

INVESTIGATION OF INDICES FOR THE AUTOMATED QUANTIFICATION OF LANDSCAPE QUALITATIVE CHARACTERISTICS USING DIGITAL GROUND PHOTOGRAPHS

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ABSTRACT

This study aims to investigate indices for the automatic evaluation and classification of landscape quality using digital ground photographs. Research efforts to date are scarce on automated extraction of qualitative information based on photographs and therefore this study contributes in this respect, i.e. the automated quantification of landscape qualitative characteristics. Based on the texture indices that are commonly used in landscape analysis, eight quantitative indices are selected and the results from the application of these indices to a sample of ground photographs are described in this paper. These indices are richness, fragmentation, diversity, dominance, grouping and complexity. Furthermore, we investigate the effectiveness of the indices selected as to the classification of the landscape's qualitative characteristics, such as relief morphology, visibility, water existence, vegetation patterns, etc. The results are compared to the results derived from a research programme of the National Technical University of Athens, in which the qualitative characteristics of the landscapes depicted in the same samples of ground photographs have been manually assessed based on the scientific opinion of seven experts. Comments and suggestions are presented based on the comparison for further investigation. The main conclusion of the investigation is that the texture measurement indices are sensitised in the landscape's qualitative characteristics, a fact that is positive and encouraging enough in order to pursue further research.

Keywords: landscape evaluation and classification, texture indices, digital ground photographs, geographical information systems.

1 INTRODUCTION

A landscape is the combined result of physiography, geological formations, vegetation, waters and the various cultural interventions that occur in a given area. This combination attributes shape, line, colour and texture to a landscape, while the aesthetic result is considered on the basis of the variety or the uniqueness offered, and is usually classified into three main classes: (1) indistinctive, (2) common and (3) distinctive [1–3]. This classification determines those landscapes that are most important and those, which are of lesser value from the standpoint of scenic quality. The classification is based on the premise that all landscapes have some scenic value, but those with the most variety or diversity has the greatest potential for high scenic value. A frame of reference is developed to judge the physical features of an area as indistinctive, common or distinctive. Features such as landforms, water forms, rock formations, and vegetative patterns are compared singularly or in combination. Through this comparison, the overall degree of scenic quality and resultant variety class rating of an area is determined. Of decisive role in landscape evaluation are also the observation post and the observation distance; since they determine the way the various objects are observed. Other variables affecting the scenic beauty evaluation, probably not to the same extent, are: the seasons, lighting and atmospheric conditions, movement and duration of the observation.

The combinations of the variables mentioned above are indefinite in number and it is therefore obvious that the more the characteristics under the examination increase, the more complex the landscape's evaluation becomes. Besides, there are many divergent views even among experts. On the other hand the landscape is a decisive environmental variable, the assessment and management of which intensify over time, in terms of both environmental planning and environmental impact assessment.

Currently, scientific approaches to the evaluation of the scenic attractiveness of a landscape and its classification into categories are indirect through the application of the geographical information systems (GIS). These approaches require the appropriate hardware, software and other mechanical equipments, specialised staff, cartographic backgrounds (usually unavailable for a variety of the variables examined) and adequate time for processing information and producing results. Several other techniques, most of them involving complex and difficult land planning problems, have been proposed [4–14]. The disadvantages of most techniques and methods of determining landscape management potential arise due to a number of factors. These often include a sub-optimal dependence on the experience of the evaluator, a time-consuming examination of the large number of attributes and interactions, and the increasing complexity of landscape evaluation as the number of estimated landscape attributes increases.

In May 2002, the Laboratory of Physical Geography and Environmental Impact of the National Technical University of Athens (NTUA) completed a pilot research programme entitled 'SCAPE-VIEWER'. The main objective of this programme was to design a user-friendly and mainly computerised instrument, which would not require specialised knowledge from the user. The methodology pursued was based on the theoretically proven characteristics of the landscape. Ten indices were selected and applied to a sample of 108 ground photographs. These indices are presented analytically in the next paragraph. All the indices have been applied to the sample of photographs and were assessed on a quality basis by seven experts. The average rating as derived from the seven experts was taken for the quantification of the indices, and the results constituted the input and training data for a neural network (NN) [15, 16]. The photos show the landscapes in perspective view and depict various landscape types, natural, urban and mixed, from different places in Greece and other countries. They were taken at various periods in order to serve teaching purposes in issues related to landscape analysis variables. This sample was considered to be satisfactory in view of this being the first effort to approach the subject matter with a research perspective. Photographic material is very often used in visual landscape inventories as a low-cost media of presentation [17]. The proposed approach has shown that NNs can be efficiently used to develop an integrated automatic landscape classification system leading to high classification performance for the three main classes of landscape (indistinctive, common and distinctive). The research carried out within the framework of this programme was at a pilot phase, but a further pursuance with an enhanced database may lead to the production of an instrument consisting of a mechanical component for data collection (camera) and a computer component for further analysis.

In the above-mentioned research programme, the selected indices were evaluated manually based on the opinion of seven experts. In order to overcome the sub-optimal dependence on the experience of the evaluator, an interesting approach would be to implement state-of-the-art image processing techniques [18, 19]. What is challenging in these techniques is how to quantify the qualitative characteristics and the group images of the landscape into semantically meaningful categories based on low-level visual features of the images, such as color and texture features. In other words, the challenge is to be able to extract high-level information such as the type of the landscape (physical or urban), the visibility range, the form of the relief, the vegetation, etc. based on low level information, such as the colour corresponding to each pixel of the image upon scanning. Indices can quantify the elements of a landscape (composition) and how the elements are spatially arranged (configuration). Indices commonly applied in landscape pattern analysis are myriad, ranging from very simple measures to complex. Therefore the automated quantification of the landscape's qualitative characteristics is an issue that requires many investigations.

Although there is a vast amount of literature on pattern recognition in aerial photographs, research efforts to date are scarce with regard to the automated extraction of qualitative information from

ground photographs [18, 19]. The research effort which is presented in this paper contributes to the direction of the automated quantification of the qualitative characteristics of the landscapes using ground photographs. On the basis of the texture measurement indices that have been established in landscape pattern analysis, eight quantitative indices are selected and designed, and the results from the application of these indices to the same sample of ground photographs that was used in the aforementioned research programme are described. Furthermore, we investigate the effectiveness of the indices selected as to the classification of the landscape's qualitative characteristics, while the results are compared to the respective ones from the research programme 'SCAPEVIEWER'. There have been no previous applications of this work in order to make a comparison of the results, but the main conclusion of this investigation is that the texture measurement indices are sensitised in the landscape's qualitative characteristics, a fact that is positive and encouraging in order to pursue research.

The use of modern technologies in planning, such as geographical information systems and remote sensing, gives us new potential to monitor and prevent environmental degradation. Landscape pattern indices quantify the composition and configuration of ecosystems across a landscape thus allowing quantitative comparison between different landscapes or within the same landscape at different times. As a consequence, planners can acquire a better knowledge on 'what has to be planned' and 'how to plan' in order to meet the target of sustainability.

2 LANDSCAPE QUALITATIVE CHARACTERISTICS

In order to quantify the various characteristics of the landscapes depicted on the photographs, 10 indices were selected and designed through the research programme 'SCAPEVIEWER'. These indices are presented here briefly as they are related to our research.

1. *Landscape naturalness Index (N)*: This index refers to the type of the landscape and, based on the presence or absence of man-made elements, takes the values: N = 1 (urban), N = 2 (mixed), N = 3 (natural).
2. *Visibility index (V)*: This index aims at assessing the view shed and is based on the main distance zones that are used in landscape analysis [12]. Depending on the maximum distance depicted, the index takes the values: V = 1 (0–100 m), V = 2 (100–1,000 m), V = 3 (1,000–5,000 m), V = 4 (>5,000 m).
3. *Observation position index (P)*: Depending on the elevation of the observer in relation to the objects observed, this index takes the values: P = 1 (inferior), P = 2 (equal), P = 3 (superior).
4. *Relief index (R)*: The relief index constitutes an overall assessment of the morphology of the relief depicted. Depending on the soil slopes and formation, this index takes the values: R = 1 (Flat: small soil slopes prevail, without hypsometric alterations), R = 2 (Flat–Mountainous: mixed category, where part of the relief depicted is flat and the remaining is hilly or mountainous; this means that there are clear distinct characteristics), R = 3 (Hilly: uniform slopes prevail with relatively smooth curves on the edges of the elements, and usual hypsometric differences), R = 4 (Mountainous: big soil slopes and sharp edges in large prevailing elements, with frequent hypsometric alterations), R = 5 (Unusual formations: mainly on rocky soil; prevailing the physiographic landscape; impressive, unique, peculiar and outstanding in size, shape and colour).
5. *Skyline index (SL)*: The skyline is a distinguishing line between the landscape and the horizon, namely the outline of the landscape, and is one of the first perceivable visual elements. This index was designed to describe the form and the complexity of the skyline and takes the values: SL = 1 (no line of sight due to limited visibility), SL = 2 (almost horizontal straight line), SL = 3 (sloped line), SL = 4 (smooth curves), SL = 5 (complex curves with acute angles).
6. *Soil coverage with vegetation index (FC)*: This index constitutes the quantitative assessment of the soil coverage with vegetation in the landscape depicted and takes the values: FC = 1

- (rare: bare soil or with rare vegetation), FC = 2 (moderate: half of the landscape depicted is covered with vegetation), FC = 3 (intense: essentially the entire landscape depicted is covered with dense vegetation).
7. *Vegetation index (F)*: This index classifies the vegetation types that appear in the landscape into three general categories: F = 1 (mossy–shrubby), F = 2 (mixed category), F = 3 (trees). These categories are basic and can be easily identified by most people, taking the height of the vegetation species as the distinctive characteristic.
 8. *Season index (S)*: Depending on the season of the photo shooting, this index takes the values: S = 1 (Spring), S = 2 (Summer), S = 3 (Autumn), S = 4 (Winter).
 9. *Water presence index (W)*: This index refers to the quantitative assessment of the presence of water or the coverage of the landscape depicted with water (rivers, lakes, sea) and takes the values: W = 1 (none), W = 2 (rare), W = 3 (moderate: up to half of the subject depicted), W = 4 (strong: water as the main subject).
 10. *Groups of objects index (G)*: This index refers to the number of individual groups of objects that are depicted and present similar visual characteristics, in a way that these objects may be considered to form a single unit. For example, the sky is a visual group distinguished from the remaining objects of the landscape depicted, and the side of a mountain at the left part of the photograph is a visual group different from the side of a mountain at the right part of the photograph. The higher the number of the visual groups of the landscape, the larger is the visual variety of this landscape. However, it should be stressed that for assessing this index, we utilise the visual groups that are created based on prevalent features and not on details.
 11. *Landscape category (C)*: In order to evaluate and classify the landscapes, the three variety classes (C1: Indistinctive, C2: Common, C3: Distinctive) of the US Forest Service's method were adapted [2, 3]. For this evaluation and classification, we adopted the average rating of the landscape category as given by seven experts of the NTUA's Laboratory of Physical Geography and Environmental Impact.

All the aforementioned qualitative indices were applied to the sample of the ground photographs and were evaluated manually by seven experts. Figure 1 presents examples of indices values in various landscape photographs and Table 1 depicts the correlations and heterocorrelations among indices. More details about these indices can be found in the paper by Mougiakakou *et al.* [16].



Figure 1: Example of (a) C1 landscape photograph with indices N = 3, V = 2, P = 2, R = 3, SL = 4, FC = 2, F = 1, S = 2, W = 1, G = 4, (b) C2 landscape photograph with indices N = 3, V = 3, P = 3, R = 2, SL = 2, FC = 2, F = 2, S = 2, W = 3, G = 5, and (c) C3 landscape photograph with corresponding indices N = 3, V = 4, P = 2, R = 4, SL = 5, FC = 2, F = 2, S = 4, W = 1, G = 6.

Table 1: Correlations and heterocorrelations among the indices and the landscape category.

V	N	R	FC	F	W	SL	G	S	P	C
V	1.000	0.421	-0.201	-0.116	-0.018	0.132	0.230	-0.012	0.472	0.612
N	0.024	1.000	0.029	-0.169	0.085	-0.051	-0.336	-0.033	-0.031	0.196
R	0.421	0.201	-0.238	-0.157	-0.323	0.343	0.126	0.037	0.153	0.579
FC	-0.201	0.029	1.000	0.490	-0.157	-0.255	-0.080	0.158	-0.278	-0.131
F	-0.116	-0.169	0.490	1.000	-0.079	-0.135	0.034	0.223	-0.123	-0.052
W	-0.018	0.085	-0.157	-0.079	1.000	-0.122	-0.011	-0.185	-0.039	-0.105
SL	0.132	-0.051	-0.255	-0.135	-0.122	1.000	0.279	0.135	0.135	0.149
G	0.230	0.126	-0.080	0.034	-0.011	0.279	1.000	0.091	0.090	0.283
S	-0.012	0.037	0.158	0.223	-0.185	0.135	0.091	1.000	-0.030	0.204
P	0.472	0.153	-0.278	-0.123	-0.039	0.135	0.090	-0.030	1.000	0.218

3 SELECTION AND DESIGN OF QUANTITATIVE INDICES

3.1 Photograph digitisation data

A sample of 108 photographs was available in the form of slides and then was digitised using the KODAK RFS3570 slides scanner. The resolution was 96 pixels per inch (ppi), and 16 million colours were used.

Given that the processing and management of 16 million colours is a hard task, the colour palette should be reduced to a maximum of 256 categories. This reduction, at least in terms of visual perception, does not cause an essential problem, taking into account that humans can perceive and assess the quality of a landscape, even based on black and white photographs [12]. Moreover, since measurement indices are created from scratch in this research, their application conditions are defined empirically in the most convenient way. From the available colour generalisation choices, the generalisation and standardisation selected was in 216 colour ($6 \times 6 \times 6$), using 6 levels for each of the basic colours/channels Red-Green-Blue. In this way, the colour category whose value ranges from 0 to 215, constitutes information that is directly comparable to all the photographs and is the arithmetic value 'z' of each pixel. The generalisation was effected using the 'Composit' (for 8 bits) corresponding algorithm availed by the Idrisi32 GIS.

The number of pixels is similar for all photographs, approximately 927×627 , but not the same in every case. The differentiations observed are small and, in most cases in the range of 5% based on the total number of pixels, at a percentage that cannot be considered to alter the general behaviour of the indices.

3.2 Selection of quantitative indices and application method

The indices selected to be examined are the most essential that prevail in landscape analysis and have been examined so as to be applied in maps and satellite representations. These are the richness, fragmentation, diversity, dominance, grouping and complexity indices, which are described below in detail.

For the sake of brevity, a codified symbolic name was defined for each index that is presented in parenthesis. The algorithm 'Texture' of the Idrisi32 GIS package was used for the calculation of the values of some indices (diversity, dominance and fragmentation index (f)); while for the rest of the indices and in the absence of readily available algorithms, these were programmed.

It should be noted that the texture indices, which were selected for application to the sample of the ground photographs, examine the heterogeneity that appears in each landscape photograph by the colour categories that exist each time. Each photograph is regarded as a spatial unit of landscape and the indices are calculated from the total number of pixels that exist in each photograph.

3.2.1 Richness index (n)

$$n = m \quad (1)$$

where n = the richness index and m = the number of the categories appearing in the part examined.

This index is defined by the previous eqn (1) and refers to the number of the present categories [20]. Its value was determined by the total number of colours in the content of each photograph (n). The more the categories present in one photograph, the greater is the richness, namely the variety of

the landscape depicted. The maximum possible sum of categories is known and is common for all the photographs ($m_{\max} = 216$).

3.2.2 Fragmentation indices (f)

$$F_1 = \text{number of appearing groups} \quad (2)$$

$$F_2 = (m - 1)/(p - 1) \quad (3)$$

where m = the number of appearing categories p = the number of pixels of the part examined.

This index appears in the literature in two different forms. In the first case, it is equal to the number of the appearing groups; the greater the number, the greater is the fragmentation of the landscape depicted (eqn (2)) [20]. In the second case, the index is calculated by eqn (3), where the same conclusion applies, i.e. the higher the value of the index, the greater is the fragmentation of the landscape depicted [21].

In this case, both eqns (2) and (3) were used for the fragmentation index. The second equation may be determined more easily than the first one. This is due to the fact that there are usually thousands of groups appearing in one real photograph that impede their processing. These groups derive from the different relative colour categories that appear irregularly and in various ways, in order to give colour, shading and texture to the object, resulting in the creation of many individual groups within the same object. In landscape analysis, this index is usually used in classified data, in which case the number of the appearing groups is significantly lower and with greater meaning.

In order to simplify the problem with the number of groups and to include this fragmentation index in the subsequent investigation, the resolution of the photograph was reduced from 96 ppi to 24 ppi using a special algorithm for this purpose. The number of groups was defined by these new photographs and matches the fragmentation index (ff).

The second fragmentation index (f) was determined by eqn (3) and was applied to the initial digitised photographs. Its value was determined by the total number of colours in the content of each photograph (f).

Furthermore, on the occasion of determining the fragmentation indices, we pursued a general classification of the appearing categories. With regard to this classification, we used the 'Cluster' algorithm of the Idrisi32 GIS package, which is based on a histogram technique developed by Richards in 1986 [22]. In order to apply this algorithm, a specific 256-colour palette was used, which was selected from the beginning of our research. This algorithm practically analyses and distinguishes the complex palette in each of the basic channels R-G-B, thus creating a three-dimensional histogram from which the peaks are determined. One peak corresponds to the value with the greater appearance frequency compared to the neighbouring values on all the sides, thus defining a classification category. Once the peaks are determined, all other possible values are included in their nearest peak, while the intermediate value among the categories is considered to be their separation point.

There are many classification algorithms that have been developed and are based on frequency histograms, but they usually refer to satellite image classification. With regard to ground photographs, only few attempts have been made so far [18, 19]. At this point, it should be stressed that the classification pursued in this research is generic and was applied so as to simplify and generalise the information and not to classify correctly the elements depicted, e.g. the sky, the vegetation and the waters, as in the case of land use classification in a satellite representation.

The above process was applied to photographs of 24 ppi resolution and the number of the appearing clusters (fcl) was determined for the resulting classified photographs, according to eqn (2).

Therefore, three indices were calculated in total by applying the aforementioned processes: (ff), (f) and (fcl).

3.2.3 Diversity index (h)

$$h = - \sum_{k=1}^m (P_k) \ln (P_k) \quad (4)$$

where P_k = is the percentage of the pixels belonging to category k and m = the number of categories of the part examined.

As in the previous cases, the value of the index was determined based on the total number of colours in each photograph (h) (eqn (4)). The absolute maximum value of the index is: $h_{\max} = \ln (m)$ and is observed when all the categories (m) appear with the same percentage [23–25].

3.2.4 Dominance index (d)

$$d = h_{\max} + \sum_{k=1}^m (P_k) \ln (P_k) \quad (5)$$

The value of this index was also determined based on the total number of colours in each photograph (d) (eqn (5)). Assuming that $P_k < 1$ is always true, the sum is negative. When comparing different landscapes with a different number of categories, h_{\max} practically standardises the index. When the values of d are high, a landscape is dominated by one or some categories; low values of the index suggest a landscape with many categories that appear with an almost equal probability. d is zero, when all the categories can be present with exactly the same probability, or when $m = 1$; therefore it is appropriate for use when a landscape is absolutely homogeneous [24–26].

3.2.5 Contagion index (c)

$$c = K_{\max} + \sum_{i=1}^m \sum_{j=1}^m (Q_{i,j}) \ln (Q_{i,j}) \quad (6)$$

where $Q_{i,j}$ = the percentage of category i neighbouring with category j and $K_{\max} = 2 \ln (m)$ is the maximum possible absolute value of the term of the summation.

This index refers to the tendency of the categories to appear as large groups (eqn (6)). The maximum possible value K_{\max} is observed when all the categories neighbour among one another with an equal probability. Since the term of the summation is always negative in this equation, K_{\max} is used again to determine the deviation of the summation term from the maximum possible value, while it also offers the necessary standardisation when comparing different landscapes.

Index c is zeroed, when the term of the summation matches K_{\max} , or when $m = 1$ [24–26]. In theory, low values of the index show that there are many small groups of objects, in which case the percentage appearance of all possible adjacencies is almost equal. Respectively, as the values of the index increase, the groups of objects become smaller in number and larger in size.

In this case, as K_{\max} is constant for all photographs, a contagion index was determined, that derived from eqn (7), and was applied to the computerised photographs (c):

$$c = - \sum_{i=1}^m \sum_{j=1}^m (Q_{i,j}) \ln (Q_{i,j}) \quad (7)$$

3.2.6 Complexity index (fdm)

Complexity indices borrow the concept of fractal dimension from the theory of fractal geometry [27]. Fractal geometry describes the physical structures that are characterised by an irregular sharp or fragmented form. Fractal geometry attributes to the structure of the total number of spatial points a number D_f , which is called fractal dimension. The fractal dimension is represented by D in the literature. Here, we use the symbol D_f in order to distinguish it from D of the entropy index.

O'Neill *et al.*, as well as many other researchers, utilise the fractal dimension for their studies in order to determine the geometric complexity of the landscape's patterns [21, 25, 28]. Various ways of calculating the fractal dimension D_f , have been developed, but the index is usually determined by eqn (8) [29]:

$$P = k \cdot A^{D_f/2} \quad (8)$$

where P = the perimeter of the closed line, A = the surface area surrounded by the closed line and k = a constant.

Therefore, by logarithmising the surface area and the perimeter of each object of interest, the fractal dimension derives from the optimum slope of the line that is adjusted to the pairs created. The higher the value of the index, the more complex is the pattern.

In the case of normalised digital data, the simplest item is the single pixel pattern, where $D_f = 1$. Therefore, from eqn (8) and with regard to a square pixel, $k = 4$, the fractal dimension of the pattern of a group of pixels is now determined by the equation [29, 30]:

$$P = 4 \cdot A^{D_f/2}$$

or

$$D_f = 2 \ln (P/4) / \ln (A) \quad (9)$$

where A = the surface area of the group and P = the perimeter of the group.

In order to be applied, the previous complexity index presupposes the determination of the appearing categories in advance, so as to calculate the perimeter and the surface area of each appearing group as required by eqn (9). Therefore, this index was applied to photographs of 24 ppi resolution, and then the weighted average was estimated from the total number of groups (fdm).

4 PRESENTATION OF THE RESULTS

Table 2 presents the descriptive data of all texture indices, which derived from their application to the sample of 108 photographs; and Table 3 their correlations. Texture indices present a variety of correlation degrees, ranging from inexistent to very strong. Strong correlations exist between the richness index 'n' and the fragmentation indices 'fcl' and 'ff', as well as with the contagion index 'c'. The contagion index 'c' has also strong correlations with the fragmentation indices 'fcl' and 'ff', as well as with the diversity index 'h'. There is also a strong correlation between the fragmentation index 'fcl' and the other fragmentation index 'ff'. Therefore, the question arises whether it is worth examining all these indices simultaneously.

The dependencies among the texture indices have been observed in other studies and applications of these indices in maps and satellite images [27]. The problem lies in which index to choose and which to ignore, and on the basis of which criteria. Some of these indices may be probably more appropriate for certain applications than others. It is obvious that the most appropriate indices should be selected each time, depending on the objective pursued. The criterion in this study is the effective classification of the landscape's qualitative characteristics to the maximum extent possible.

Table 2: Descriptive data of quantitative indices.

Index	Average	Standard deviation	Minimum value	Maximum value
n	48.91	13.63	27	104
fcl	1479.78	1011.28	19	5721
ff	5879.95	3272.7	1267	17875
f	90.00×10^{-6}	37.17×10^{-6}	44.5×10^{-6}	228.2×10^{-6}
h	2.41	0.31	1.72	3.21
d	1.45	0.27	0.92	2.10
c	3.35	0.62	2.16	5.28
fdfm	1.58	0.08	1.39	1.81

Table 3: Correlation coefficients among measurement indices.

	n	fcl	ff	f	h	d	c	fdfm
n	1	0.737	0.716	0.536	0.556	0.313	0.702	0.580
fcl		1	0.919	0.325	0.552	0.048	0.825	0.685
ff			1	0.231	0.579	0.010	0.829	0.772
f				1	0.335	0.132	0.475	0.257
h					1	-0.602	0.856	0.627
d						1	-0.313	-0.165
c							1	0.800
fdfm								1

5 THE ABILITY OF THE INDICES IN THE CLASSIFICATION OF THE LANDSCAPE'S QUALITATIVE CHARACTERISTICS

The following investigation took place with the aim to address the question of whether, and to what extent, the texture indices selected and examined in this research, either individually or in combination, may assess the qualitative indices that were developed in the framework of the research programme 'SCAPEVIEWER', as well as the final category of the landscapes depicted, with regard to their visual value.

Table 4 presents the correlation coefficients between the quantitative and the qualitative indices from which we generally observe negligible to low correlations. This means that none of the texture indices is able to describe any of the qualitative characteristics sufficiently. Maybe the combination of these texture indices could give more information about the qualitative characteristics, but this is a question that is examined in the following paragraph. However, even under such circumstances, certain texture indices seem to be sensitised in some landscape's qualitative characteristics. For example, the correlation coefficient between the indices 'fdfm' and 'P' is almost $r_{xy} = -0.5$, which can show a trend that the higher the values of the complexity index, the more inferior is the observation position. This trend is logical, as in inferior positions more information of the landscape is usually observed and depicted in a ground photograph. In the same way, the correlation coefficients between the indices 'n', 'fcl', 'ff' and 'V' are almost $r_{xy} = -0.5$, which can show a trend that the greater the values of the richness and the fragmentation indices, the smaller is the maximum distance depicted in a photograph.

Table 4: Correlation coefficients between measurement and qualitative indices.

Indices	n	fel	ff	f	h	d	c	fdfm
N	-0.1027	0.0499	-0.0198	0.0776	-0.1002	-0.0010	-0.0014	0.0137
V	-0.4244	-0.4480	-0.4717	-0.1201	-0.1619	-0.2145	-0.3232	-0.3090
P	-0.2449	-0.4264	-0.4575	-0.0430	-0.2834	0.0940	-0.4094	-0.4994
R	-0.4202	-0.3418	-0.3151	-0.0991	-0.2754	-0.0768	-0.3187	-0.2506
SL	-0.2073	-0.3204	-0.3212	0.1021	-0.2719	0.1229	-0.2860	-0.2376
FC	0.2531	0.1564	0.1939	0.0638	0.0783	0.1295	0.1406	0.1328
F	0.1752	0.1380	0.1869	0.1019	0.1109	0.0275	0.1504	0.0950
S	0.0021	-0.1495	-0.1402	0.1652	0.0383	-0.0614	-0.0060	-0.0563
W	-0.0400	0.0499	0.0566	-0.1512	-0.0055	-0.0409	0.0407	0.1085
G	0.0521	0.0154	0.0067	0.0874	0.0232	0.0335	0.0245	-0.0175
C	-0.3238	-0.2491	-0.2790	-0.0093	-0.1565	-0.1518	-0.1828	-0.2313

This is also logical as the smaller the maximum distance of a landscape, the more details of colours and shapes are observed and depicted in a ground photograph. Colours in nature vary in proportion to the increase of the distance. This is attributed to the interference of the atmosphere. Owing to the vapour and to the minute particles of dust in the atmosphere, the tones of the colours of the landscape tend to lighten and to gradually acquire a hazy tint, similar to that of the sky. Therefore it is absolutely reasonable that the richness and fragmentation indices take greater values when a micro landscape is depicted in a ground photograph. The previous observations are quite encouraging in order to pursue further research, as in some cases the behaviour of texture indices seems to have a logical meaning.

5.1 Classification of the landscape's qualitative characteristics

The classification is made using the linear discrimination method and with the use of the SPSS. It should be stressed here that the sample of the photographs is relatively small, the classification approaches examined are pilot and, obviously, the models derived cannot be suggested for applications. They may, however, show the possibilities that exist in this direction and therefore they are investigated.

All the classification methods have been developed in order to classify observations, whose grouping is not known in advance. However, they are frequently used in order to verify the accuracy of a classification. This means that they are applied to observations whose grouping is known, so as to calculate the percentage of the correctly classified observations. This percentage verifies the accuracy of the process and the separation degree of the groups [31]. This is the purpose of the following analysis. The observations, in our case the photographs, are already classified in the groups defined by each qualitative index. The quantitative indices constitute the distinctive variables that are used for separating the groups of the qualitative indices. The percentage of the correctly classified observations shows the ability of the measurement indices to classify the qualitative characteristics, or otherwise to assess the qualitative indices, since in this case the values of the latter are equivalent to groups.

The process mentioned above was followed for each index separately by adopting two different classification techniques. In the first technique, all measurement indices took place at the same time as distinctive variables, without having examined in advance their distinctive ability. In the second technique, a stepwise selection of the variables was chosen according to their distinctive ability, which was defined using the Mahalanobis distance as a criterion [32]. According to this technique, a variable that maximises the distance between two successive groups is selected in each step. In order to introduce a variable in the equation, the partial ratio F should be higher than a critical value that corresponds to the distribution value F for a certain level of importance (α). For this study, α is defined as $\alpha = 0.05$. The ratio F practically quantifies the distinction achieved by a variable, after taking into account the distinction of groups that has taken place already, using the variables that were previously entered. The results from the two classification methods are presented in Tables 5 and 6 below.

Table 5: Percentage of successful classification of each qualitative index using all the quantitative indices.

	N	V	P	R	SL	FC	F	S	W	G	C
%	55.56	49.07	54.63	50.00	44.44	51.85	52.78	46.30	51.85	41.67	62.04

Table 6: Results from the classification of qualitative indices with the stepwise technique, for $\alpha = 0.05$.

Qualitative index for classification	Selected distinctive variables	Successful classification percentage (%)
N	None	0
V	ff	39.81
P	fdfm	48.15
R	ff	25.00
SL	fcl, f	28.70
FC	n	43.52
F	None	0
S	ff	30.56
W	None	0
G	None	0
C	fdfm	52.78

Table 5 shows that in the classification of the landscape's visual class 'C', one of the highest percentages of successful classification is presented (62.04%). This result is satisfactory enough, taking into account that the application of the respective linear discrimination method in the classification of the landscape's visual value, with the use of all the sample observations and of all the qualitative indices, gives successful classification results of 87.96%. In other words, the percentage may be lower, but the reliability is much higher, since the quantitative indices derive objectively from mathematical equations and not subjectively from personal evaluations, as in the case of qualitative indices. The result of the classification of the landscape's visual class that derived from the stepwise technique with the complexity index (fdfm), is even more satisfactory, as with a single quantitative index, proper classification is achieved (52.78%), (Table 6).

With the exception of the characteristics referring to visibility (V), skyline (SL), season (S) and visual groups (G), all the qualitative characteristics were classified successfully, with a percentage of more than 50%, using all of the quantitative indices (Table 5). The highest percentage of successful classification is presented in the index that refers to the landscape's naturalness 'N' (55.56%) and the lowest to the visual groups index 'G' (41.67%).

There is a different picture when it comes to classifying the qualitative characteristics, based on the stepwise technique (Table 6). In this case, due to the strict criteria applied, the percentages of successful classification range from zero to satisfactory (0–48.15%), using one to two distinctive variables. The selection of the small number of distinctive variables is of particular interest in this analysis, as it shows that there are certain quantitative indices much more effective than the others in the classification of the landscape's qualitative characteristics. For example, in the case of visibility 'V', only the fragmentation index (ff) classifies successfully 39.81% of the cases, when altogether the measurement indices in the first method classify 49.07%. The same, and an even more intense, phenomenon appears in the characteristic of the observation position 'P', where the complexity index (fdfm) classifies successfully 48.15% of the cases, when altogether the indices in the first technique classify 54.63%.

In comparison to that, a very high percentage of successful classification is achieved in land coverage with vegetation 'FC', where with a single index, i.e. the richness index (n), 43.52% of the

cases are classified correctly, when all the measurement indices together classify 51.85%. Similar is the situation regarding the characteristic of the relief's form 'R' and season 'S'.

With regard to the characteristic of the skyline (SL), two distinctive variables are used, while the classification percentages achieved are not higher than the ones of the remaining characteristics previously mentioned.

There are four cases of qualitative characteristics (N, F, W, G), for which classification is impossible. In these four cases, all the quantitative indices are rejected, because they do not satisfy the criterion F for the given level of importance. Three of these cases (N, W, G), in contrast to the others, have as a common characteristic the poor distribution of observations in their individual groups. This means that the sample of photographs, due to its small size, could not have offered an equal, or almost an equal number of observations in all the groups; therefore some of them are inferior in terms of resolution.

Another observation deals with the number of categories/groups in each qualitative characteristic. The qualitative indices of relief 'R' and of the skyline 'SL', which take five possible values, present some of the lowest percentages of successful classification. The same applies to the index of the visual groups 'G'. Therefore, if these qualitative indices were divided into fewer categories, the classification percentages could have been higher, since the observations would have been more and better distributed among the individual groups.

6 OBSERVATIONS ON THE METHOD

In this study, eight measurement indices were selected and applied to a sample of 108 ground landscape photographs. The qualitative characteristics of this sample of photographs were previously examined and recorded during a research programme that took place in the Laboratory of Physical Geography and Environmental Impact of the NTUA. Each photograph was seen as a spatial landscape unit and each index took a value in each photograph. The application of quantitative indices in the sample of photographs was effected in a way that aimed at describing the general heterogeneity of the landscape appearing in each photograph. The quantitative indices were compared initially among one another and then to the recorded qualitative characteristics. Furthermore, this study attempted to evaluate and classify the recorded qualitative characteristics, using general quantitative indices and applying the discrimination method.

From all the previously effected investigations, the quantitative indices that were used in the classification of the qualitative indices, either individually or in combination, are: (n), (fcl), (ff), (f), (fc12) and (fdm), of which the fragmentation indices seem to be used more. Therefore, the first observation is that in the classification of the qualitative characteristics and of the visual quality, of important role are the quantitative indices deriving from the photographs and from the classified images. Hence, the object-oriented analysis of photographs may probably lead to new and useful quantitative indices.

The sample of the ground photographs used was small, as mentioned above, and therefore does not allow conclusions to be drawn because of the possible inappropriateness of certain quantitative indices which were not used in a certain classification. The remaining indices, which have not appeared so far, may probably be used in another investigation with a bigger sample of photographs.

The results were quite encouraging for the continuance of the research. The quantitative indices seem to be sensitised, in general, in the qualitative characteristics of the landscape and can be used for their classification in generic categories, as well as for the landscape's classification with regard to its visual quality. The experience gained from the implementation of the research programme 'SCAPEVIEWER' show that NNs can achieve much higher percentages of successful classification in relation to the linear discrimination method, using exactly the same variables. It is therefore

reasonable to suppose that in this particular case, the same will apply and the percentages of successful classification with the use of NNs will be higher than the ones presented in Tables 5 and 6.

Some qualitative characteristics, such as the vegetation type 'FC', did not give enough satisfactory results in the attempt of their classification with the use of quantitative indices that were selected and investigated in this study. In this specific qualitative index, the three generic categories (grassy–shrubby, mixed category and trees) have as a basic characteristic their vertical size. However, due to the distance, it is not easy to distinguish whether one sees a tree or a shrub, except when there are other elements that facilitate comparison. This problem leads to the suggestion of using stereo couple photographs, where it is possible to create a stereo model of the relief. In this way, the various problems of evaluating distances and hypsometric differences would be minimised, while new quantitative indices would be designed for the classification of the landscape's qualitative characteristics. Furthermore, in order to develop a reliable classification model, the sample of photographs should be enriched and the research continued.

7 DISCUSSION AND CONCLUSIONS

The aim of this study was the investigation of quantitative indices for evaluating and classifying the landscape's quality using digital ground photographs. The texture indices that were selected for application to the sample of the ground photographs examine the heterogeneity that appears in each landscape photograph by the colour categories that exist each time.

The advantages of using ground photographs in landscape visual analysis are very important; considering that maps, aerial photography and satellite representations are not what a human observes when moving on a landscape. Issues of perspective, relative position, movement, direction, lighting and seasonality are depicted on a ground photograph and help at interpreting perception.

As an important facet of society and environment, the visual quality of the landscape attracts the attention of the people. To satisfy people's appreciation for high quality landscapes, planners improve the visual sustainability in urban and natural landscapes and maintain valuable natural landscape resources with high visual quality. Visual landscape evaluation includes three major problems: the technical problem of how to visualise possible changes in the landscape; the theoretical problem of how to evaluate the scenic beauty; and the administrative problem of how to integrate the visual aspects in the planning process [3, 33]. The texture indices can contribute to visual landscape evaluation, as they offer an objective tool for the description and evaluation of landscape qualitative characteristics. The 'aesthetic result' is certainly not related only to the variety or uniqueness offered; otherwise landscape aesthetics and landscape evaluation would not be such a difficult topic. There is also the subjective component that should not be ignored [5, 6, 11]. However, there are objective characteristics of landscapes that can be described with texture indices and this paper is a contribution in this direction. Texture indices can help planners to acquire a better knowledge on 'what has to be planned' and 'how to plan' in order to meet the target of SUSTAINABILITY.

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