is necessary to highlight that the future land-use/land-cover maps were generated based on historical land-use/land-cover data without considering any physical, political or socioeconomic factors (e.g., population growth, environmental policies, etc.). The consideration of such variables would improve the reliability of the prediction. In this study, these factors were overlooked due to the lack of data.

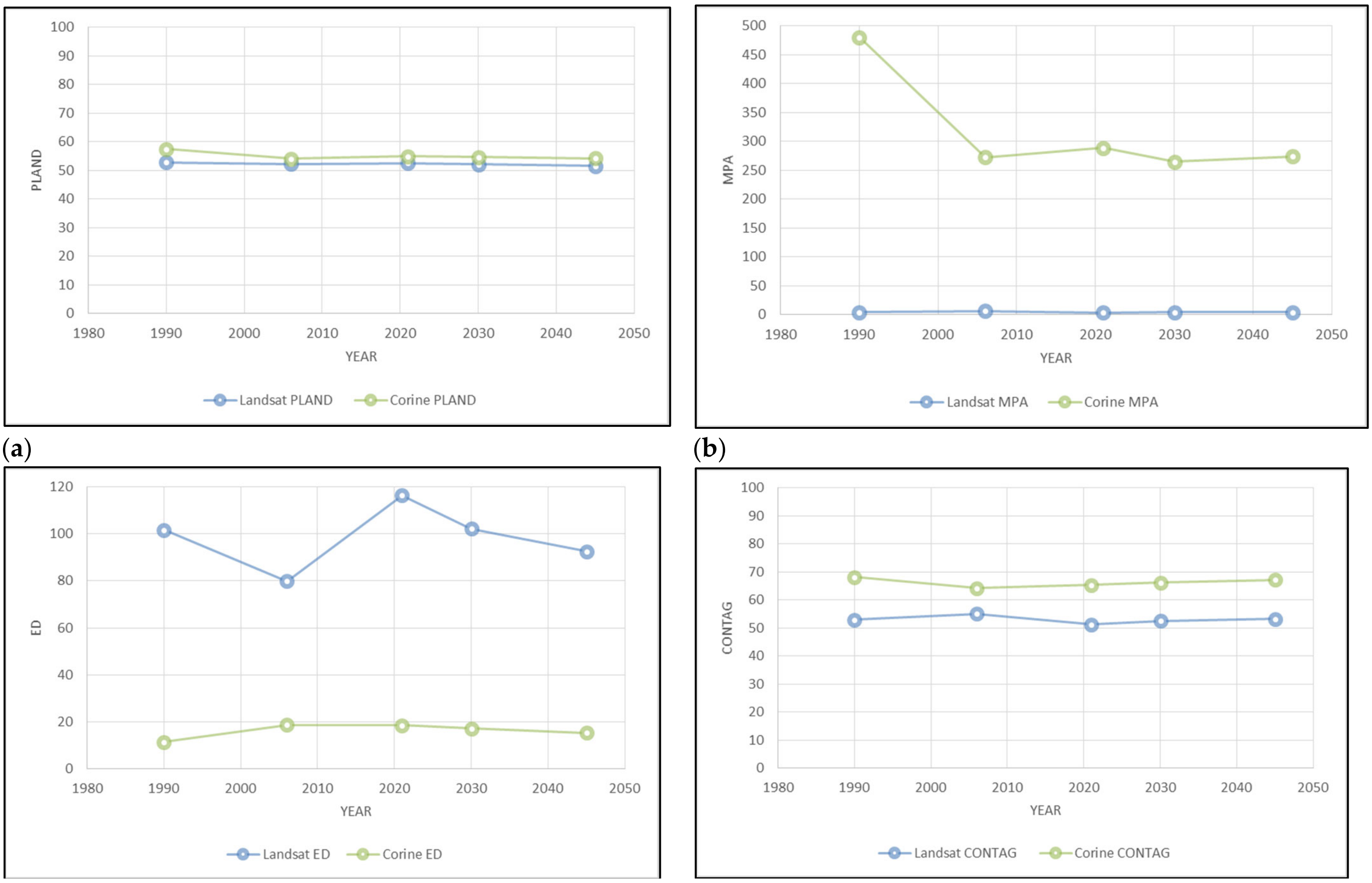
3.2. Landscape Quality Analysis

3.2.1. Landscape Quality within Chania Prefecture

Structural Dimension

The structural quality within Chania was assessed based on the results of the selected landscape metrics computed using the FRAGSTATS software. According to the results of Student's t-test, four selected structural landscape indicators—namely percentage of landscape occupied by a class of the highest share (PLAND), mean patch area (MPA), edge density (ED) and contagion index (CONTAG)—were statistically sensitive to the land-use/land-cover dataset, with p-values of 0.0044, 0.0017, 0.0002 and 0.0002, respectively.

In accordance with the results of the image analysis section, the outcomes of PLAND values (Figure 4a) confirmed that for both datasets, the highest share of the landscape was occupied by sparse vegetation and grassland for the three studied years and remained valid for the projected years of 2030 and 2045. Even though the type of the class of the highest share was the same for both Landsat classified images and Corine maps, a statistically significant difference was recorded in the percentage of landscape occupied by this class, ranging between 52.74% and 51.44% in the case of Landsat and between 57.4% and 54.1% in the case of Corine. Similarly, mean patch area values (Figure 4b) were 87 to 109 times higher according to Corine compared to Landsat classified images. This result derived from the differences in terms of spatial resolution and minimum mapping units between the two datasets. Analogously, a similar trend was observed for the edge density results (Figure 4c), with a statistically significant difference between the two datasets. Moreover, the results showed that CONTAG values (Figure 4d) were significantly higher in the case of the Corine dataset compared to Landsat. In fact, a higher mapping unit and a lower spatial resolution of the Corine dataset resulted in higher values of CONTAG, indicating a more compact structure of land cover with fewer and larger patches.



(c) (d)

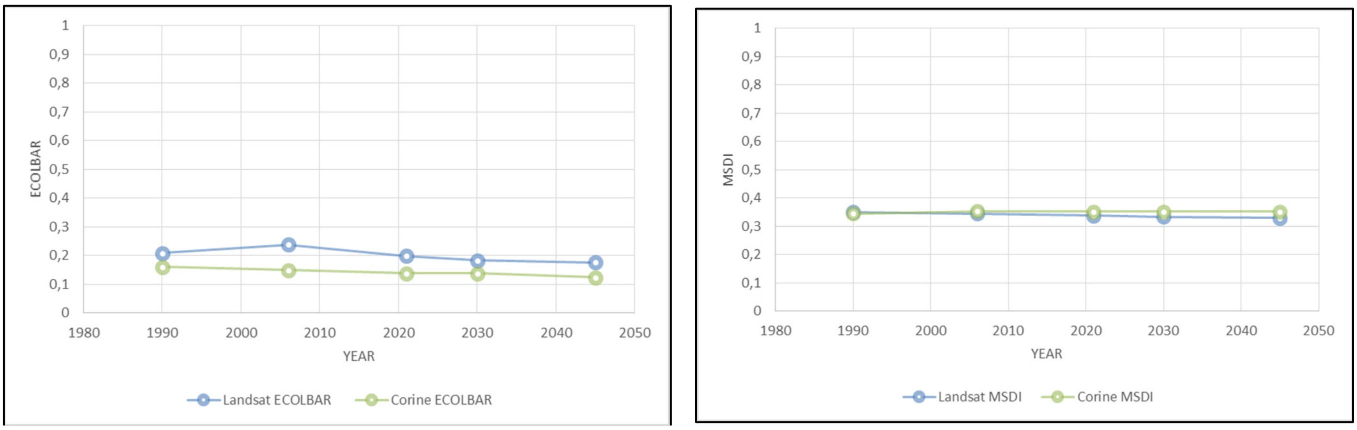
Figure 4. Landscape structural indicators: (**a**) PLAND, (**b**) MPA, (**c**) ED and (**d**) CONTAG.To sum up the outcomes of the landscape metrics revealed a relatively high structural quality within the prefecture of Chania. However, no specific trend characterizing the diachronic evolution of the overall structural value for our study area exists.

Ecological Dimension

The ecological aspect of the landscape was evaluated based on two indices dealing with the fragmentation and the diversity of the landscape, namely the density of the ecological barriers (ECOLBAR) and the modified Shannon diversity index (MSDI).

Ecological barriers were regarded as fragments of paved roads crossing natural and seminatural land-cover forms. The results showed a low density of the ecological barriers (Figure 5a) for both datasets (<0.3 km/km^2). A slight decrease in the values of this index, meaning an improvement in the ecological quality, has been observed over the years for both datasets. Given that the road network did not experience an essential historical change and that we maintained this trend when assessing the future ecological quality, this decline in ECOLBAR values could be explained by the loss of natural and seminatural areas (e.g., due to forest fires). From this perspective, the decrease in ECOLBAR should be understood not as an amelioration of the ecological values but instead as a result of slight land-use/land-cover deterioration. Additionally, a statistically significant difference at the 95% confidence interval has been recorded between the results derived from the two data sources.

The outcomes of the modified Shannon diversity index, taking into account the degree of ecological significance of different land-cover forms, showed relatively low values of MSDI (Figure 5b), ranging between 0.35 and 0.33 in the case of Landsat and between 0.39 and 0.4 in the case of Corine. Given that MSDI = 0 when all the landscape is covered by only anthropogenic land-cover forms and MSDI = 1 when natural land-cover forms cover all the landscape, the distribution is perfectly even. The results of Student's *t*-test showed that the difference between the outcomes derived from the Corine database and the Landsat classified maps was not statistically significant.



(**a**) (**b**)

Figure 5. Landscape ecological indicators (**a**) ECOLBAR and (**b**) MSDI.

Generally, the time series of the ECOLBAR and MSDI values analysis revealed a quite stable ecological quality within Chania. However, some studies [62,63] highlighted the extinction likelihood of endemic flora species in Crete, challenging hence the island's plant diversity and thus the landscape's ecological aspect.

Visual Dimension

For both datasets, more than 50% of the area of Chania prefecture was covered by elements positively impacting the visual landscape quality, namely water bodies and natural and seminatural vegetation. According to the Landsat classified maps, the share of the positive land-cover forms (Figure 6a) declined by 1.8% from 1990 to 2021 and −t is susceptible to recording a 2% decrease between 2021 and 2045. Based on the results derived from the Corine database, the historical quantified loss in the land-cover forms perceived as positive is two times more important than the predicted loss by 2045.

Additionally, elements having a negative impact on the visual landscape quality were regarded as buildings and roads. Unsurprisingly, the share of land-cover forms perceived as negative (NLCF) (Figure 6b) experienced a historical increase of about 0.9% for both data sources. The future prediction revealed a continued increase in NLCF values by 0.6% in the case of Corine (from 2018 to 2045) and 1.3% in the case of Landsat-derived maps (from 2021 to 2045).

The form and color disharmony index (FCDHI) (Figure 6c) deals with the anthropogenic objects perceived as negative elements for visual landscape quality. For both datasets, FCDHI values were expected to increase from 0.6 in 1990 to 0.7 in 2045. The rather high values recorded for FCDHI indicate quite a degraded state of the landscape in terms of form and color.

The shape disharmony index (SDHI) (Figure 6d) involved the proportion of areas with different levels of anthropogenic transformation and the shape index calculated by means of the Fractal Dimension Index (FRAC). For both datasets and for the different years, the results showed low values of SDHI of around 0.1 (approaching 0), indicating a high harmony of shapes.

The statistical analysis at the 95% confidence interval revealed a statistically significant difference between the two data sources when measuring the share of positive land-cover forms and the form and color disharmony index. On the contrary, a statistically insignificant difference has been observed between the two datasets when measuring the share of negative land-cover forms and the shape disharmony index. The two analyzed data sources are derived from medium-resolution satellite data; hence, the statistical difference occurred only for indicators dealing with natural and seminatural land-cover forms, which are better classified than anthropogenic land-cover forms (e.g., road infrastructure). To sum up, the use of the land-cover dataset enabled the evaluation of the landscape as a whole. However, it is likely to misinterpret the impact of land-cover change on the visual value due to the limitation of such datasets in capturing the visible features of the landscape. In other words, the effectiveness of land-cover data in assessing the visual aspect of the landscape depends on how detailed the classification is. Thus, it is advised to diversify and combine the data sources to expand and diversify the indicators used for more reliable results [26].

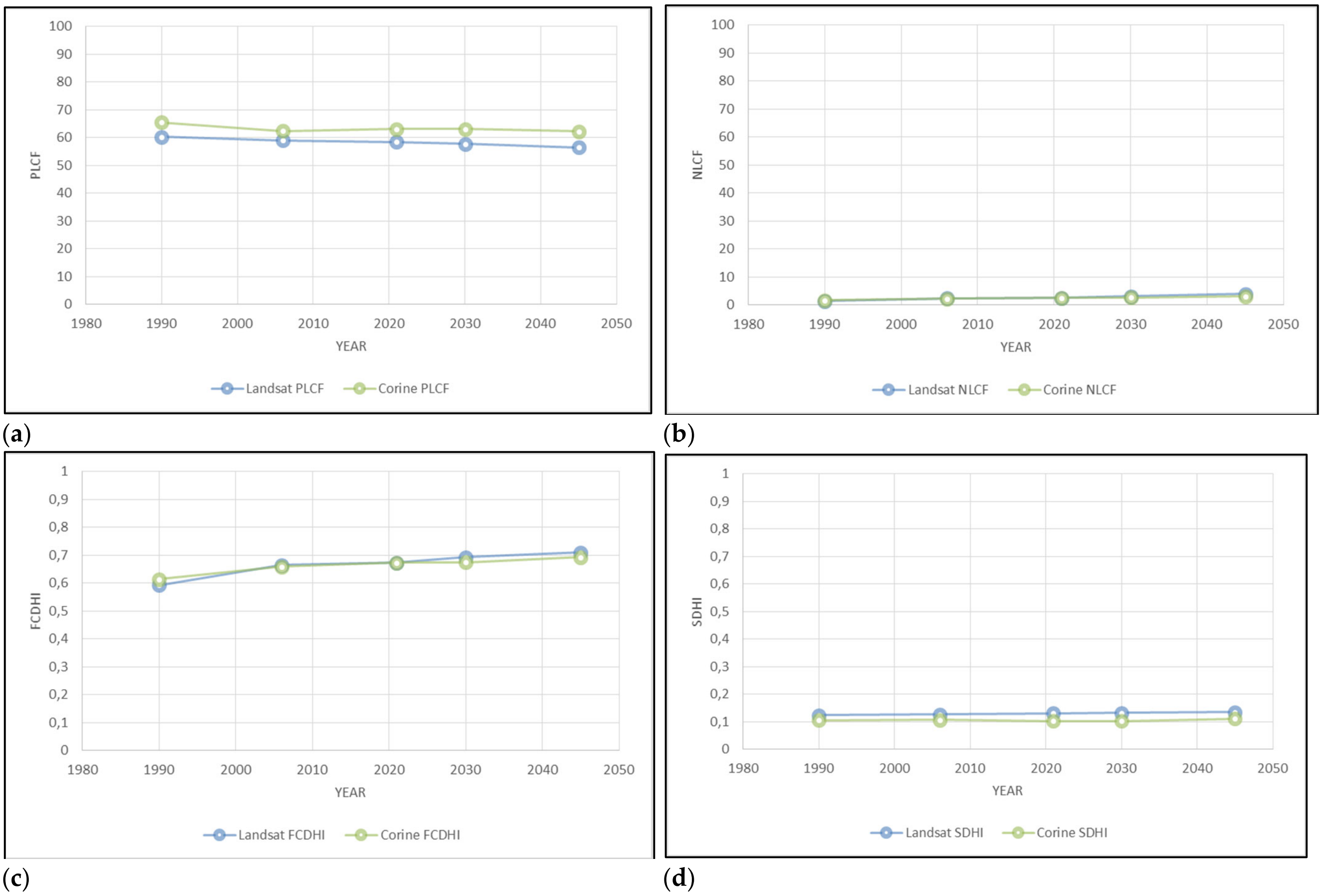


Figure 6. Landscape visual indicators: (**a**) PLCF, (**b**) NLCF, (**c**) FCDHI and (**d**) SDHI.

Cultural Dimension

The historical monuments index assessed the cultural facet of the landscape, showing a low cultural value of 0.1 within the Chania prefecture. Figure 7 presents the spatial distribution of the 263 historical monuments located within our study area. It is necessary to highlight that according to the literature, cultural quality is assessed through tangible values dealing with built heritage, man-designed gardens and parks and intangible cultural heritage [14,57,58]. Given that intangible values could not be captured and evaluated based on Earth-observation data and the missing data quantifying the man-designed greenery within Chania, a confirmation of this result requires both additional analysis and data.

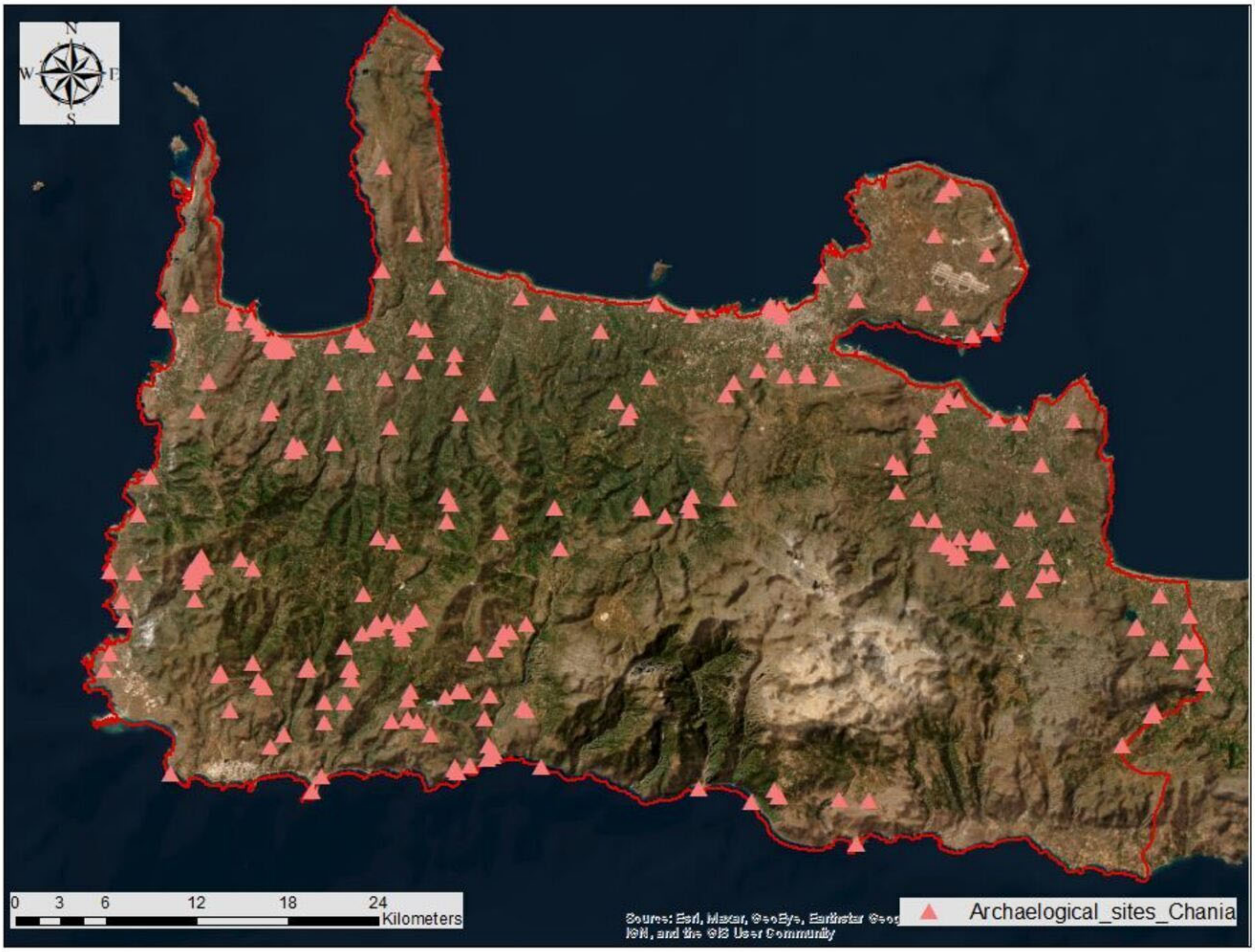


Figure 7. Historical monuments located within Chania prefecture.

3.2.2. Impact of Scale

Spatial Resolution

In order to better investigate the impact of spatial resolution on the landscape indices, the results of the measured indicators derived from the high-resolution dataset, namely the PlanetScope satellite, was compared to those derived from medium-resolution data sources, specifically Landsat and Corine. Landscape indicators were measured for the Keritis watershed located within Chania prefecture (Figure 8).

The results (Table 6) confirmed the previous findings, showing that landscape structural indicators are sensitive to the land-use/land-cover data. For instance, for both PlanetScope and Landsat data sources, the highest share of the Keritis landscape according to the PLAND index was occupied by agricultural land, with a notable difference in the percentage of land occupied by agricultural areas of 14.7% between the two datasets. In the case of Corine, the highest share was occupied by a different land-cover form, namely sparse vegetation and grasslands.

Additionally, mean patch area (MPA) values were greatly higher in the case of the Corine dataset compared to both Landsat and PlanetScope. The lowest value was recorded in the case of PlanetScope (0.17 ha), which was 15 times lower than Landsat and 1735 times lower than Corine. In the case of the Corine dataset, the smallest mapped spatial feature covers 25 ha, meaning that the patch area is equal to or greater than 25 ha. On the other hand, for the classified satellite images, the patch area is equal to or greater than the pixel size (30 × 30 m for Landsat and 3 × 3 m for PlanetScope), which explains the critical difference in the mean patch area's values.

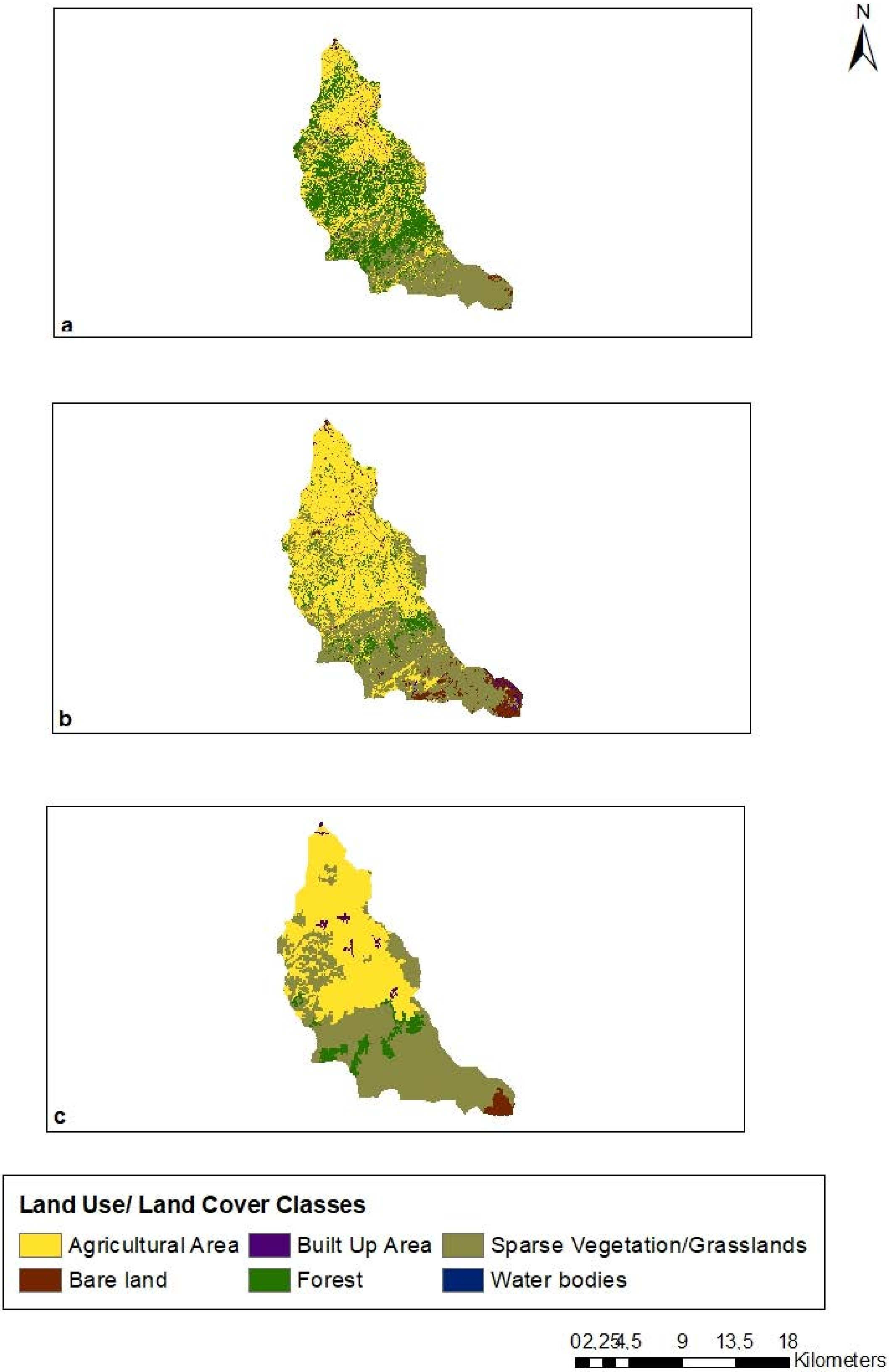


Figure 8. Land-use/land-cover map of Keritis derived from (**a**) PlanetScope data, (**b**) Landsat data and (**c**) Corine data.

Table 6. Landscape indicators: Results of the different spatial resolutions.

	PlanetScope	Landsat	Corine
PLAND	32.848	47.546	48.534
MPA	0.170	2.507	294.993
ED	519.009	129.865	15.856
CONTAG	53.541	45.932	65.998
ECOLBAR	0.239	0.120	0.064
MSDI	0.459	0.363	0.329
PLCF	0.655	0.471	0.533
NLCF	0.010	0.014	0.010
FCDHI	0.499	0.595	0.486
SDHI	0.091	0.169	0.143
PROTAP	0.069	0.069	0.069

Similarly, a considerable difference has been observed in the edge density (ED) values between the three datasets. The ED value in the case of PlanetScope was 32.8 times greater than in the case of Corine and 4 times greater than for Landsat images. These differences derived also from the differences in the spatial resolution and the minimum mapping units between the different datasets' data sources.

Concerning the ecological state, the results showed a low density of ecological barriers for the three datasets (ECOLBAR) (<0.3 km/km^2). We notice an increase in ECOLBAR values with a decrease in the minimum mapping units. Unfortunately, we could not evaluate the statistical significance of these findings due to the availability of PlanetScope data. Similar results have been observed for the modified Shannon diversity index (MSDI).

The results of the visual value indicators showed different values between the three datasets. However, there is no trend characterizing the relationship between these indices and the spatial resolution of the data sources. The cultural dimension index was not affected by the spatial resolution of the satellite data, since it was not acquired from land-use/land-cover maps.

Spatial Extent

For this study, the extent of Chania prefecture has been considered as the landscape-level unit for the analysis. Given the broad geographic area, such an extent could comprise several landscape subunits of variable qualities and impact the relevance of the observed elements corresponding to the different aspects. Thus, in order to evaluate the effect of the scale at which the landscape is investigated in the assessment, the results of the landscape indices calculated for Chania prefecture have been compared to those measured for the Keritis watershed, presenting a subunit of the total extent (Table 7).

The 95% confidence interval statistical analysis revealed a statistically significant difference in PLAND values between the two spatial extents for the two data sources. In the Corine dataset case, both Chania and Keritis were mostly occupied by grasslands and sparse vegetation. On the other hand, in the case of the Landsat classified images, the highest shares of Chania and Keritis were occupied by different land-use/land-cover forms, namely grasslands and agriculture, respectively. The mean patch area index seemed to be independent from the spatial extent. However, we cannot conclude whether there is a correlation between edge density and contagion indicators and the spatial extent of the landscape. The difference in edge density values between Chania and Keritis was statistically significant in the case of Corine and nonsignificant in the case of the Landsat data source. A similar outcome has been observed for the contagion index, where the difference between the two studied spatial extents was significant only for the Landsat classified images.

Concerning the ecological state, the results of both ECOLBAR and MSDI demonstrated a significant difference between Chania and Keritis, thus proving the relationship between the landscapes' indicators and the spatial scale at which the ecological quality is evaluated.

In addition, the visual aspect seemed to be related to the landscapes' spatial extent. For both datasets, the outcomes of the visual indicators (except the FCDHI index in the case of Landsat) revealed a statistically considerable difference between the two analyzed landscape scales. The outcome of the cultural dimension has also been affected by the spatial extent.

Table 7. Landscape indicators: Results of the different spatial extents.

Year	**1990**	**2006**		**2021**		**2030**		**2045**		
Extent	**Chania**	**Keritis**	**Chania**	**Keritis**	**Chania**	**Keritis**	**Chania**	**Keritis**	**Chania**	**Keritis**
	Landsat Data Source									
PLAND	52.745	41.246	52.273	45.339	52.491	47.546	52.113	48.252	51.439	48.563
MPA	4.130	3.836	6.233	7.328	3.091	2.507	3.824	3.042	4.397	3.451
ED	101.614	108.137	79.909	75.661	116.449	129.865	102.186	113.577	92.591	104.676
CONTAG	52.903	50.669	54.978	51.993	51.286	45.932	52.468	47.684	53.233	49.109
ECOLBAR	0.208	0.106	0.238	0.106	0.199	0.120	0.184	0.104	0.177	0.100
MSDI	0.350	0.397	0.345	0.382	0.337	0.363	0.334	0.359	0.329	0.353
PLCF	0.602	0.501	0.590	0.491	0.584	0.471	0.577	0.463	0.564	0.460
NLCF	0.014	0.003	0.023	0.001	0.025	0.014	0.031	0.016	0.039	0.016
FCDHI	0.592	0.000	0.664	0.000	0.673	0.595	0.692	0.616	0.710	0.617
SDHI	0.124	0.158	0.126	0.160	0.130	0.169	0.132	0.171	0.135	0.171
PROTAP	0.112	0.069	0.112	0.069	0.112	0.069	0.112	0.069	0.112	0.069
	CORINE Data Source									
PLAND	57.413	52.794	54.091	48.749	54.844	48.534	54.655	48.414	54.185	47.753
MPA	480.062	470.394	272.078	294.993	288.238	294.993	264.806	322.307	273.643	341.266
ED	11.437	8.806	18.692	16.418	18.611	15.85.62	17.256	15.436	15.368	13.264
CONTAG	68.080	71.858	64.142	65.726	65.347	65.998	66.187	66.452	67.083	67.531
ECOLBAR	0.161	0.072	0.149	0.066	0.139	0.064	0.138	0.063	0.124	0.061
MSDI	0.344	0.302	0.353	0.329	0.352	0.329	0.352	0.328	0.352	0.326
PLCF	0.654	0.558	0.624	0.535	0.631	0.533	0.631	0.532	0.622	0.523
NLCF	0.016	0.010	0.022	0.009	0.025	0.010	0.026	0.010	0.031	0.010
FCDHI	0.613	0.500	0.659	0.477	0.673	0.486	0.674	0.488	0.692	0.511
SDHI	0.105	0.133	0.106	0.142	0.103	0.143	0.103	0.143	0.111	0.146
PROTAP	0.112	0.069	0.112	0.069	0.112	0.069	0.112	0.069	0.112	0.069

These findings confirm the extreme importance of the spatial extent on the relevance of the landscape's elements corresponding to the different facets and thus the landscape assessment [21,58,60,64].

4. Conclusions

The combination of Earth-observation data and Geographic Information Systems (GIS) with the application of landscape indicators proved to be a useful tool for a rather rapid and low-cost diachronic landscape assessment. Moreover, both Corine and Landsat classified images seemed to be efficient in measuring these indices. However, the outcomes revealed a significant difference between the two datasets, especially when assessing the structural facet of the landscape. The important difference between the two datasets, especially for the mean patch area and edge density indicators, results mainly from the important difference in the minimum mapped unit varying from the pixel size of 30 × 30 m for Landsat to 25 ha for Corine. The ecological state within the prefecture is quite stable for our study period, especially because Chania had not experienced a colossal extension in its road network during the last few years. Furthermore, the visual quality within Chania is quite high, with around 60% of its total area covered by land-use/land-cover forms perceived as visually positive. However, a susceptible decrease in the visual quality is likely to be observed by 2045, resulting mainly from a susceptible potential increase in anthropogenic land-use/land-cover forms. Finally, despite the presence of numerous historical monuments (263 monuments) located in Chania, the cultural quality of the prefecture has been evaluated as low with a cultural value of 0.1, which requires further assessment. To sum up, the Corine program presents a very potential data source to use when evaluating the landscape's ecological and visual dimensions, given its easy accessibility and its direct usefulness and taking into account the similar general evolution trends between the two datasets (Landsat and Corine) when assessing these landscapes' aspects. Yet, the coarse spatial granulation of the Corine land cover poses a limitation when assessing the landscape's structural values.

The analysis of the impact of the scale on the landscape quality assessment revealed that the landscape's structural indicators are significantly affected by the spatial resolution of the data source. On the other hand, the ecological and visual aspects seemed to be statistically related to the spatial extent at which the landscape quality is evaluated. Moreover, the cultural aspect is independent from the spatial resolution of the data source but is affected by the spatial extent of the landscape and the corresponding number of cultural sites, with a lower cultural value observed within Keritis compared to the total area of Chania.

Even though the general aim of this study has been achieved, there are some limitations that need to be highlighted. Most of the applied indicators are derived from land-use/land-cover data, so improving the image classification accuracy is necessary. Additionally, this study was mainly based on Earth-observation data, which to some extent could be insufficient in evaluating the landscape in all its complexity, especially when studying the cultural components. Moreover, landscape as understood nowadays as being highly related to its complex social and economic context. Hence, the incorporation of socioeconomic variables is crucial for more reliable results.

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