International Journal of Applied Earth Observation and Geoinformation 26 (2014) 176–183

Contents lists available at ScienceDirect

International Journal of Applied Earth Observation and Geoinformation

journal homepage: www.elsevier.com/locate/jag

Mapping the heterogeneity of natural and semi-natural landscapes

Amjad Ali[a,b,*], C.A.J.M. de Bie[a], A.K. Skidmore[a], R.G. Scarrott[c], P. Lymberakis[d]

[a] Faculty of Geo-Information Science and Earth Observation (ITC), University of Twente, P.O. Box 217, 7500 AE Enschede, The Netherlands
[b] Pakistan Space and Upper Atmosphere Research Commission (SUPARCO), Sector 28, Gulzar-e-Hijri, Karachi 75270, Pakistan
[c] Coastal and Marine Research Centre, Environmental Research Institute, University College Cork, County Cork, Ireland
[d] Natural History Museum of Crete, University of Crete, P.O. Box 2208, GR-71409 Irakleio, Crete, Greece

ARTICLE INFO

Article history:
Received 3 December 2012
Accepted 21 June 2013

Keywords:
Mapping
Landscape
Heterogeneity
Hyper-temporal
NDVI
MODIS

ABSTRACT

Natural and semi-natural landscape cover is heterogeneous. Ideally, mapping land cover requires an approach that represents both gradients and land covers spatiotemporal variability. These aspects can be visualized and depicted by applying a new spatio-temporal analysis based Landscape Heterogeneity Mapping (LaHMa) method to natural and semi-natural landscapes. Using MODIS NDVI 16-day imagery (February 2000–July 2009) for Crete, a 65-cluster image was selected from ISODATA classification results using the separability values of the divergence statistics. The 65 clusters appropriately generalize the spatial and temporal variability in land cover. Using classified outputs from 10 to 65 clusters, the frequency of pixels identified as boundaries of homogeneous land cover classes was translated into the form of a landscape heterogeneity map, which was then validated using field data. The results show that the heterogeneity map had moderate correlation ($R^2 = 0.60$ and 0.63 in two transects) with the sum of differences between neighbouring transect pixels in all land cover components. In general, the study found this new approach (LaHMa) to be suitable for mapping landscape heterogeneity in the natural and semi-natural landscape of Crete, Greece. The new method appears to be of potential use for informing gradient analyses in landscape ecological studies.

1. Introduction

The degree of heterogeneity in a landscape is dictated primarily by interactions amongst natural and anthropogenic processes, and disturbance in landscape (Turner and Gardner, 1991). Quantification of landscape heterogeneity is necessary to understand and study interactions and relationships between ecological processes and spatial patterns (Turner et al., 2003; Peters et al., 2006). Furthermore, management of dynamic landscapes requires maps and monitoring tools that portray the nature of the landscapes spatiotemporal heterogeneity (Gustafson, 1998) at selected spatial and temporal scales (Kent et al., 1997; Gustafson, 1998).

Quantifying the natural and semi natural landscape heterogeneity using continuous values is appropriate because natural and semi natural landscape exhibit spatially continuous variations in vegetation communities (Austin, 1990; Begon et al., 1990; Couteron et al., 2006). Spatially, different species (flora) in a natural and semi-natural landscape show considerable overlap, creating gradients that represents gradual changes in space of vegetation density and/or in species composition (Kent et al., 1997; Müller, 1998). Presenting such a landscape in gradient form is important for ecological studies to understand the basic structure of landscape (Gosz, 1992).

Landscape heterogeneity is considered to be a dynamic phenomenon, as it fluctuates over time (Dunn et al., 1991; Fahrig, 1992; Gustafson, 1998). Underlying factors that determine land cover heterogeneity are spatiotemporally varied at different scale, and include soil, geology, climate and topography (Foody and Boyd, 1999). The spatial pattern and the intra-annual (temporal) changes should be considered to quantify landscape heterogeneity (de Bie et al., 2012). Therefore at a landscape level, the continuously changing environment and the dynamic nature of land cover necessitate an understanding of both the spatial and temporal processes of land cover (Fortin et al., 2000; Fagan et al., 2003).

Efforts to quantify the landscape heterogeneity began in the early 1980s (Romme, 1982; Baker and Cai, 1992); However; to-date, the approaches depicting land cover heterogeneity in a map format poorly represent spatiotemporal variability and gradient representation. One approach to quantifying landscape heterogeneity is the Patch Mosaic approach (Goodchild and Quattrochi, 1997; Gustafson, 1998), which builds on information contained in categorical or thematic maps. Information is presented on

* Corresponding author at: Faculty of Geo-Information Science and Earth Observation (ITC), University of Twente, Enschede, The Netherlands.
Tel.: +31 053 487 4444; fax: +31 053 487 4400.
E-mail addresses: a.ali-1@utwente.nl, amjadalee65@yahoo.com (A. Ali).

1569-8432/$ – see front matter © 2013 Elsevier B.V. All rights reserved.
http://dx.doi.org/10.1016/j.jag.2013.06.007

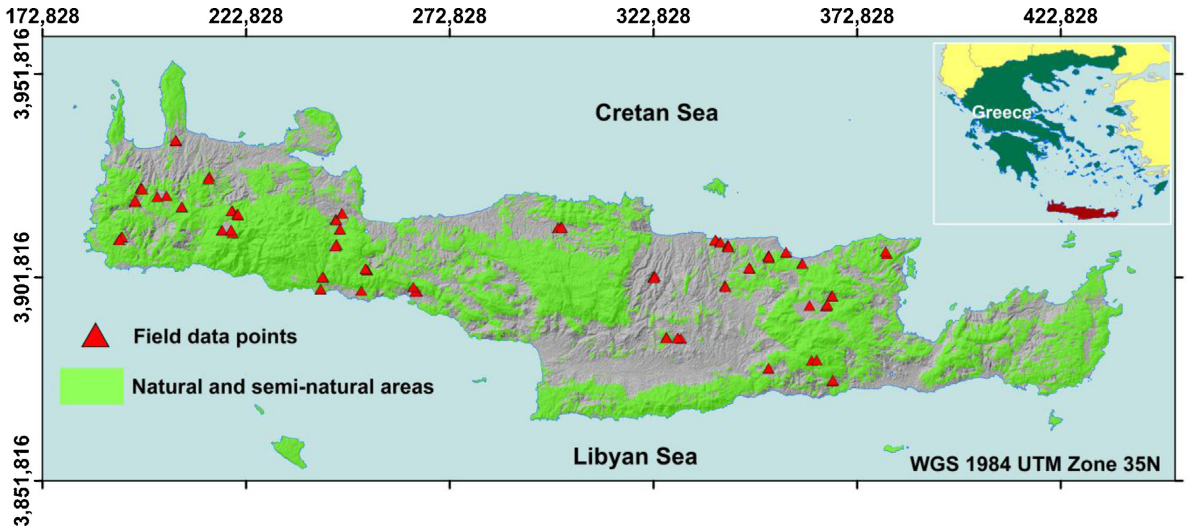

Fig. 1. The Greek island of Crete. Natural and semi-natural areas (extracted from CORINE map) are displayed with general relief. Field data points are also shown.

spatial aspects such as the area, shape, patch density and fractal dimensions of the landscape, while the non-spatial aspects are represented in the form of a matrix containing information on a category's proportions, evenness, richness and diversity (Li and Reynolds, 1995; Gustafson, 1998). The discrete representation of landscape is an incorrect form of representation and prone to errors in land cover class definitions (Gosz, 1992; Southworth et al., 2004; Boyd and Foody, 2011). They are not based on spatiotemporal explicit data which are important for accurate characterization of land cover (Sakamoto et al., 2006; Nguyen et al., 2011). A second approach involves the application of statistical analyses to point data collected through surveys, uses semi-variograms and correlograms amongst other statistical tools (Li and Reynolds, 1995; Gustafson, 1998), and attempts to place a relative value on a landscape's heterogeneity. The point data are always limited, both in space and time, and so cannot accurately represent the spatiotemporal explicit landscape heterogeneity. Thus, all the approaches that claim to capture landscape heterogeneity ignore the likely presence of gradients. In addition to this, research concerning the accurate mapping of landscape heterogeneity has not specifically focused on the high-frequency temporal dimension of land cover, even though this has already been found to be very helpful in land cover mapping and monitoring (Xiao et al., 2006; Sakamoto et al., 2007; Nguyen et al., 2011).

Although techniques such as auto-correlation, semi-variogram analysis, fourier spectral analysis and fractals analysis (Perry et al., 2002; Couteron et al., 2006) do consider gradients in representation, these assume land cover to be aperiodic and always repeating itself within a certain time period (Bradshaw and Spies, 1992). In reality land cover is highly dynamic, and isolating a genuine periodicity is difficult to achieve (Couteron et al., 2006). Therefore, the ability of these techniques to quantify the spatiotemporal aspects of landscape heterogeneity is also limited.

Natural and semi-natural landscapes show more spatially continuous changes than landscapes dominated by the boundary features common to human landscape administration (Puech, 1994; Couteron et al., 2006). To be accurately characterized, any method must ensure the presence of gradients in land cover as well as spatiotemporal variability is adequately accounted for in the mapping process. Therefore, an approach used for agricultural landscapes by de Bie et al. (2012) called the Landscape Heterogeneity Mapping (LaHMa) approach, which was originally applied in agricultural and man-made landscape, is selected to map landscape heterogeneity in the natural and semi-natural landscapes of island of Crete, Greece. This method was not validated with field data therefore a thorough validation was undertaken using field data composed of the fractional complexity of the area's land cover components.

LaHMa involves calculating the relative heterogeneity of each pixel area, using the long-term spatiotemporal variability in land cover. Differences in spectro-temporal characteristics of land cover present in a particular pixel is considered here as landscape heterogeneity. The technique exhibits spatial heterogeneity at various strengths of boundaries (ecotones and ecoclines) at any selected scale therefore it can be useful for understanding landscape structures and functions (Wu and Archer, 2005; Peters et al., 2006). It is also robust for locating vegetation assemblages which are important characteristics of the natural and semi-natural landscape. The heterogeneity determined may be arising by soil, vegetation discontinuities, changes in species composition and its distribution.

2. Study area

Crete (Fig. 1) is characterized by high mountains and plateaus (Chartzoulakis and Psarras, 2005). The geology also varies from mountainous areas to lowlands having calcareous rocks to limestone, sandstone and marls respectively (Sarris et al., 2005). The island has a sub-humid climate, with dry summers and mild wet winters (Sluiter, 1998; Chartzoulakis et al., 2001). An average of about 900 mm of precipitation falls on the island annually. This varies locally, with approximately 300 mm falling at lower altitudes, and up to 2000 mm falling in the mountain areas (Chartzoulakis et al., 2001; Chartzoulakis and Psarras, 2005). The landscape is dominated by both natural and semi-natural land cover, intermixed across the island with herbaceous and woody plant species that form varying proportions of local plant communities (Turland et al., 1993; Montmollin and Iatrou, 1995; Chartzoulakis et al., 2001; Chartzoulakis and Psarras, 2005). The high variability in topography, weather, geology results in high variability in vegetation compositions and structure in Crete, hence creates a heterogeneous landscape. The complex landscape and intermixed vegetation with variable climatic conditions could only be detected if both the spatial and temporal aspects of land cover are considered.

3. Method

3.1. Remote sensing data and maps used

Hyper-temporal time-series Normalized Difference Vegetation Index (NDVI) imagery is freely available at different spatial and temporal resolutions from sensors such as SPOT (1 km), MODIS (1000 m, 500 m, 250 m), MERIS (300 m, 1200 m) and MSG (1 km). NDVI is a well-recognized indicator of green vegetation biomass (Tucker and Sellers, 1986; Henebry, 1993). Sixteen-day maximum value composite (MVC) NDVI image data at a spatial resolution of 250 m, collected by the MODIS Terra sensor between February 2000 and July 2009, was obtained using NASA's Warehouse Inventory Search Tool (WIST) facility. The associated vegetation index quality (VIQ) layers of the data product package were used to identify and remove all pixels affected by haze, cloud and other atmospheric conditions. The per-image pixel NDVI values were rescaled to a Digital Number format (0–255) (de Bie et al., 2012) to facilitate data processing without degrading essential information (Roderick et al., 1996). The dataset was then processed using an Adaptive Savitzky Golay filter (ASAVGOL) to accommodate poor quality data that had been removed by the initial screening, and account for outlying spurious data values (Jönsson and Eklundh, 2004; Beltran-Abaunza, 2009). This method is based on Savitzky–Golay and logistics fitting function (Jönsson and Eklundh, 2004). This is found useful for noisy and non-uniform NDVI time series datasets (Jönsson and Eklundh, 2004; Feng et al., 2008; Beltran-Abaunza, 2009; Boschetti et al., 2009).

Fine-resolution 10 m ALOS AVNIR-2 multispectral images acquired on 9 July 2009, 14 July 2009, 26 July 2009, 9 May 2008 and 4 November 2008 were used to support field data collection. These images were acquired from the Remote Sensing Technology Centre (RESTEC) (http://www.alos-restec.jp/products_e.html).

The Coordination of Information on the Environment (CORINE) land cover map for the year 2000 was obtained from the European Environmental Agency (EEA), and used to facilitate the gathering of field data.

3.2. Landscape heterogeneity mapping

The time-series image dataset, composed of 293 sequential image layers, was classified using the Iterative Self-Organizing Data Analysis (ISODATA) algorithm (Ball and Hall, 1965; Tou and Gonzalez, 1974). ISODATA unsupervised classifications were run to generate maps with outputs containing 10–100 clusters (Khan et al., 2010; de Bie et al., 2011; Nguyen et al., 2011; de Bie et al., 2012). For each run, the maximum number of iterations was set to 50 and the convergence threshold was set to 1, which were proved useful for optimal classification results in studies for example's (Khan et al., 2010; de Bie et al., 2011; Nguyen et al., 2011; de Bie et al., 2012). The maximum iterations control the ISODATA so that it stops at a certain threshold. The convergence threshold prevents the ISODATA utility from running indefinitely. After classification, both average and minimum separability values, expressed in the form of divergence statistics, were derived for each run output (Swain and Davis, 1978). Average divergence denotes the mean similarity between temporal signatures amongst all possible pairwise combinations of output clusters, while the minimum divergence value expresses the similarity between the temporal signatures of the two most similar clusters. The divergence statistics were used to aid the selection of the number of clusters to generalize the variability in the time-series NDVI dataset (Singh, 1984; Khan et al., 2010). The number of clusters present in the data is based on highest value of divergence statistics used as a validation index (Davies and Bouldin, 1979; Bezdek and Pal, 1998; Halkidi et al., 2001).

All output cluster maps (10 clusters up to selected generalized cluster map) were used to derive the landscape heterogeneity map using the process presented by de Bie et al. (2012). Each cluster output map was converted from raster to vector polygon format, merely maintaining the pixel outlines and therefore the locations of boundaries. The vector polygon file was then converted into a vector polyline format, following which the polylines were subsequently converted into a raster format, with a pixel resolution of 125 m (compared to the original 250 m pixel resolution). Each output cluster file was processed in this manner. Following this, the sum product of the boundary processed raster files was obtained. This sum product was processed further, initially being converted from a raster to a vector polyline format, and subsequently being converted back into a raster format. Finally, a majority filter of eight cells was run over the modified sum product image to ensure that no non-value raster cells remained. This produced the output landscape heterogeneity map, in which the heterogeneity value at a particular location was essentially determined by the number of times the pixel boundaries represented the boundary line between homogenous units of vegetation. A landscape heterogeneity map shows the strength (within a maximum range of y minus x) with which two adjacent pixels are classified differently.

3.3. Validation

The landscape heterogeneity map was evaluated using a transect sampling scheme (Skidmore and Turner, 1992; Fortin et al., 2000; Hennenberg et al., 2005) with two linear transects composed of 65 pixels of 250 m × 250 m in two different locations randomly selected. The high resolution ALOS AVNIR-2 image datasets (10 m) were used to analyze pixels within the transects, assisted by data gathered from ground observations. The length of the two transects were based on availability of field data collected to define image objects based on ALOS AVNIR-2 imagery.

Ground observation data were collected between 22 September and 11 October 2009, using a stratified clustered random sampling scheme. NDVI clusters based on a selected NDVI cluster map were considered as strata, which were randomly selected based on areas that did not coincide with the urban and agricultural land cover as designated by the CORINE 2000 land cover dataset. 29 NDVI clusters were visited in the field. Within each selected NDVI cluster, samples were collected based on image objects identified on the ALOS AVNIR-2 images. Different image objects were identified using features such as tone, pattern, shape, texture and association (Feranec, 1999). In total, 230 locations (image objects) were sampled and appraised concerning their land cover characteristics. At each sample location, estimates of the proportions of trees, shrubs, grass, bare soil, stone and litter cover were made. In all the layers of land cover estimates, only vertical projection to the ground was considered, and the sum of all the cover estimates equal to 100%.

To upscale the field data to transect pixel resolution (250 m), an image legend was derived using snapshots of ALOS image objects, along with a field description in terms of percentage cover of land cover components. On the basis of this image legend, the ALOS image transect area was digitized and described. The digitized image objects, known as "ALOS map units", were then combined with transect pixels to calculate percent contribution of ALOS map unit within each pixel (Eq. (1)).

$$\text{Area fraction} = \frac{\text{Area of map unit} \times 100}{\text{Area of MODIS pixel}} \quad (1)$$

where, "*Area fraction*" represents fraction of the area covered by each map unit within a MODIS pixel, "*Area of unit*" shows sum of map unit area in MODIS pixel and "*Area of MODIS pixel*" presents total area of the MODIS pixel.

After calculation of area fraction, through weighted up-scaling the cover fraction of tree, shrub, grass, bare soil, stone and litter cover were derived using the formula given in Eq. (2).

$$\text{Weighted land cover} = \frac{\text{Area fraction} \times \text{Mean land cover}}{100} \quad (2)$$

where weighted land cover is the sum of fraction of ALOS units within each pixel and mean land cover (%) is the mean value for each ALOS classes based on field calculated percent cover.

Finally fraction cover of each component was added up to calculate the total fraction cover of land cover components individually in each pixel.

Regression analysis was then used to appraise the relationship between landscape heterogeneity (in terms of boundary strength) and the proportional difference in land cover components (from the adjacent transect pixels). The absolute difference in percentage cover between two neighbouring pixels of the transect was calculated for each land cover component, and was also summarized as green cover (trees, shrubs and grass cover), non-green cover (litter, bare and stone cover), and the sum of all components.

4. Results

4.1. The landscape heterogeneity map

Ninety-one cluster maps were initially produced as outputs from ISODATA unsupervised classifications, and the cluster map containing 65 clusters was deemed to represent the optimal generalization of the hyper-temporal NDVI dataset. As shown in Fig. 2, a coincident peak occurred in both sets of divergence values at 65 clusters. Sixty and 99 cluster outputs show peaks in average divergence; however, these are not coincident with peaks in minimum divergence value. The selection of the optimal cluster map served to outline the number of clusters output maps (output of 10–65 clusters) used for generating the landscape heterogeneity map.

The landscape heterogeneity map was prepared using the 56 output cluster maps (i.e. the maps produced from 10 to 65 clusters, respectively), and is presented in Fig. 3. The map details landscape heterogeneity in the form of spatial gradients. Visually complex patterns are located in areas where high variability in local topography and complex vegetation cover is present. Some parts in the map look less heterogeneous with plain yellow colour, they represent high mountains with hardly any vegetation and also valley's having less diversity in land cover and land use.

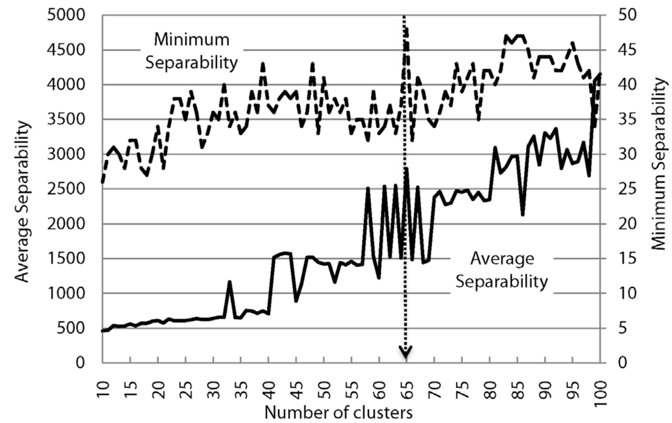

Fig. 2. Selection of the optimal number of clusters (65-cluster map) with which to generalize the hyper-temporal dataset.

The two transects used for validation are also displayed in Fig. 3. They were located in two different areas exhibiting high local variations in land cover along a topographical gradient.

4.2. Validation

Fig. 4(i) details transect 1 overlaid on the ALOS AVNIR-2 image and image legend (homogenized snap shots of ALOS image objects surveyed); Fig. 4(ii) displays the digitized polygons used for up-scaling; and Fig. 4(iii) shows part of the landscape heterogeneity map represented in the form of graduated boundary strengths.

The result obtained from the transect analysis with regard to the fractions of land cover components in each transect area is illustrated in Fig. 5, which indicates the variations in the cover fractions of trees, shrubs, grass, bare soil, stone and litter cover in relation to variations in boundary strength. In both transects, variations in spatial aggregations of green land cover components such as tree, shrub and grass cover closely correspond to the variations in boundary strength.

In the case of transect 1, from the results showing the correlation between boundary strength and the differences in fractional land cover components between neighbouring pixels, the sum of differences with respect to all land cover components (trees, shrubs,

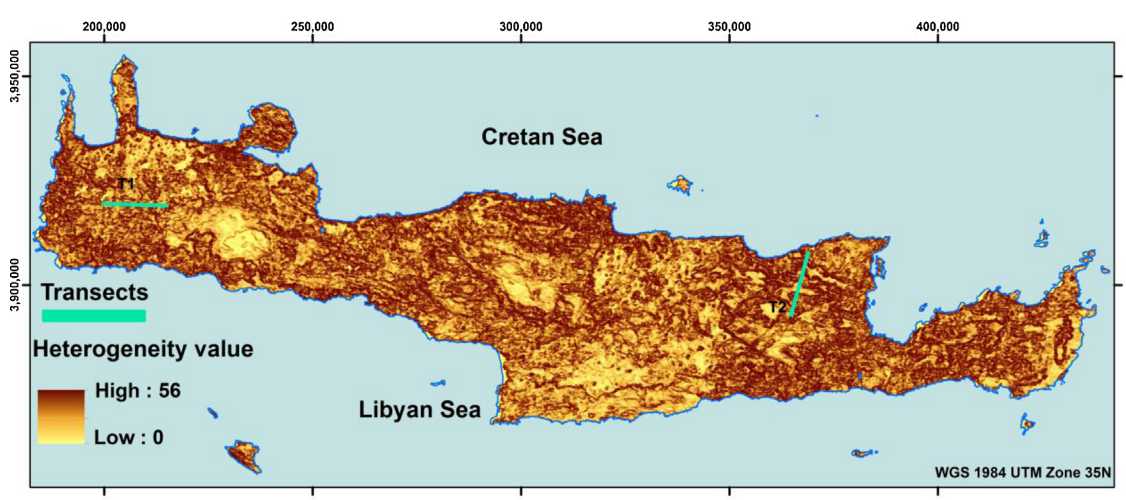

Fig. 3. The output landscape heterogeneity map of Crete, Greece, depicting spatial heterogeneity patterns resulting from analysis of spatiotemporal vegetation fluctuations over the area. The locations of the two sampling transects, Transect 1 (T1) and Transect 2 (T2), are also outlined.

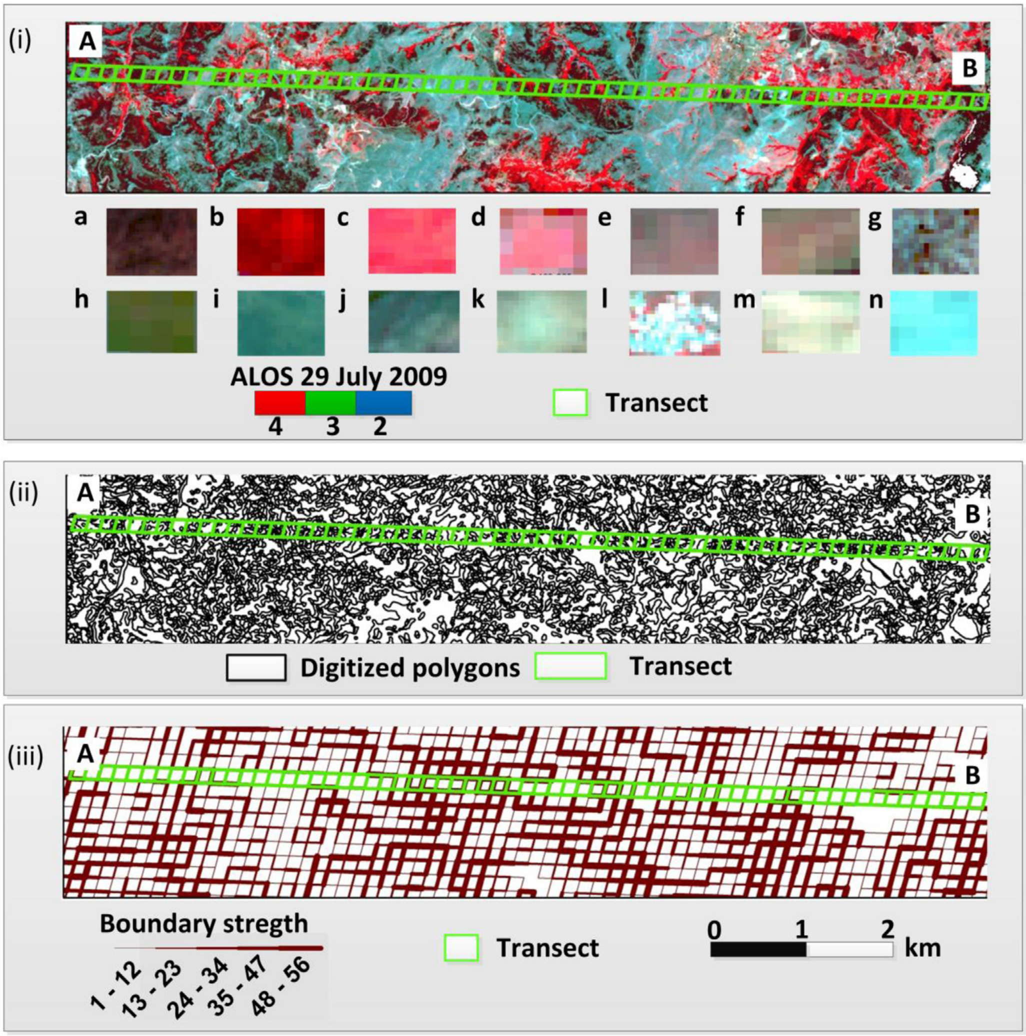

Fig. 4. Sample Transect 1, composed of 250 m × 250 m areas, overlaid on (i) the ALOS AVNIR-2 10 m resolution RGB (4, 3, 2) image, with the legend used for interpretation (snapshots of ALOS image objects); (ii) digitized polygons; (iii) the boundary strength map.

grass, bare soil, stone and litter) was found to be higher than those for green and non-green components, having an R^2 value of 0.60 and being associated with the lowest standard error (SE = 10.06). The R^2 values indicate that 49% of the variation in boundary strength is correlated with differences in the fraction of green land cover components, with a standard error of 11.26. The sum of differences with respect to non-green (bare soil, stone, litter) land cover has a lower coefficient of determination ($R^2 = 0.20$), and a higher standard error (SE = 14.20).

The results for individual components (i.e. trees, shrubs, grass, bare soil, stone and litter cover) show significant correlation ($p < 0.05$) while stone cover has R^2 of 0.4 and is non-significant ($p > 0.05$). However, the coefficient of determination is low in all cases, with the exception of trees ($R^2 = 0.40$) and shrubs ($R^2 = 0.46$) (Table 1).

Furthermore, transect 2 gives R^2 of 0.63 for the sum of differences with respect to all land cover components (trees, shrubs, grass, bare soil, stone and litter); also have low SE (11.03). Similarly as in transect 1, green cover ($R^2 = 0.59$, SE = 11.61) was found to be more closely correlated than non-green components ($R^2 = 0.26$, SE = 15.56). The results with individual components are low which is summarized in Table 2. All the results were found significant at $p < 0.05$ except grass cover ($p > 0.05$).

5. Discussion

The heterogeneity of natural and semi-natural landscapes can be characterized and presented in continuous units using this technique. Such a continuous spatial representation of landscape heterogeneity is consistent with the concept of landscapes being

Table 1
Results showing correlation between boundary strength and differences in all individual land cover components as well as the sum of these differences between neighbouring pixels of transect 1 ($n = 65$).

Fraction land cover components (%)	R^2	Standard error (SE)	p-Value
Sum of land cover difference between pixels	0.60	10.06	0.00
Green cover (trees, shrubs, grass)	0.50	11.26	0.00
Non-green cover (bare soil, stone, litter)	0.20	14.20	0.00
Trees	0.40	12.33	0.00
Shrubs	0.46	11.70	0.00
Grass	0.20	14.07	0.00
Bare soil	0.29	13.34	0.00
Stone	0.04	15.26	0.15
Litter	0.07	15.23	0.04

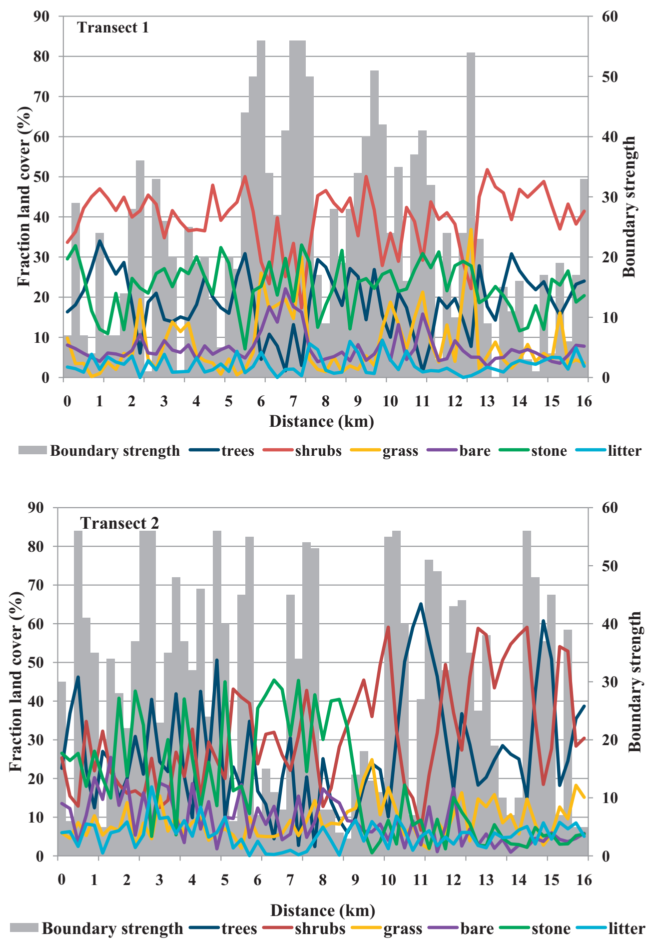

Fig. 5. Associations between variations in boundary strength and variations in the fractional cover of different land cover (trees, shrubs, grass, bare soil, stone and litter) from A to B in transects 1 and 2.

characterized by land cover gradients, and incorporates a realistic approach to summarizing and presenting ground conditions (Whittaker, 1967; Cushman et al., 2010). Legendre and Legendre (1998) and Legendre et al. (2002) noted that in nature spatial patterns are found as gradients that are due to the continuous changes in the physical environment. Continuous spatial fluctuations in natural and semi-natural land cover result in spatially continuous variations in vegetation communities (Puech, 1994).

Further to advocation by de Bie et al. (2012); the rapid follow up of imagery is found to be effective when mapping landscape heterogeneity in natural and semi natural landscapes as well. The high

Table 2
Results showing correlation between boundary strength and differences in all individual land cover components as well as the sum of these differences between neighbouring pixels of transect 2 ($n = 65$).

Fraction land cover components (%)	R^2	Standard error (SE)	p-Value
Sum of land cover difference between pixels	0.63	11.03	0.00
Green cover (trees, shrubs, grass)	0.59	11.61	0.00
Non-green cover (bare soil, stone, litter)	0.26	15.56	0.00
Trees	0.46	13.33	0.00
Shrubs	0.34	14.72	0.00
Grass	0.05	17.63	0.07
Bare soil	0.10	17.07	0.00
Stone	0.19	16.25	0.00
Litter	0.11	17.05	0.00

frequency imagery is important for accurate characterization and mapping of land cover due to its ability to closely track seasonal profiles and changes (Lunetta et al., 2004; Xiao et al., 2006; Lu and Weng, 2007; Sakamoto et al., 2007; Alexandridis et al., 2008; Zhang et al., 2009; Khan et al., 2011). Hyper-temporal imagery is also found effective at mapping the spatial patterns in vegetation cover that represent gradual changes in the form of gradients, which originated due to the local vegetation seasonal trends (Ali et al., 2013). These seasonal variations are specific to different species, its density and composition, which can help in land cover type and state identification (Justice et al., 1985; Neeti et al., 2011; Ali et al., 2013). The spatiotemporal imagery projects the influence of different biotic and abiotic environmental factors such as soil, temperature, solar illumination, photoperiod and moisture over time which is responsible for landscape heterogeneity.

The heterogeneity output maps were shown to be relatable to spatial variation in land cover heterogeneity. Results from the evaluation element of the study revealed that differences in land cover could be related (R^2 of 0.60 and 0.63 in two transects used for validation, $p < 0.05$) to the variation in heterogeneity values expressed in the output map. This moderate level of explained variability could be attributed to the duration of field data collection and single date ALOS imagery used for validation, whereas the output heterogeneity map incorporates seasonal variations spanning a long period of time (February 2000–July 2009). Hyper-temporal datasets are essentially an automated record that captures the effects of landscape dynamics (seasonality), while the field data, being limited in space and time, do not account for these dynamics.

The output landscape heterogeneity map of Crete represents landscape as advocated by many scientists (Gosz, 1992; Kent et al., 1997; Martín et al., 2006). The inherent mosaic structure originates from small spatial and temporal scale changes (e.g. climate change/fire disturbances, growing season length, moisture availability, species compositions, local patterns in soils or micro-topography), as well as the effects of grazing management or other anthropogenic activities (Gosz, 1991, 1992). However, those seasonal changes which occur in a certain homogenous area without change across space, may not contribute to heterogeneity of the area. The spatial and temporal scale of the imagery used proved sufficient for this diverse and complex landscape. This is evident from results shown in Fig. 5, in which there are no such anthropogenic factors such roads, gardens etc. can be seen as pointed out by de Bie et al. (2012) in case of MODIS imagery.

6. Conclusion

To be accurately characterized, any mapping method must ensure the presence of gradients in land cover, as well as the landscape's spatiotemporal variability, are sufficiently represented. Currently, approaches attempting to capture landscape heterogeneity do not sufficiently account for the likely presence of gradients, and do not account for the high-frequency temporal dimension of land cover. To address these issues, a Landscape Heterogeneity Mapping (LaHMa) approach which considers both the presence of gradient and the long-term spatiotemporal characteristics of land cover is applied and tested in the natural and semi-natural landscapes of island of Crete, Greece. The output is a landscape heterogeneity map showing the strength with which two adjacent pixels are classified differently, calculating the relative heterogeneity of each pixel's area on the basis of differences in long term spatio-temporal characteristics. The method is found to be appropriate for the task of characterizing the heterogeneity of natural and semi-natural landscapes. It was successfully validated using field data composed of the fractional complexity of the area's land cover components and found relatable to the spatial variation on ground. The heterogeneity determined may be arising by soil, vegetation discontinuities, changes in species composition and its distribution. As such, the method may be helpful for ecologists to further strengthen their analysis and sampling strategies with respect to long-term spatiotemporal variability and landscape structure in natural and semi natural landscape. Future studies should involve more rigorous evaluation of the methodology with the incorporation of more study sites into ground sampling and over a greater variety of land cover. It is recommended that the performance and informative abilities of the LaHMa technique should be compared to other landscape heterogeneity mapping techniques.

Acknowledgements

The authors gratefully acknowledge the financial support of the Higher Education Commission of Pakistan, the Pakistan Space and Upper Atmosphere Research Commission (SUPARCO) and of the ITC research fund. We would also like to thank ITC MSc students Johanna Ngula Niipele and Shirin Taheri for their help in collecting field data for this study. Special thanks are extended to Janice Collins for help with English editing's. We would like to thank two anonymous reviewers for their constructive comments to improve this manuscript.

References

Alexandridis, T.K., Gitas, I.Z., Silleos, N.G., 2008. An estimation of the optimum temporal resolution for monitoring vegetation condition on a nationwide scale using MODIS/Terra data. International Journal of Remote Sensing 29, 3589–3607.
Ali, A., de Bie, C.A.J.M., Skidmore, A.K., Scarrott, R.G., Hamad, A., Venus, V., Lymberakis, P., 2013. Mapping land cover gradients through analysis of hyper-temporal NDVI imagery. International Journal of Applied Earth Observation and Geoinformation 23, 301–312.
Austin, M.P., 1990. Community theory and competition in vegetation. In: Grace, J.B., Tilman, D. (Eds.), Perspectives in Plant Competition. Academic Press, New York, pp. 215–233.
Baker, W.L., Cai, Y., 1992. The r.le programs for multiscale analysis of landscape structure using the GRASS geographical information system. Landscape Ecology 7, 291–302.
Ball, G.H., Hall, D.J., 1965. Isodata: A Method of Data Analysis and Pattern Classification. Stanford Research Institute, Menelo Park, CA, United States.
Begon, M., Harper, J.L., Townsend, C.R., 1990. Ecology: Individuals, Populations and Communities, second ed. Blackwell Scientific Publications, Oxford.
Beltran-Abaunza, J.M., 2009. Method Development to Process Hyper-temporal Remote Sensing (RS) Images for Change Mapping. University of Twente, Enschede, The Netherlands.
Bezdek, J.C., Pal, N.R., 1998. Some new indexes of cluster validity. Systems, Man, and Cybernetics, Part B: Cybernetics. IEEE Transactions on 28, 301–315.
Boschetti, M., Stroppiana, D., Brivio, P.A., Bocchi, S., 2009. Multi-year monitoring of rice crop phenology through time series analysis of MODIS images. International Journal of Remote Sensing 30, 4643–4662.
Boyd, D.S., Foody, G.M., 2011. An overview of recent remote sensing and GIS based research in ecological informatics. Ecological Informatics 6, 25–36.
Bradshaw, G.A., Spies, T.A., 1992. Characterizing canopy gap structure in forests using wavelet analysis. Journal of Ecology 80, 205–215.
Chartzoulakis, K., Psarras, G., 2005. Global change effects on crop photosynthesis and production in Mediterranean: the case of Crete, Greece. Agriculture, Ecosystems and Environment 106, 147–157.
Chartzoulakis, K.S., Paranychianakis, N.V., Angelakis, A.N., 2001. Water resources management in the Island of Crete, Greece, with emphasis on the agricultural use. Water Policy 3, 193–205.
Couteron, P., Barbier, N., Gautier, D., 2006. Textural ordination based on Fourier spectral decomposition: a method to analyze and compare landscape patterns. Landscape Ecology 21, 555–567.
Cushman, S.A., Gutzweiler, K., Evans, J.S., McGarigal, K., 2010. The gradient paradigm: a conceptual and analytical framework for landscape ecology. In: Cushman, S.A., Huettmann, F. (Eds.), Spatial Complexity, Informatics, and Wildlife Conservation. Springer, Japan, pp. 83–108.
Davies, D.L., Bouldin, D.W., 1979. A Cluster Separation Measure. Pattern Analysis and Machine Intelligence. IEEE Transactions on PAMI-1, 224–227.
de Bie, C.A.J.M., Khan, M.R., Smakhtin, V.U., Venus, V., Weir, M.J.C., Smaling, E.M.A., 2011. Analysis of multi-temporal SPOT NDVI images for small-scale land-use mapping. International Journal of Remote Sensing 32, 6673–6693.
de Bie, C.A.J.M., Nguyen, T.T.H., Ali, A., Scarrott, R., Skidmore, A.K., 2012. LaHMa: a landscape heterogeneity mapping method using hyper-temporal datasets. International Journal of Geographical Information Science 26, 1–16.
Dunn, C.P., Sharpe, D.M., Guntenspergen, G.R., Yang, Z., 1991. Methods for analyzing temporal changes in landscape pattern. In: Turner, M.G., Gardner, R.H. (Eds.), Quantitative Methods in Landscape Ecology. Springer-Verlag, New York, pp. 173–198.
Fagan, W.F., Fortin, M.J., Soykan, C., 2003. Integrating edge detection and dynamic modeling in quantitative analyses of ecological boundaries. BioScience 53, 730–738.
Fahrig, L., 1992. Relative importance of spatial and temporal scales in a patchy environment. Theoretical Population Biology 41, 300–314.
Feng, G., Morisette, J.T., Wolfe, R.E., Ederer, G., Pedelty, J., Masuoka, E., Myneni, R., Bin, T., Nightingale, J., 2008. An algorithm to produce temporally and spatially continuous MODIS-LAI time series. IEEE Geoscience and Remote Sensing Letters 5, 60–64.
Feranec, J., 1999. Interpretation element association: analysis and definition. International Journal of Applied Earth Observation and Geoinformation 1, 64–67.
Foody, G.M., Boyd, D.S., 1999. Fuzzy mapping of tropical land cover along an environmental gradient from remotely sensed data with an artificial neural network. Journal of Geographical Systems 1, 23–35.
Fortin, M.J., Olson, R.J., Ferson, S., Iverson, L., Hunsaker, C., Edwards, G., Levine, D., Butera, K., Klemas, V., 2000. Issues related to the detection of boundaries. Landscape Ecology 15, 453–466.
Goodchild, M.F., Quattrochi, D.A., 1997. Scale, multiscaling, remote sensing, and GIS. In: Goodchild, M., Quattrochi, D. (Eds.), Scale in Remote Sensing and GIS. CRC Press, Florida, p. 406.
Gosz, J.R., 1991. Fundamental ecological characteristics of landscape boundaries. In: Holland, M.M., Risser, P.G., Naiman, R.J. (Eds.), Ecotones: The Role of Landscape Boundaries in the Management and Restoration of Changing Environment. Chapman and Hall Inc, New York, pp. 8–30.
Gosz, J.R., 1992. Gradient analysis of ecological change in time and space: implications for forest management. Ecological Applications 2, 248–261.
Gustafson, E.J., 1998. Quantifying landscape spatial pattern: what is the state of the art? Ecosystems 1, 143–156.
Halkidi, M., Batistakis, Y., Vazirgiannis, M., 2001. On Clustering Validation Techniques. Journal of Intelligent Information Systems 17, 107–145.
Henebry, G.M., 1993. Detecting change in grasslands using measures of spatial dependence with landsat TM data. Remote Sensing of Environment 46, 223–234.
Hennenberg, K.J., Goetze, D., Kouamé, L., Orthmann, B., Porembski, S., Austin, M.P., 2005. Border and ecotone detection by vegetation composition along forest-savanna transects in Ivory Coast. Journal of Vegetation Science 16, 301–310.
Jönsson, P., Eklundh, L., 2004. TIMESAT – a program for analyzing time-series of satellite sensor data. Computers and Geosciences 30, 833–845.
Justice, C.O., Townshend, J.R.G., Holben, B.N., Tucker, C.J., 1985. Analysis of the phenology of global vegetation using meteorological satellite data. International Journal of Remote Sensing 6, 1271–1318.
Kent, M., Gill, W.J., Weaver, R.E., Armitage, R.P., 1997. Landscape and plant community boundaries in biogeography. Progress in Physical Geography 21, 315–353.
Khan, M.R., de Bie, C.A.J.M., van Keulen, H., Smaling, E.M.A., Real, R., 2010. Disaggregating and mapping crop statistics using hypertemporal remote sensing. International Journal of Applied Earth Observation and Geoinformation 12, 36–46.
Khan, M.R., Smaling, E.M.A., van Keulen, H., de Bie, C.A.J.M., 2011. Crops from Space: Improved Earth Observation Capacity to Map Crop Areas and to Quantify Production. University of Twente Faculty of Geo-Information and Earth Observation (ITC), Enschede.
Legendre, P., Dale, M.R.T., Fortin, M.-J., Gurevitch, J., Hohn, M., Myers, D., 2002. The consequences of spatial structure for the design and analysis of ecological field surveys. Ecography 25, 601–615.
Legendre, P., Legendre, L., 1998. Numerical Ecology. Elsevier, Amsterdam, The Netherlands.
Li, H., Reynolds, J.F., 1995. On definition and quantification of heterogeneity. Oikos 73, 280–284.
Lu, D., Weng, Q., 2007. A survey of image classification methods and techniques for improving classification performance. International Journal of Remote Sensing 28, 823–870.
Lunetta, R.S., Johnson, D.M., Lyon, J.G., Crotwell, J., 2004. Impacts of imagery temporal frequency on land-cover change detection monitoring. Remote Sensing of Environment 89, 444–454.
Martín, M., De Pablo, C., De Agar, P., 2006. Landscape changes over time: comparison of land uses, boundaries and mosaics. Landscape Ecology 21, 1075–1088.
Montmollin, d.B., Iatrou, G.A., 1995. Connaissance et conservation de la flore de l' île de Crète. Ecologia Mediterranea 21, 173–184.
Müller, F., 1998. Gradients in ecological systems. Ecological Modelling 108, 3–21.
Neeti, N., Rogan, J., Christman, Z., Eastman, J.R., Millones, M., Schneider, L., Nickl, E., Schmook, B., Turner, B.L., Ghimire, B., 2011. Mapping seasonal trends in vegetation using AVHRR-NDVI time series in the Yucatán Peninsula, Mexico. Remote Sensing Letters 3, 433–442.
Nguyen, T.T.H., de Bie, C.A.J.M., Ali, A., Smaling, E.M.A., Chu, T.H., 2011. Mapping the irrigated rice cropping patterns of the Mekong delta, Vietnam, through hyper-temporal SPOT NDVI image analysis. International Journal of Remote Sensing 33, 415–434.
Perry, J.N., Liebhold, A.M., Rosenberg, M.S., Dungan, J., Miriti, M., Jakomulska, A., Citron-Pousty, S., 2002. Illustrations and guidelines for selecting statistical methods for quantifying spatial pattern in ecological data. Ecography 25, 578–600.

Peters, D., Gosz, J., Pockman, W., Small, E., Parmenter, R., Collins, S., Muldavin, E., 2006. Integrating patch and boundary dynamics to understand and predict biotic transitions at multiple scales. Landscape Ecology 21, 19–33.
Puech, C., 1994. Thresholds of homogeneity in targets in the landscape. Relationship with remote sensing. International Journal of Remote Sensing 15, 2421–2435.
Roderick, M., Smith, R., Cridland, S., 1996. The precision of the NDVI derived from AVHRR observations. Remote Sensing of Environment 56, 57–65.
Romme, W.H., 1982. Fire and landscape diversity in subalpine forests of Yellowstone National Park. Ecological Monographs 52, 199–221.
Sakamoto, T., Van Nguyen, N., Kotera, A., Ohno, H., Ishitsuka, N., Yokozawa, M., 2007. Detecting temporal changes in the extent of annual flooding within the Cambodia and the Vietnamese Mekong Delta from MODIS time-series imagery. Remote Sensing of Environment 109, 295–313.
Sakamoto, T., Van Nguyen, N., Ohno, H., Ishitsuka, N., Yokozawa, M., 2006. Spatio-temporal distribution of rice phenology and cropping systems in the Mekong Delta with special reference to the seasonal water flow of the Mekong and Bassac rivers. Remote Sensing of Environment 100, 1–16.
Sarris, A., Karakoudis, S., Vidaki, C., Soupios, P., 2005. Study of the morphological attributes of crete through the use of remote sensing techniques. In: IASME/WSEAS International Conference on Energy, Environment, Ecosystems and Sustainable Development, Athens, Greece. 2, pp. 1043–1051.
Singh, A., 1984. Some clarifications about the pairwise divergence measure in remote sensing. International Journal of Remote Sensing 5, 623–627.
Skidmore, A.K., Turner, B.J., 1992. Map accuracy assessment using line intersect sampling. Photogrammetric Engineering and Remote Sensing 58, 1453–1457.
Sluiter, R., 1998. Desertification and Grazing on South Crete, a Model Approach. Universty of Utrecht.
Southworth, J., Munroe, D., Nagendra, H., 2004. Land cover change and landscape fragmentation – comparing the utility of continuous and discrete analyses for a western Honduras region. Agriculture, Ecosystems and Environment 101, 185–205.
Swain, P.H., Davis, S.M., 1978. Remote Sensing: the Quantitative Approach. McGraw-Hill, New York.
Tou, J.T., Gonzalez, R.C., 1974. Pattern Recognition Principles. Addison-Wesley, Reading, MA.
Tucker, C.J., Sellers, P.J., 1986. Satellite remote sensing of primary production. International Journal of Remote Sensing 7, 1395–1416.
Turland, N.J., Chilton, L., Press, J.R., 1993. Flora of the Cretan Area. Annotated Checklist and Atlas, London.
Turner, M.G., Gardner, R.H., 1991. Quantitative Methods in Landscape Ecology. Springer-Verlag, New York.
Turner, M.G., Pearson, S.M., Bolstad, P., Wear, D.N., 2003. Effects of land-cover change on spatial pattern of forest communities in the Southern Appalachian Mountains (USA). Landscape Ecology 18, 449–464.
Whittaker, R.H., 1967. Gradient analysis of vegetation. Biological Reviews 42, 207–264.
Wu, X., Archer, S., 2005. Scale-dependent influence of topography-based hydrologic features on patterns of woody plant encroachment in Savanna landscapes. Landscape Ecology 20, 733–742.
Xiao, X., Boles, S., Frolking, S., Li, C., Babu, J.Y., Salas, W., Moore III, B., 2006. Mapping paddy rice agriculture in South and Southeast Asia using multi-temporal MODIS images. Remote Sensing of Environment 100, 95–113.
Zhang, X., Friedl, M.A., Schaaf, C.B., 2009. Sensitivity of vegetation phenology detection to the temporal resolution of satellite data. International Journal of Remote Sensing 30, 2061–2074.