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QUANTITATIVE APPROACH FOR COMPLEMENTARY ANALYSIS OF A TOURISTIC COASTAL LANDSCAPE: THE CASE OF ERDEMLİ (MERSİN), TURKEY

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Abstract

Coastal landscapes face increasing demands for space and the resources that they support. These demands generally conflict with each other and with the functioning of landscape systems. Owing to the fact that landscapes of interest on the coast are complex, multifaceted quantitative analysis is highly necessary to understand biophysical variations in space and time resulting from natural and/or human-induced processes. This complexity of landscape systems requires analytical procedures that involve utilization of state-of-the-art tools and methodologies to collect and combine landscape-level environmental information for use in landscape planning, design and management. In this respect, five consecutive steps may be described for complementary analysis of landscapes: (1) dataset selection (2) land cover mapping, (3) analysis of patterns, (4) analysis of processes and (5) future projections. Recently completed research project in a coastal region on Turkish Mediterranean coast (TUBITAK Grant No: 111Y253) provided a framework for comprehensive analysis of coastal landscapes. This paper provides a brief summary of the outcomes from this project. Quantitative analysis procedures were highlighted and discussions were made in the light of analysis results.

Keywords: Landscape, coastal zone, Turkey, Mediterranean, quantitative analysis

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1. INTRODUCTION

Coastal landscapes support diverse biological/physical systems and processes since they have unique composition and configuration of topography, hydrological resources, vegetation and other land cover features. Techniques for landscape-level monitoring of coastal areas have developed remarkably due to advancements in space imaging technologies and related computer processing tools and methodologies. In this process landscapes have been studied in many different aspects. Kang, Ding, Xu, Zhang, and Ge (2017) stated that remote sensing is an established technique for measuring coastal topography and described these techniques as increasingly important with respect to achieving sustainable development targets. They used a series of 21 multi-temporal satellite images to extract waterlines based on feature extraction techniques and artificial further modification. Similarly, several other authors either mentioned or demonstrated the utility of topographic information (Ayad, 2005; Fasona & Omojola, 2009; Kotilainen & Kaskela, 2017; Mialhe et al., 2016; Schwarz & Manceur, 2015; Sertel, Findik, Kaya, Seker, & Samsunlu, 2008; Yan & Baas, 2018).

Information technologies have been proved to be useful for quantifying biophysical components of landscapes (i.e., land cover) and conceptualizing change trends and landscape-level environmental processes. To this end, dataset selection, land cover mapping, analysis of map patterns, change detection and change prediction can be regarded as five consecutive steps of the complementary analysis of landscape resources. The importance of complementary analysis arises from the fact that landscapes are spatially complex organisms and they are subject to change due to natural and human induced processes.

A complementary analysis requires thematic representation of a landscape of interest, e.g., on the basis of land cover classes that are described at different hierarchy levels and spatial scales. Landscapes are in fact unique composition and configuration of land cover types. Therefore, any analytical procedure aiming to conceptualize the uniqueness of patterns help to understand landscapes more effectively. Urbanization, coastal erosion, agricultural encroachment are some examples of landscape-level environmental processes. These and many other phenomena can be conceptualized by employing numerous change detection techniques that rely on traditional, contemporary and/or hybrid techniques. This helps understand environmental processes in landscapes of interest. Above mentioned layers of information on patterns and processes can be used as inputs for change prediction models such as those that are based on Cellular Automata (CA).

This paper describes a complementary landscape analysis approach that involves data selection, land cover mapping, quantification of landscape patterns, change detection and change prediction. In this respect, discussions were made in the light of digital information and map outputs from a recent research project conducted in a coastal region on Turkish Mediterranean coast (TUBITAK Grant No: 111Y253). Digital information and map outputs that are produced within this project were introduced as parts of this complementary approach.

2. STUDY AREA AND METHODOLOGY

2.1. Study Area

The coastal zone of Erdemli, located in the west of the central district of Mersin (SE Mediterranean Coast of Turkey) is designated as the study area. The area has faced problems due to development of multistory buildings near the coastline. These buildings have been built to serve as summer apartments particularly for domestic tourism and recreation. However, this development threatened both agriculture areas and natural vegetation and caused landscape fragmentation. The development occurred in a narrow zone of built-up patches aligned with the coastline, that generally did not exceed a few hundred meters in width (Alphan & Celik, 2016; Alphan & Derse, 2013). Due to these spatial characteristics of the development, mapping and monitoring of built-up development on the Mediterranean coast requires analyses at finer spatial levels. Complex landscape patterns resulting from agricultural, natural and built-up patches of varying spectral responses also requires multispectral capabilities for understanding patterns and processes in these landscapes (Alphan, 2017; Alphan & Guvensoy, 2016; Alphan & Yilmaz, 2005).

The facts that acceleration of the above mentioned built-up development trends date back to 1980s and that the landscape patterns are complex make it necessary to provide historical datasets (i.e., satellite images) of regularly repeated land observations with high spatial and multispectral details for effective monitoring (Alphan, 2003, 2013; Alphan & Derse, 2013; Alphan, Doygun, & Unlukaplan, 2009). The extent of study area is given in Fig. 1.

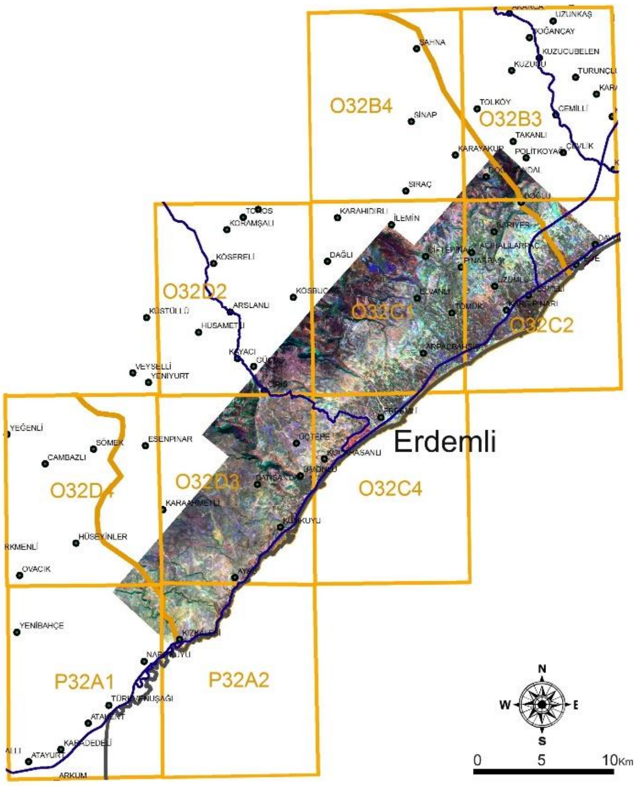

Figure 1: Extent of study area

2.2. Proposed Workflow and the Analysis Procedures

A five-step analysis procedure may be described for complementary assessment of coastal landscapes in the Mediterranean. The quality of the information strongly depends upon

- dataset selection,
- land cover mapping,
- quantitative representation of patterns,
- change analysis and
- modeling of future development.

Dataset Selection

Selection of digital datasets (i.e., satellite images) is the most critical part of a complementary analysis of coastal landscape resources. There are many reasons that support this statement. Coastal landscapes are complex systems. This complexity arises from spatial and temporal diversity of biological and physical systems and human activities interfering with these systems. This diversity requires representation of landscapes in different spatial and time scales. Inherent diversity of spatial and time scales required for complementary assessment of landscapes makes it necessary to run analyses (e.g. landscape mapping and change detection) using datasets from different sources. In this respect, each dataset has its own merits and costs. For example, a change study that focuses on built-up changes on coastal zone requires a broader time period and relatively higher spatial resolution. These requirements should be met simultaneously to perform a complementary landscape assessment on the coastal zone.

Land Cover Mapping

Vegetation is the strongest indicator for describing landscapes and evaluating processes that take place in landscapes. In this respect it has been investigated using many different data sources and analytical techniques regarding remote sensing and Geographical Information Systems (GIS) (Menon & Bawa, 1997; Misra, Murali, & Vethamony, 2015; Mohamed, Holechek, Bailey, Campbell, & DeMers, 2011; Mondal, Trzaska, & de Sherbinin, 2018; Pourebrahim, Hadipour, & Bin Mokhtar, 2015; Ustaoglu, 2012). White, Piraino, Shortridge, and Arbogast (2019) analyzed vegetation change on coastal sand dunes using Geographic Object-based Image Analysis (GEOBIA) incorporating spatial context into the classification process. The GEOBIA technique was applied to estimate the extent of vegetation change from 1938 to 2014 in coastal dune systems along much of the eastern coast of Lake Michigan. Marzialetti et al. (2019) used Sentinel-2 datasets of European Space Agency (ESA) to determine natural costal dune vegetation types using a phenology-based mapping approach.

Coastal wetlands have attracted attention in the last decades as they provide many different ecosystem services and as they are home to numerous threatened/endangered species. Remote sensing data have also been used widely to study ecology of wetlands and landscape level processes (Alphan & Yilmaz, 2005; Choi & Han, 2013; Jia et al., 2015; Li et al., 2017; F. Meng, Yu, Liu, & Cui, 2011).

Quantitative Representation of Patterns

As demonstrated above, remote sensing has been widely used for characterizing topography, vegetation, wetlands and other land cover features in coastal landscapes. However, despite its critical importance, land cover mapping may not provide extensive information for landscape composition and configuration. To this end, analysis of landscape patterns may be regarded as critical as it provides more complete picture of the landscapes of interest. Landscape structure indices may be used for conceptualizing composition and configuration characteristics of landscape patterns. These indices have been used as indicators for the status of landscapes and the processes that take place in the landscapes of interest (Cao, Suo, & Sun, 2017; Kayhko, Fagerholm, Asseid, & Mzee, 2011; Munroe, Nagendra, & Southworth, 2007; Nagendra & Utkarsh, 2003; Pourebrahim et al., 2015; Rabehi, Guerfi, Mahi, & Rojas-Garcia, 2019; Stoops et al., 2008; Turner et al., 2004; Ustaoglu, 2012; White et al., 2019; Yang et al., 2016; Yilmaz, 2010; Zald, 2009).

Change Analysis

Change detection is an important step for comprehensive and complementary characterization of landscapes as it helps conceptualize landscape-level processes. This is particularly important to reveal underlying causes of environmental disturbance and to provide a spatial basis for problem detection. Landscape planning decisions can be made more easily and design solutions can be brought to fore more effectively using change information as indicator for understanding landscape-level processes such as urbanization, deforestation, agricultural encroachment, etc. Due to this critical importance, many authors utilized remote sensing and GIS for monitoring change processes all around the world (Al-Ruzouq & Shanableh, 2014; Alphan, 2005, 2011; Alphan & Celik, 2016; Alphan & Derse, 2013; Alphan & Guvensoy, 2016; Alphan & Yilmaz, 2005; Choi & Han, 2013; Cohen et al., 2002; Dodd, Barichivich, Johnson, & Staiger, 2007; Esbah, Kara, Deniz, & Kesgin, 2010; Fraser et al., 2014; Garcia & Ustin, 2001; Hasani, Sakieh, Dezhkam, Ardakani, & Salmanmahiny, 2017; Heathfield & Walker, 2015; Jones et al., 2013; Kayhko et al., 2011; Misra et al., 2015; Roy, Mahapatra, & Chakraborty, 2019; Zhang, Thapa, Ross, & Gann, 2016).

Modelling of Future Development

Change detection provides information on environmental trends and helps to understand underlying causes of landscape-level environmental disturbance. This information is vital for drafting landscape planning and management guidelines in many cases. However, it needs to be complemented by the spatial information on future development as far as effective planning of landscapes is concerned. As an example, projected spatial distribution of urban areas for future under given scenarios can be used to revise development plans so that they can meet the needs of planners and decision makers to ensure high level of community benefits, while protecting the landscape-level environmental resources including the landscapes themselves (e.g., scenic quality) and the ecosystems that they support. In this respect, numerous models have been developed. Cellular automata (CA)-based models are among these models. SLEUTH is one of the numerous urban change prediction models that falls within CA category. This model has been used to predict future development in many world cities (Aguejdad, Doukari, Houet, Avner, & Viguie, 2016; Ayazli & Bilen, 2019; Bajracharya, Lippitt, & Sultana, 2019; Bihamta, Soffianian, Fakheran, & Gholamalifard, 2015; Chaudhuri & Clarke, 2019; Jantz, Goetz, Donato, & Claggett, 2010; Jantz, Goetz, & Shelley, 2004; Mahiny & Clarke, 2012, 2013; Oguz, 2012; Oguz & Bozali, 2014; Rienow & Goetzke, 2015; Sakieh, Amiri, Danekar, Feghhi, & Dezhkam, 2015; Sangawongse, Sun, & Tsai, 2005; Serasinghe Pathiranage, Kantakumar, & Sundaramoorthy, 2018; Shi, Wu, & Shi, 2017; Yi & He, 2009; Yin et al., 2016; Zheng et al., 2018).

CA Markov is another model for projecting future land cover. This model has also been used for projecting future state of various environmental phenomena such as urbanization, forest cover change and desertification (Aburas, Ho, Ramli, & Ash'aari, 2017; Adhikari & Southworth, 2012; Akin, Berberoglu, Erdogan, & Donmez, 2012; Al-sharif & Pradhan, 2014; Alexakis et al., 2013; Aliani, Malmir, Sourodi, & Kafaky, 2019; Arsanjani, Helbich, Kainz, & Boloorani, 2013; Azizi, Malakmohamadi, & Jafari, 2016; Barros et al., 2018; Chotchaiwong & Wijitkosum, 2019; Durmusoglu & Tanriover, 2017; Fu, Wang, & Yang, 2018; Gai et al., 2018; Gidey, Dikinya, Sebego, Segosebe, & Zenebe, 2017; Guan, Zhao, & Tan, 2019; Hamad, Balzter, & Kolo, 2018; X. Q. Meng & Chen, 2013; Moghadam & Helbich, 2013; Omar, Sanusi, Hussin, Samat, & Mohammed, 2014; Sinha & Kumar, 2013; Su, Zhu, Zeng, & Liu, 2012).

As far as complementary analysis of landscapes is concerned, visibility of landscapes is also an important field of study. Visibility of landscapes is an asset that determines human preferences for some activities. For example, several researches show that good scenery is an important criterion for site selection in building development and, therefore, it adds an economic value to the property values. For these and many other reasons, management of coastal landscapes is a complex issue due to inherent biophysical diversity of ecological systems and competing demands of land uses (Aguilar, Ano, Valera, & Sanchez, 2006; Alphan & Guvensoy, 2016; Basnou et al., 2013; Esmail, Ali, & Negm, 2016; Hossen & Negm, 2016; Parcerisas et al., 2012; Zitti, Ferrara, Perini, Carlucci, & Salvati, 2015).

3. RESULTS AND DISCUSSION

Above mentioned proposed workflow is conceptualized for complementary analysis of landscapes. A discussion is also provided using the results from a research project conducted on the Mediterranean coast of Turkey.

3.1 Dataset Selection

Dataset selection may be regarded as initial step of a complementary analysis. This is particularly important, since further processing of datasets requires information from a preceding step. Therefore, spatial and temporal characteristics of datasets strongly need to be capable of demonstrating compositional and configurational characteristics of land cover in a landscape of interest. Temporal characteristics of datasets, such as frequency of image acquisition is also critically important regarding the portrayal of landscape change trends and the change phenomena such as urbanization.

Eastern Mediterranean coast of Turkey near the city of Mersin witnessed rapid building development. This development took place in the form of agglomeration of the patches that are occupied by large multistory apartment blocks. These apartment blocks were built to serve as summer apartments. Sometimes a single apartment building contains 100-150 apartment units that are frequently used for a short time period in a year between July and August. Acceleration of this development dates back to 1980’s. Therefore, monitoring of development strongly required relatively higher resolution datasets dating back to these dates.

In this respect, SPOT datasets (*Satellite Pour l’Observation de la Terre)* have a number of advantages regarding the analysis of these characteristic changes on the coast. SPOT, an acronym for a series of French satellites, have been acquiring panchromatic and multispectral images with considerably high spatial resolution for over three decades. Due to provision of very high spatial resolution at 1980s, SPOT datasets were used for image analyses. Fig. 2 clearly shows above mentioned building development in Erdemli on the subsets of SPOT panchromatic images acquired between 1989 and 2007.

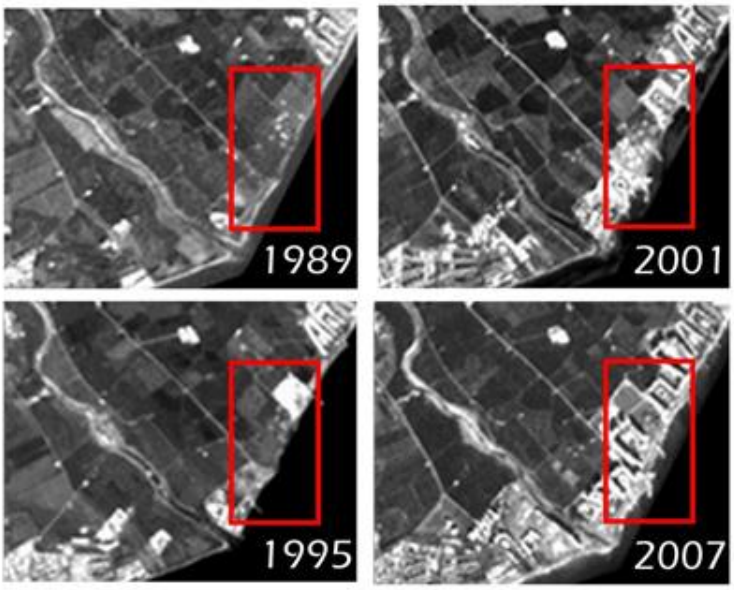

Figure 2: Development of built-up patches over time.

As shown in Figure 2, start date of image series is 1989, while the end date is 2007. Frequency of image acquisitions is six years. This Figure shows critical importance of spatial and temporal specifications of image datasets.

Determining a start date in a time series is critically important for a change analysis. This helps to analyze driving forces for development and their impacts on the environment. As shown in Fig. 2, tourism development on the east coast of Erdemli (Turkey) started in early 1990's (i.e., bright areas). This statement can be justified by checking the 1989 image. As depicted in Fig. 1, areas on the coast are free of development in 1989 (i.e, red rectangle). Start of the development can be seen on the 1995 image. Built-up areas emerge as bright patches on this image. The 2001 image suggests that development accelerated after 1995. As a result, the coast was extensively occupied by buildings and other sealed surfaces. This development was even more extensive after 2001. Between 2001 and 2007, the coastline is completely occupied by buildings.

Relatively higher resolution datasets are required for such change phenomena that has been observed on Erdemli coast. To cope with the difficulties associated with mapping small and dispersed pattern of built-up areas, spatial enhancement techniques may be employed on the input datasets. Data merging can be used as a tool for spatial enhancement. Near-anniversary Landsat and SPOT pairs were selected and merged for spatial enhancement. PCA resolution merge was employed using SPOT and Landsat scenes to produce a time series between 1989 and 2007 (Fig. 3).

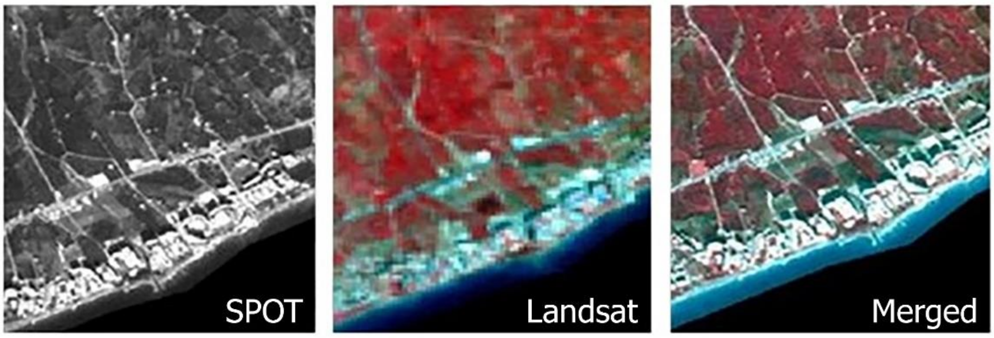

Figure 3: An example for spatial enhancement using PCA merging (left: SPOT panchromatic, center: Landsat TM, right: enhanced image)

3.2. Land Cover Mapping

Mapping can be considered as the first step for analyzing landscape systems. Many analytical techniques that deal with land cover patterns and landscape-level environmental processes need accurate land cover maps.

Traditional land cover classification approaches need *a proiori* defined land cover classes. In this approach, land cover classes are defined prior to any classification. This hierarchical description of thematic information is also called classification scheme. CORINE land cover classification scheme was used during classification.

Selection of an appropriate classification algorithm strongly depends on the quality of datasets and the level of thematic information required. In such cases that a perfect temporal and spectral consistency cannot be achieved, a hybrid approach may be performed. Image segmentation may yield satisfactory results.

Image segmentation is a part of so-called object-based image analysis procedure. In this approach, image datasets are coded as groups of segments that contain spectrally similar pixel groups. These segments may then be classified using *a priori* defined land cover classes.

Landscapes on the coast of Erdemli were classified using object-based image analysis. Building patches on the coastal zone represent a physical character that contrasts with the surrounding environment. Majority of the areas without building development consist of agriculture areas. Owing to the fact that agriculture areas are mostly citrus groves, the land surface is vegetated throughout the year. This even increases the impact of contrasting composition of bright grey appearance of building blocks and green vegetation (Fig. 4).

Figure 4: An example of map representation resulting from segmentation classification in Arpaçbahşiş and its surroundings (left) and aerial view of massive apartment buildings in the coastal zone (right)

3.3. Analysis of Landscape Pattern

Landscapes are diverse in the Mediterranean. Therefore, spatial arrangement and the composition of land cover change very rapidly due both to natural processes and human interference. Composition and configuration need to be analyzed in order to employ a complementary analysis of landscape systems and the change processes that they support. Area-edge, shape, aggregation and diversity metrics can be analyzed both at class and landscape levels. Table 1 and Figure 5 show description of two area metrics and their change trend in the case of Erdemli (Turkey), respectively.

Table 1: Area (CA, LPI) metrics for characterizing landscape changes in study area

Description of Metric Type	Formulation
CA: It shows how much of a landscape of interest is comprised of a particular patch type. It is one of the most fundamental measures of landscape composition.	$CA = \sum_{j=1}^{n} a_{ij}\ (1/1000)$ a_{ij}= area of patch "*ij*" (m^2)

LPI: It quantifies the percentage of total landscape area comprised by the largest patch of a focal class. It simply measures dominancy.	$$LPI = \frac{max_{j=1}^{n}(a_{ij})}{A}(100)$$ a_{ij}= area of patch "*ij*" (m^2), A= Total landscape area

Source: MC Garigal, 2014

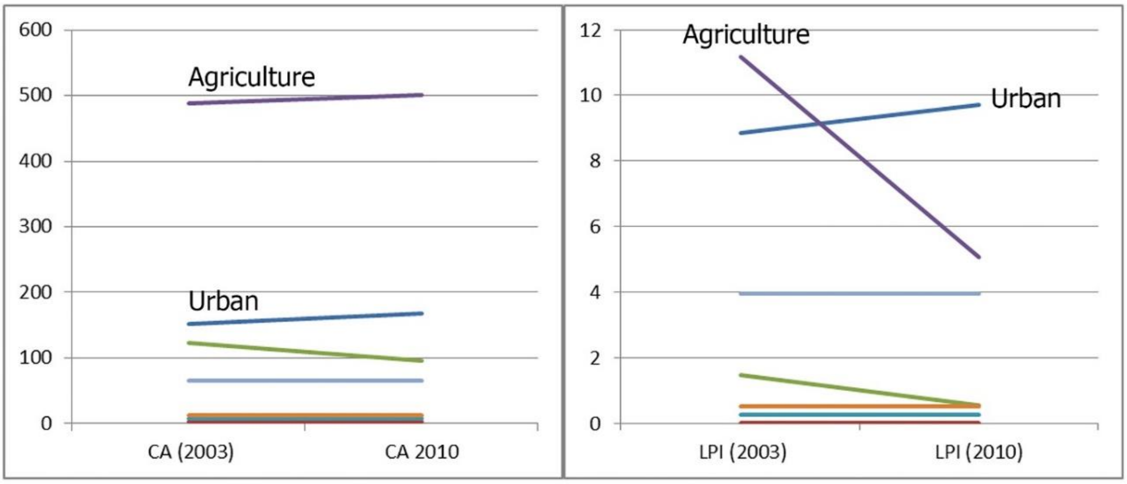

Figure 5: Change of two composition indices for developed areas (i.e., summer apartments), class area (CA) and largest patch index (LPI), in Arpacbahşiş (Erdemli, Mersin) and its surroundings between 2003 and 2010.

Pattern indices provide critical information about the trends and the phenomena that take place in an area of interest. As depicted in Fig. 5, class area for agriculture and urban classes slightly increase over time. However, more information is required to assess spatial characteristics of agricultural expansion and urbanization phenomena in the area. As suggested in Fig 5 (right) pattern metrics can also reveal information about the patch characteristics. Fig 5 (right) shows that LPI for urban areas tend to increase, while it decreases for urban areas. These trends of LPI indicate the aggregation of urban patches and fragmentation of agriculture patches throughout the study area.

3.4. Analysis of Change

Change analysis in the Mediterranean landscapes requires careful selection of image processing protocols due to the facts that (1) landscape patches are rather small and (2) instead of clear boundaries, transition gradients exist between various land cover classes.

Land cover change analysis includes pre- and post-classification techniques. Pre-classification may generally yield better results when medium resolution images are involved. In case of very high spatial resolution datasets, pre-classification is prone to environmental heterogeneity and variation in an image dataset. Therefore, post classification comparison can also be considered for change analysis. Road development and coastline changes can also be analyzed for use as either individually or as inputs to other models such as urban development models.

The development trend may be seen more clearly in Fig. 6, which belongs to the neighboring coast in the east.

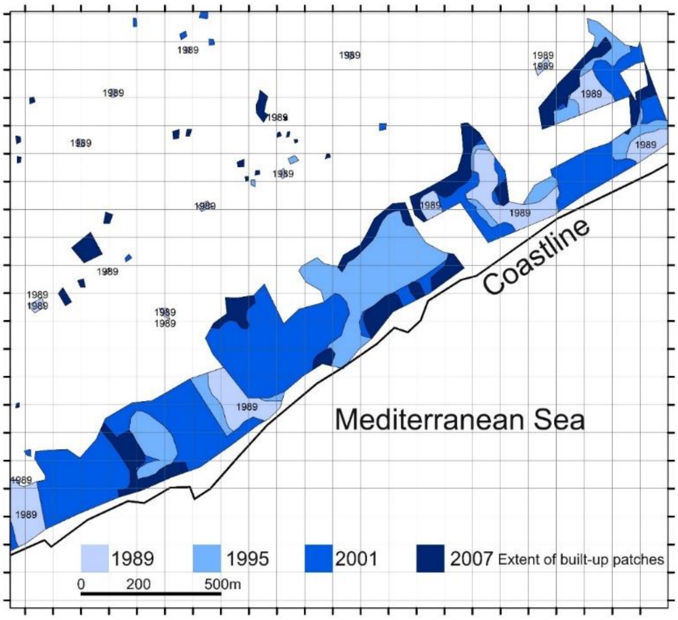

Figure 6: Thematic representation of coastal built-up change resulting from tourism development in Arpacbahsis, near Erdemli (Turkey).

As Seen in Fig. 6, major proportion of the coast is occupied during the period between 1995 and 2001. There is not an extensive built up change at this part of the coast after 2001. This is due to the fact that space for building development became scarce until 2001. As a result, development with relatively smaller patches was observed in the period between 2001 and 2007.

3.5. Projections for Future Development

Predictions for future development may be an important input during preparation of development plans. This information may act as a basis to manage future growth on a sustainable manner.

Several development models exist for urban growth. SLEUTH, UrbanSim, CLUE and CA-Markov models can be used to analyze future growth. For those areas that support small patches of built-up areas in a linear development pattern along the coastline, the models originally produced to predict urban growth may not work effectively. Relative effectiveness of these models needs to be tested

Figure 7: An aerial view of the region (left) and projected land cover for 2030 using CA-Markov model (right)

4. CONCLUSION

Natural and and/or human-induced processes strongly affect Mediterranean coastal landscapes. Anthropogenic impacts are far stronger than the natural processes in shaping and transforming these landscapes. This paper provided a brief summary of a recently completed research project conducted in the Mediterranean coastal region of Turkey. It highlighted the importance of incorporating digital geo-referenced information on coastal landscapes and bio-physical resources that they support.

Since landscapes are composed of biophysical systems and processes working at various spatial and time scales, complementary analysis requires studying of these systems and processes using a multi-level approach. This multi-level approach must combine information derived from various spatial and time scales. To do so, may help understand landscapes more effectively. This will obviously provide a strong assistance to decision making processes with regard to land management issues. This holds a strong potential for optimal use of land and water resources and for achieving sustainable resource allocation

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