Urban landcover mapping using Multiple Endmember Spectral Mixture Analysis

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The spatial and spectral variability of urban environments are fundamental challenges in deriving accurate remote sensing information for urban areas. Multiple Endmember Spectral Mixture Analysis (MESMA) technique was used to map the physical components of urban land cover for the city of Constantza, Romania, using Landsat Thematic Mapper (TM), Enhanced Thematic Mapper (ETM+) and IKONOS imagery during period of 1989 and 2006 years. Field spectra of vegetation, soil, and impervious surface areas collected with the use of a fine resolution and IKONOS image and pixel purity index tool in ENVI 4.3 software were modeled as reference endmembers in addition to photometric shade that was incorporated in every model. This study employs thirty endmembers and six hundred and sixty spectral models to identify soil, impervious, vegetation, and shade in the Constantza area. The mean RMS error for the selected land use land cover classes range from 0.0025 to 0.019. This paper demonstrates the potential of moderate-and high resolution, multispectral imagery to map and monitor the evolution of the physical urban environment.

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1. Introduction

Satellite remote sensing has been widely recognized as one of the essential technological tools for sustainable development. A considerable number of recent studies have been conducted utilizing satellite sensor data in the analysis of urban land use /land cover change [1]. The findings of these studies have enriched our understanding of the physical and socioeconomic drivers of changes in urban land cover and the implications of these changes on land use practices and resource management in cities. Some of these studies went further beyond the characterization of change and its causes and attempted to integrate remotely sensed data with models of urban growth in order to project future changes in a given city.

Looking back at how these studies have informed and been linked to sustainability policies, one can easily observe the sole focus on only one type of sustainable development, the so called “smart growth, “managed growth,” or “new urbanism.” These and other similar approaches direct attention to changes that occur at the urban fringe, as in the case of periburban communities in Romania. Urban landscapes change over time as new urban fabric is added and also as the existing fabric is internally modified (e.g. new buildings replace old ones, plots are amalgamated or subdivided, street layouts are modified). These patterns of urban densification and internal modifications are of major concern to sustainable development because they represent the physical manifestation of a range of social, economic, cultural, and political dimensions associated with urban dynamics. Moreover, densification typically takes place locally within urban neighborhoods where the impact of sustainable policies is more spatially and socially manifested. Hence, a better characterization and quantification of densification patterns at the local level will both provide a rich understanding of the processes involved and challenge the credibility of policy, citizens’ preferences for sustainable living space, and Earth that is the basis for better-informed decision-making. The key to understanding the Earth’s dynamics and system complexity is to integrate observations at local, regional and global scales, over a broad portion of the electromagnetic spectrum with increasingly refined spectral resolution, spatial resolution and over time scales that encompass phenomenological lifecycles with requisite sampling frequency. Advances in computational science and numerical simulations are allowing the study of correlated systems, recognition of subtle patterns in large data volumes, and are speeding up the time necessary to study long-term processes using observational data for constraints and validation. Integrating remotely sensed data into predictive models requires measurements at resolutions substantially superior to those made in the past when the observational systems and the discipline of natural hazards research were less mature than they are today. Furthermore, assimilation of data and model outputs into decision support systems must meet operational requirements for accuracy, spatial coverage and timeliness in order to have positive impact on disaster risk management.

2. Methods

2.1. Subpixel analysis

The traditional hard classifiers (e.g., minimum distance, Mahalanobis distance, maximum likelihood) can label each pixel only with one class [2]. Information on the fractional amount of spatially mixed spectral signatures from different ground-cover features is not possible with the per-pixel classifiers (hard classifiers). Hence, the traditional classification of mixed pixels may lead to information loss, degradation of classification accuracy, and degradation of modeling quality in successive applications. Subpixel analysis that can provide the relative abundance of surface materials within a pixel is a potential solution to per-pixel classifiers especially when dealing with medium to coarse spatial resolution satellite sensor images.

2.2. Linear Spectral Mixture Analysis (SMA)

Spectral mixture analysis (SMA) [3] (Adams et al., 1993) is one of the techniques proposed to provide a solution to the problem of mixed pixels in urban satellite imagery with medium spatial resolution (i.e. 20 m or lower).

Linear spectral mixture analysis (SMA) (Fig. 1) uses the multiple linear regression to define the endmembers abundance in the image, which provides subpixel endmember abundance information, being probably the most commonly used approach of all subpixel analysis techniques. The approach is based on the assumption that the spectrum at each pixel is a linear combination of the spectra of all ground components within the pixel, and that the linear mixture coefficients are equal to the fractional area of each ground component in a pixel. The mathematical model of linear spectral mixture analysis can be defined as:

$$X_i = \sum_{k=1}^{n} f_k X_{ik+e_i} \tag{1}$$

Where, X_i = Total spectral reflectance of band i of a pixel; k = number of endmembers; f_k = fraction of an endmember k within a pixel; X_{ik} = known spectral reflectance of endmember $k;$ within the pixel in band $I;$ e_i = error term for band $i.$

The root mean square (RMS) error is given by:

$$RMS = \frac{\left(\sum_{i=1}^{m}(e_i)^2\right)^{0.5}}{m} \tag{2}$$

where e_i are the error terms for each of the m spectral bands considered. The above constrained least-squares estimate assumes the followings:

$$\sum_{k=1}^{n} f_k = 1 \quad \text{and} \quad 0 \le f_k \le 1 \tag{3}$$

2.2.1. Limitations of Linear SMA

Findings from recent studies indicate that although SMA provides superior results to traditional per-pixel classification techniques when applied to urban imagery, a considerable degree of error may be associated with SMA models [4]. This is because the standard SMA model implements an invariable set of endmembers to model the spectra in all the pixels within an image. This assumption fails to account for the fact that, due to the diversity of urban materials, the number and type of components within the satellite sensor's field of view are variable.

Limitations of linear SMA are:

(1) Linear spectral mixture classifier does not permit number of representative materials (endmembers) greater than the number of spectral bands.

(2) An invariable set of endmembers to model the spectra in all pixels. This assumption could potentially fail to account for the fact that the number and type of land cover components within each pixel are highly variable. The endmembers used in SMA are the same for each pixel, regardless of whether the materials represented by the endmembers are present in the pixel.

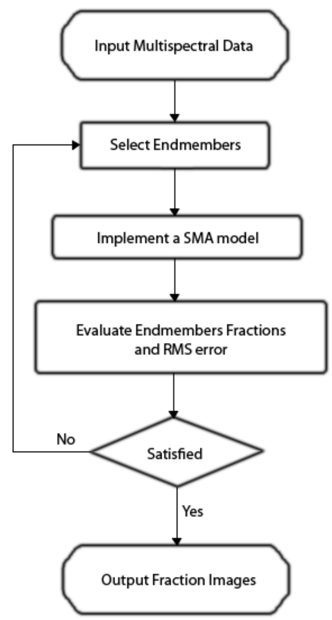

Fig. 1. Spectral Mixture Analysis .

2.3. Multiple Endmember Spectral Mixture Analysis (ESMA)

An extension of SMA approach that allows the number and type of endmembers to vary for each pixel within an image. MESMA has been proven to be effective in identifying different types of materials in a variety of environments. The MESMA adopts as the best model the one that has smaller root mean square (RMS) error when compared to the spectral curve of the pixel. The algorithm produces the RMS error and the shade information in each pixel as separate layers. It was proposed a solution to this problem by developing a modified SMA algorithm that allows the number and type of endmembers to vary for each pixel in an image [5]. This technique is referred to as multiple endmember spectral mixture analysis or MEMSA. Thus, MESMA can be described as a modified linear SMA approach in which many simple SMA models are first calculated for each pixel in the image. The objective is then to choose, for every pixel in the image, which model amongst the candidate models provides the best fit to the pixel spectrum while producing physically reasonable fractions.

The procedure of applying MESMA to urban satellite imagery to a single-date image starts by selecting a set of candidate endmembers believed to represent a relatively pure spectral response of the target materials in the scene. Urban areas may be described in terms of proportions of Vegetation (V), Impervious surfaces (I), and Soil (S). The process of endmember selection is commenced by applying the Pixel Purity Index (PPI) method to screen all the pixels in the image in terms of their relative purity. In the next step, a series of standard SMA models are applied based on a variety of possible combinations of the selected endmembers. The performance of all models is evaluated so that a smallest subset of candidate models can be selected for every pixel in the image. A reliable candidate model is one that produces physically realistic fractions (i.e. 0-100% range) and does not exceed a certain threshold of error. From the selected candidate models, an optimal model is then identified for each pixel based on the classical maximal covering problem. Finally, the fraction values produced by these optimal models are utilized to map the abundance of general land cover components in the urban scene at a given point of time.

3. Study area and data used

Study area, Latitude 44.142280, Longitude of 28.657680 was urban zone Constantza on Romanian Black Sea coastal zone with complex morphological patterns that are rapidly changing due to a range of complex, interrelated forces of urbanization (Fig. 2).

Fig. 2. Test site positioning of Constantza area.

The data utilized in the application of proposed methodology included subsets (3113 lines X 4801 samples) from two Landsat TM and ETM+ images acquired in 20/08/1989 and 16/07/2000 and two IKONOS 29/07/2005 and 16/09/2006 images. Both images have 0% cloud cover.

The investigations were focused on estimating of urban environmental parameters from satellite. In situ-monitoring additional data were used. ENVI 4.3, IDL 6.3 and ILWIS 3.1 softwares were used.

3. Data analysis

The proposed methodology for quantifying the ecological patterns of urban densification consists of three sequential phases. In the first phase, the MESMA technique is separately applied to individual images in order to derive per-pixel physical measures of urban land cover abundance at a given point of time. Land cover fractions of individual dates are then validated against test data to determine the accuracy of MESMA-derived measures. Once acceptable, multi-date fractions of corresponding land cover materials are used to calculate per-pixel temporal differences in these fractions. Hence, the resultant fractional differences will represent a direct measure of the changes that take place in the composition of urban morphological patterns over time due to such processes as urban densification and urban sprawl (Fig. 3).

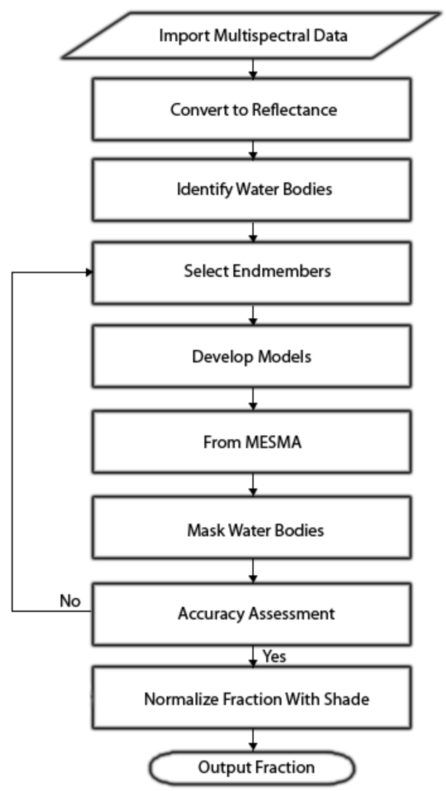

Fig. 3. Research flow chart.

4. Results

Spectral Endmember Characterization: The criteria for endmember selection are to balance the minimization of RMS error, to derive physically meaningful endmember spectra (representative of physically realistic materials) and to produce a well bounded endmember fraction map. Two different methods are used to study the difference between the linear and nonlinear approaches. One is to use 3 endmembers to simulated a “minimum” endmembers solution. The other uses 6 for the “maximum” situation. Was found fundamentally different sets of endmembers for the reflectance vs. SMA data sets in order to reach the optimum solution. This is especially true when the number of endmembers input into SMA is more than three and one less than the maximum. In this case, one needs to have more end members in the higher albedo range than in the lower albedo range for the linear approach, while more low albedo relative to high albedo endmember are required for the nonlinear situation.

Subpixel Abundance Quantification: Linear SMA gives an adequate representation of the spatial relationship and physical abundance of the components if the mixing systematics are linear. However, in many situations, intimate mixing is the norm and nonlinear mixing should be employed for more accurate abundance determination. For the arid soils in the urban region, is expected the endmembers to be intimately mixed at the 1-3 meter scale. The absolute differences in abundance can be as much as 30%. Detailed analysis of this data cloud for each individual component reveals two distinctively different relationships, one being linear, and the other curve-linear. Each of the trends maps out the spatial relationship of the scene for the given endmember. The other major difference between these two different approaches is described by the amount of super positive and negative points in the scene. The nonlinear model is often much better constrained and has less super positive and negative data numbers.

Error Magnitude and Distribution: The average RMS error for the nonlinear SMA is generally one half the average RMS of the linear SMA solution, regardless the number of endmembers used in the analysis. In addition, the average RMS error (less than 1%) for the nonlinear model is comparable with the instrumental error. Therefore, the selection of image endmembers must be done carefully to avoid endmembers that model the instrumental error. Spatially, the error map from nonlinear SMA shows a more random pattern than from the linear SMA. Exhaustive study of multiple image endmember combinations suggests that the endmember set from the least RMS error solution may produce fractions that are not well connected to physical abundance. Equally important is that endmember selected from spectral libraries (Lab or field based) may not be comparable to the reflectance of image endmember in hyperspectral data set. Thus it seems that the best approach is to model the image data using image endmember, and that the image endmember be modeled with lab or field data subsequently. Urban land covers (e.g., cement parking lots, asphalt roads, shingle rooftops, rass, tress, exposed soil) can only be recorded as either present or absent in each pixel when using traditional per-pixel classifiers. Subpixel analysis approaches that can provide the relative fraction of surface covers within a pixel may be a potential solution to effectively identifying urban impervious areas. Spectral mixture analysis approach is probably the most commonly used approach that models image spectra as spatial average of spectral signatures from two or more surface features. However, spectral mixture analysis does not account for the absence of one of the surface features or spectral variation within pure materials since it utilizes an invariable set of surface features. Multiple endmember spectral mixture analysis (MESMA) approach addresses these issues by allowing endmembers to vary on a per pixel basis. The MESMA technique was employed in this study to model Landsat Thematic Mapper (TM), Enhanced Thematic Mapper (ETM+) imagery for 1989 – 2005 periods in the Constantza town. Field spectra of vegetation, soil, and impervious surface areas collected with the use of a fine resolution and IKONOS image and pixel purity index tool in ENVI 4.3 software were modeled as reference endmembers in addition to photometric shade that was incorporated in every model. This study employs thirty endmembers and six hundred and sixty spectral models to identify soil, impervious, vegetation, and shade in the Constantza area. The mean RMS error for the selected land use land cover classes range from 0.004 to 0.018. The Pearson correlation between the fraction outputs from MESMA and reference data from IKONOS 1m panchromatic resolution data for soil, impervious, and vegetation were 0.7052, 0.7249, and 0.8184 respectively. The results can be summarized in the Table 1. In this analysis, we apply MESMA to LANDSAT TM and ETM satellite data IKONOS hyperspectral data and focus on 3 key issues: spectral endmember characterization, subpixel component abundance quantification, and error magnitude and distribution for band residuals and total RMS errors.

Fig. 4 is presenting a map of the subpixel abundance of generalized urban materials (impervious surfaces, vegetation, and soil), of Constantza urban and periurban areas based on Landsat TM 20/08/1989 satellite data. Fig. 5 is showing Landsat ETM 16/07/2000, landcover classification map for Constantza town.

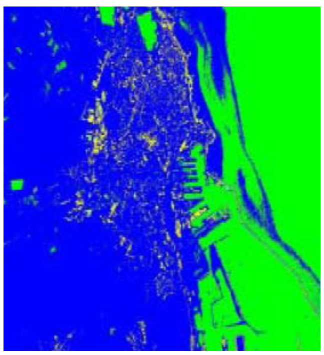

Fig. 4. Landsat TM 20/08/1989 map of the subpixel abundance of generalized urban materials (impervious surfaces, vegetation, and soil for Constantza town.

This study explored the utility of multiple endmember spectral mixture analysis (MESMA) to capture patterns of change in Constantza urban and periurban land cover through time. MESMA models measured spectra as the linear sum of spectrally pure endmembers and allows endmembers to vary on a per-pixel basis. Was analyzed test area Constantza using Landsat TM/ETM and IKONOS imagery corresponding to the years 1989, 2000, 2005 and 2006.

Fig. 5. Landsat ETM 16/07/2000, landcover classification map for Constantza town.

Table 1. Mean fraction values of soil, impervious, vegetation, shade, and RMS error of the selected land use / land cover classess for Constantza urban area, Romania

	Mean Fraction Values				RMS error
Land use /Land cover classes	Soil	Imper-vious	Veget a-tion	Shade	
Agriculture	0.024	0.015	0.796	0.078	0.018
Harbor	0.229	0.339	0.012	0.113	0.006
Airport	0.158	0.384	0.009	0.362	0.010
Commercial	0.227	0.338	0.047	0.302	0.016
Exposed soil	0.517	0.170	0.085	0.151	0.08
Forest and vegetation	0.146	0.047	0.312	0.409	0.003
Residential	0.261	0.279	0.092	0.119	0.007
Rugged terrain	0.254	0.096	0.080	0.524	0.004

Fig. 6 shows Constantza urban and periurban growth on IKONOS 16/09/2006 image.

Fig. 6. IKONOS 16/09/2006 Constantza urban growth.

MESMA was applied to each sample, and two categories of maps were generated: (a) maps of the subpixel abundance of generalized urban materials (impervious surfaces, vegetation, and soil), and (b) maps of model complexity (i.e., the number of endmembers required to adequately model each pixel). Model complexity was found to be highly correlated with degree of human impact on the landscape. The relationships between model complexity, urban growth, and changes in the periurban landscape were explored in the context of this Black Sea coastal zone frontier environment.

In urbanizing landscapes, the first type of change corresponds with urban expansion, the conversion of periurban land cover, such as crops or forest, to built-up land cover. The second type of change is characterized by internal modification of urban land-cover, for example, in-filling of open spaces with high-density buildings, paving of roads, regrowth of vegetation, etc. Most conventional methods of assessing land-cover change only identify transitions between classes, neglecting change within classes due to land-cover modification. This can result in significant error, underestimating the total area experiencing land-cover change, while overestimating the magnitude of change. Additionally, identifying change between classes may not be appropriate in an environment where most change occurs at scales finer than the resolution of the imagery, or where land-cover types are continuous. This work aimed to provide a comprehensive characterization of the Constantza urban landscape in terms of physically meaningful, continuous variables using moderate resolution remote sensing imagery of Landsat Tm/ETM and high resolution IKONOS imagery. *Spatial* variability of Constantza urban environment was addressed by mapping the subpixel components of land cover using spectral mixture analysis (SMA), which models each pixel as a linear sum of spectrally ‘pure’ endmembers. *Spectral* variability of urban land cover was addressed by applying multiple endmember spectral mixture analysis (MESMA), a methodology that allows the number and type of endmembers to vary on a per-pixel basis. The products of this work include a set of maps representing the per-pixel fractional cover of the primary components of urban land cover (i.e., vegetation, impervious surfaces, and soil), as well as maps of spectral complexity (i.e., the number of endmembers necessary to model each pixel). The results are locally specific, capturing the spectral variability that is distinct to the region, yet globally representative of urban land cover, allowing comparison of urban composition across regions and through time.

5. Conclusions

Remote sensing is very useful for urban landcover/use changes assessment, especially in the context of rapid increasing of urbanization in Constantza, Romania. Since LANDSAT TM and ETM contain complementary information, environmental quality and landuse/lancover changes of urban areas mapping is more efficient when the images are used in synergy with high resolution imagery IKONOS. Results from this study demonstrated that the MESMA approach is reliable and the subpixel processor picked out the signatures effectively. It should be noted that a careful selection of endmembers that represent all land covers under study play an important role in the MESMA approach. It was noticed that there is some signature confusion between dry exposed soil/sand bars vs. bright impervious surface and water vs. tar roads/parking lots. It is important as all possible models (combinations of all surface materials) to be considered in the analysis. It is also important to note that number of surface features and all possible combinations of endmember models are increased and generate fraction layers repeatedly until a satisfactory result is received. The MESMA approach not only allows unlimited endmembers regardless of the specific components to map the physical abundance of generalized urban materials, but this is providing a methodology for endmember selection which incorporates multiple sources of spectra for variability of materials present on the landscape as well as accuracy assessment for fraction images corresponding to each physical component. These techniques adequately characterize the diversity of materials that compose landcover within a diverse urban area, and at the same time provide a conceptual structure for grouping the specific materials into three general classes—vegetation, impervious, and soil. These generalized classes can characterize urban land cover regardless of specific construction materials or local environmental variation, facilitating comparison of urban data sets on a global scale.

References

[1] C. Weber, A. Puissant, Urbanization Pressure and Modeling of Urban Growth: Example of the Tunis Metropolitan Area, Remote Sensing of Environment, **86**, 341–352 (2003).

[2] M. Batty, D. Howes, D., Predicting temporal patterns in urban development from remote imagery, J. P. Donnay, M. J. Barnsley, P. A. Longley (Eds.), Remote sensing and urban analysis, 185–204, London: Taylor and Francis (2001).

[3] J. B. Adams, M. O. Smith, A. R. Gillespie, Imaging Spectroscopy: Interpretation based on Spectral Mixture Analysis. In: C. M. Pieters and P. Englert (Editors), Remote Geochemical Analysis: Elemental and Mineralogical Composition. Cambridge University Press, Cambridge, pp. 145-166 (1993).

[4] C. Small, Estimation of Urban Vegetation Abundance by Spectral Mixture Analysis. International Journal of Remote Sensing, **22**(7), 1305-1334 (2001).

[5] D. A. Roberts, G. T. Batista, J. L. G., Pereira, E. K. Waller, B. W. Nelson. Change Identification Using Multitemporal Spectral Mixture Analysis: Applications in Eastern Amazonia. In: R. S. Lunetta and C. D. Elvidge (Editors), Remote Sensing Change Detection: Environmental Monitoring Applications and Methods. Ann Arbor Press, Ann Arbor, MI, pp. 137-161 (1998).

[6] J. R. Carr, K. Matanawi, K. Correspondence analysis for principal components transformation of multispectral and hyperspectral digital images. Photogrammetric Engineering and Remote Sensing, **65**, 909–914 (1999).

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