© EARSeL and Warsaw University, Warsaw 2005. *Proceedings of 4th EARSeL Workshop on Imaging Spectroscopy. New quality in environmental studies*.
Zagajewski B., Sobczak M., Wrzesień M., (eds)

ITERATIVE MESMA UNMIXING FOR FRACTIONAL COVER ESTIMATES – EVALUATING THE PORTABILITY

Martin Bachmann[1,2], Andreas Müller[1], Martin Habermeyer[1], Michael Schmidt[1,2] and Stefan Dech[1,2]

1. DLR-DFD German Remote Sensing Data Center, D-82234 Wessling, Germany
2. University of Würzburg, Dep. of Geography, RS Unit, D-97074 Würzburg, Germany

Corresponding author: martin.bachmann@dlr.de

ABSTRACT

This paper introduces an automated spectral unmixing approach. This approach is based on multiple endmember spectral mixture analysis (MESMA) where the mixture model is iteratively improved using residual analysis and knowledge-based feature identification. A combined criterion for model selection and criteria to detect errors in the mixture model itself are also discussed, as well as methods to include neighbourhood information in the unmixing process. Examples for an evaluation methodology based on scene simulations and HyMap imagery from Spain and Namibia are given.

INTRODUCTION

Semi-arid and dry sub-humid ecosystems have been under ecological pressure since historical times. Especially during the last decades, human activities endanger the biological and economic productivity of drylands, observable by processes like soil erosion and long-term loss of vegetation. To identify these changes and the underlying driving processes, it is essential to monitor the current state of the environment and to include this information in land degradation models. The ground cover fraction is a frequently used parameter in such models (e.g. i), since the cover type (bare soil or plants), the degree (sparse vs. dense canopies) and the spatial distribution pattern alter surface runoff and thus the erosion potential. When plant cover is low, the observed signal from remote sensing systems can be greatly influenced by dry vegetation, variable soil brightness, biological surface crusts (especially lichens) and litter. Thus simple ratios like NDVI are of limited value in order to estimate ground cover fractions. To overcome the limitations, an approach based on the linear mixture model was successfully applied in a large number of studies (an introduction to spectral unmixing and a list of previous studies can be found in ii). Based on the physical relationship between subpixel constituents and sensed signal, the proportion of a material in the signal sensed is assumed to be equal to the actual ground cover fraction of this material in the area observed, thus surface fractions can be quantitatively derived. In a strict sense, this is only valid for the assumption that a photon interacts with only one ground cover type, i.e. all non-linear effects like multiple scattering in plant canopies are neglected. Nevertheless, as many plants in semi-arid regions are adapted to the harsh environment by thick leaves or wax coating having only little transmittance, and since lichens also show low transmittance, the linear mixture model is a valid working hypothesis.

Since plant species and soil types are normally inconstant in one scene, it is unlikely that only one green and dry vegetation and one soil component can adequately represent the spectral variability of its ground cover class and thus model the entire image. One way to handle with the variety of possible scene components is to include all possible EM in one mixture model. But this often results in wrong abundances because the problem with linear dependent EMs is enhanced. Next, even though the linear mixture model can be solved as long as the number of EMs is less than the number of bands plus one, the intrinsic dimensionality of hyperspectral data is smaller due to the high degree of correlation between bands, preventing comprehensive sets of EMs.

A better approach is to optimize the EM set for each pixel independently. Recent examples for these multiple endmember spectral mixture analysis (MESMA) approaches and applications for semi-arid and arid environments can be found in (iii) for the mapping of chaparral, in (iv) where it was found that cover fractions could be reliably determined, but problems arose for the identification of vegetation type, and (v) who applied a Monte Carlo unmixing only using the SWIR2 region for the mapping of desertification. In the following, a new iterative MESMA approach is outlined (also described in vi).

METHOD

While most MESMA approaches mainly optimize for total root mean square (RMS) error and abundance constraints, the present approach also aims to identify which mixture model is meaningful in terms of absorption features of the spectra. Examples are chlorophyll absorption, clay-OH-absorption, and ligno-cellulose absorption among others. After the first unmixing iteration with an initial EM set, the measured spectrum and the residual (i.e. the difference between the measured and the modelled spectra of a pixel) are checked for significant features. If this divergence is characteristic it can then be identified. For example, when an underestimation of iron in a soil appears, the mixture model for this pixel is adjusted, i.e. a soil with higher iron content is used to model the pixel in the next unmixing iteration. The spectral identification is accomplished using correlation and specified narrow-band features similar to Tetracorder (vii) and includs the shape of the spectrum. The model selection criterion is thus based on a combined error score of wavelength-weighted RMS, deviation from constraints, and knowledge-based analysis of features in the residuum and signal sensed. This model selection criterion is further used as a feasibility measure, which also includes the local incidence angle among other parameters.

As a step towards automation, the EM used for unmixing are selected from a spectral library of image-derived EM from existing HyMap imagery at DLR. Based on a large number of scenes from dry-subhumid and semi-arid regions, spectra are selected for the relevant material groups of photosynthetic active vegetation, non-photosynthetic active vegetation (NPV, which includes dry, senescent and dead plants), and bare soils and rocks. All other material groups are not of interest in this study and thus excluded.

After the first unmixing iteration, pixels with high error score are determined and tested if these spectra may represent EMs not included in the starting library. This approach known as Iterative Error Analysis (IEA, viii) was originally intended for automated unmixing without knowledge of any EM, but is used here in a slightly different way, i.e. to add scene-specific EM to a given generalized EM library. In the present approach, this step is not yet fully implemented, but a brief outline is given below. The classification to one of the relevant material groups (i.e. green vegetation, non-photosynthetic vegetation, and bare soil) is based on spectral similarity measures like SAM, correlation, and knowledge-based spectral feature identification. If a spectrum can not be surely identified or shows features of more than one class, it is discarded from further processing. Next, the potentially new EM is tested for linear dependency with existing EM, and checked if it extends the EM library. The latter can be achieved by using the methodology described in (ix). Currently, a manual evaluation of the proposed new EM is still necessary to ensure the pureness of EMs.

Another improvement of MESMA unmixing is based on the fact that in nature, small-scaled changes of soil type rarely occur. Although when using MESMA without normalisation or shade component, the soil EM is often affected by changes in overall albedo. This results in a small-scaled mosaic of different soil EMs (Fig. 1). Therefore, it is checked if a pixel can be modelled with the dominant soil EM in the neighbourhood without increasing the error score too much, resulting in less patches and more realistic EM abundances (Fig. 1 & 2).

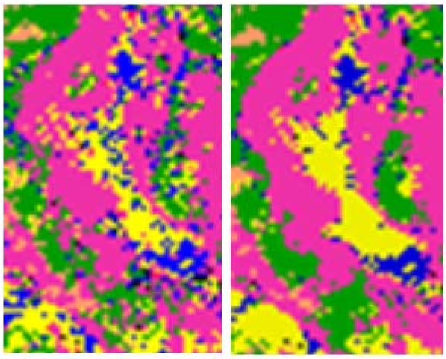

Figure 1: Maps of soil EM used for unmixing. Left: without / Right: with neighbourhood iteration.

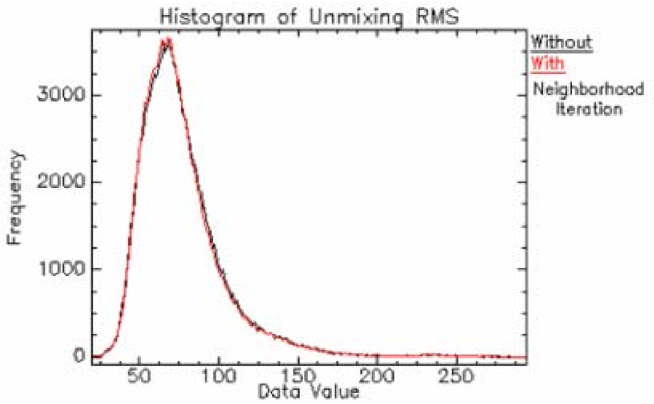

Figure 2: Unmixing RMS with and without neighbourhood iteration

RESULTS AND CONCLUSIONS

As shown by previous studies (iii, iv, v among others), MESMA can model hyperspectral imagery with a significantly smaller RMS than normal unmixing (Fig. 3 and 4), but further steps are required to ensure that results are correct.

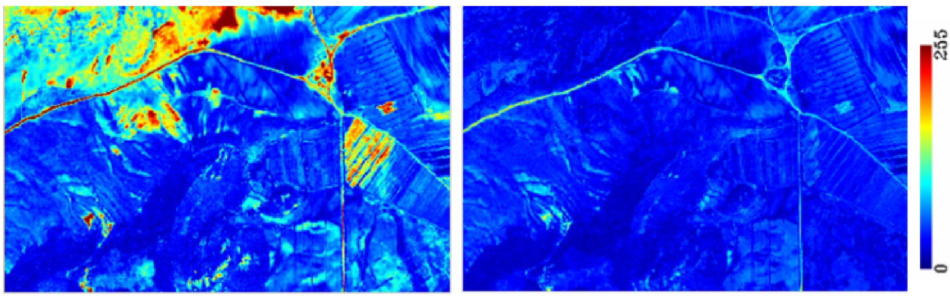

Figure 3: Unmixing RMS for HyMap scene Cabo de Gata (subset) Left: standard unmxing using 3 EM. Right: MESMA optimized for RMS. Note the area in the northwest with calcareous soils, which can not be modelled with standard unmixing when the fixed soil EM represents the low-calcareous soils in the southern parts of the image.

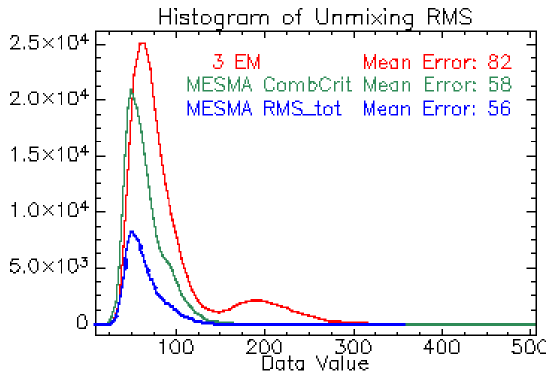

Figure 4: Total RMS error for HyMap scene Cabo de Gata when using standard unmixing (denoted 3EM), MESMA with optimization for total RMS (RMS_tot) and when using a combined optimization criterion (CombCrit)

Some criteria for unmixing fidelity are inherent in the unmixing model itself. First of all, the residual (i.e. the part of the signal which can not be modelled) should not contain meaningful information. If the residual spectrum can be interpreted, e.g. when absorption features are still present, a better model for this pixel can be found. Next, if the selected EMs are linearly dependent, unmixing results are likely to be false. Another indicator for an incorrect mixture model is the deviation from the constraints, i.e. when abundances greater than 100% or less than zero occur or when they don't sum to 100%, but this also depends on the algorithm used. Finally, when including a shade component, shade abundances should mainly represent illumination conditions and, to a lesser degree, canopy shade effects. If this is not the case, the shade component is also used to reduce errors for incorrect set EMs. In reality, it is impossible to fulfil all these criteria, but they can be used to determine a correct mixture model, and may be used as a feasibility measure for unmixing quality.

Next, simulations are used to fine-tune and to evaluate the unmixing methodology. Based on field spectroscopic measurements, the linear mixture model is used to generate synthetic scenes (described in e.g. iv, x). During the Cabo de Gata field campaigns in close cooperation with GFZ and local project partners (see xi and vi for more details), and during fieldwork by DLR-DFD in the framework of the BIOTA South project in Namibia, comprehensive field spectroscopic measurements were taken. Using these pure spectra of various plants and soils, a large number of synthetic scenes are generated as "perfect" reference. An illustration of a synthetic scene is shown in Fig. 5.

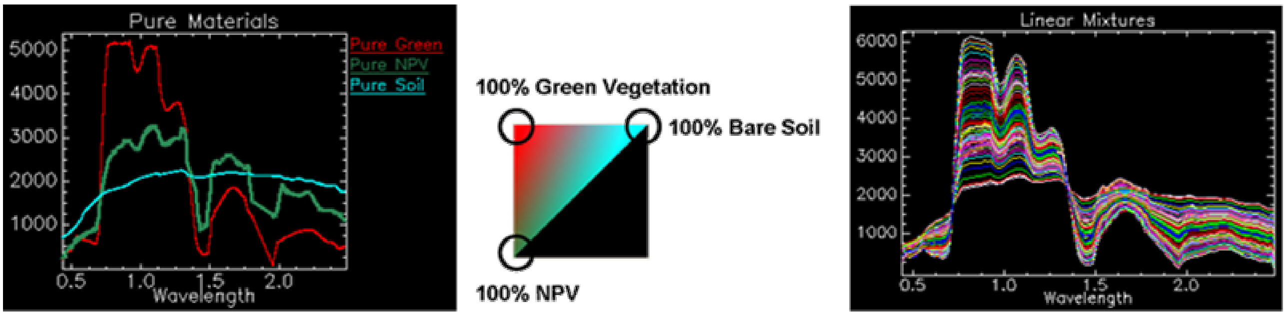

Figure 5: Illustration of synthetic scenes. Left: Input spectra of pure materials. Center: Synthetic image based on linear mixture of the input spectra. Right: Example for simulated mixed spectra.

In Fig. 6, scene simulations based on field spectral measurements of Spain and Namibia are shown. Using image-derived EM from the HyMap imagery of Cabo de Gata for unmixing, errors are normally well within 10% abundance except for low coverage (Fig. 6 left). In case that no suitable EM is included in the library, errors may raise significantly, as depicted in the right part of Fig. 6, indicating the need to extend the EM library used in the presented simulation.

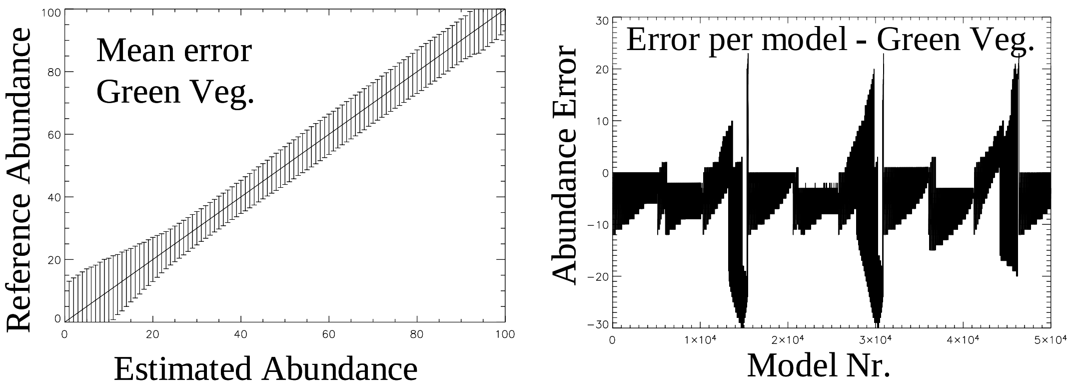

Figure 6: Statistics of unmixed synthetic scenes. Left: Reference vs. estimated abundances for green vegetation. Right: Plot of unmixing errors per model for green vegetation (subset).

Another common error in MESMA is caused by the selection of a wrong EM, also depicted in Fig. 7. While one spectrum for each ground cover class is used for the scene simulation, 3 different soil EMs are used for unmixing, in addition to one green vegetation EM and one NPV EM. This results in wrong abundances even though the EM model with the smallest RMS is selected. To cope with this source of error, knowledge-based residual analysis is used to select meaningful EMs in terms of spectral absorption features, and the inclusion of a feasibility measure indicates pixels with low model accuracy.

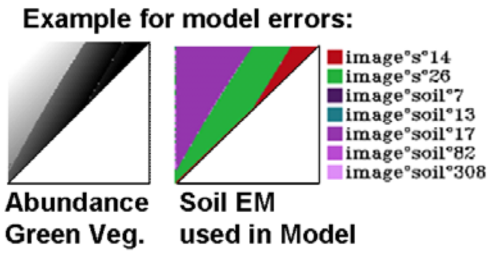

Figure 7: Illustration of MESMA errors based on scene simulation (optimized for RMS). Left: Abundances for green vegetation. Right: Soil EM used in the unmixing model.

OUTLOOK

As a next step, this MESMA approach is currently evaluated on HyMap imagery (Fig. 3 & 8). For the main testsite Cabo de Gata in southeast Spain, a total of 16 HyMap flightlines was acquired at different phenological states and years, and at different flight altitudes and flight orientations. Thus the influence of scale and bidirectional reflectance distribution function (BRDF) can be assessed, and ground measurements can be used for evaluation. In addition, HyMap overflights for the BIOTA testsites in Namibia will be included in the evaluation in order to test the portability of the approach. Using this atmospheric and geometric corrected imagery and corresponding ground truth data, the proposed unmixing methodology will be further evaluated.

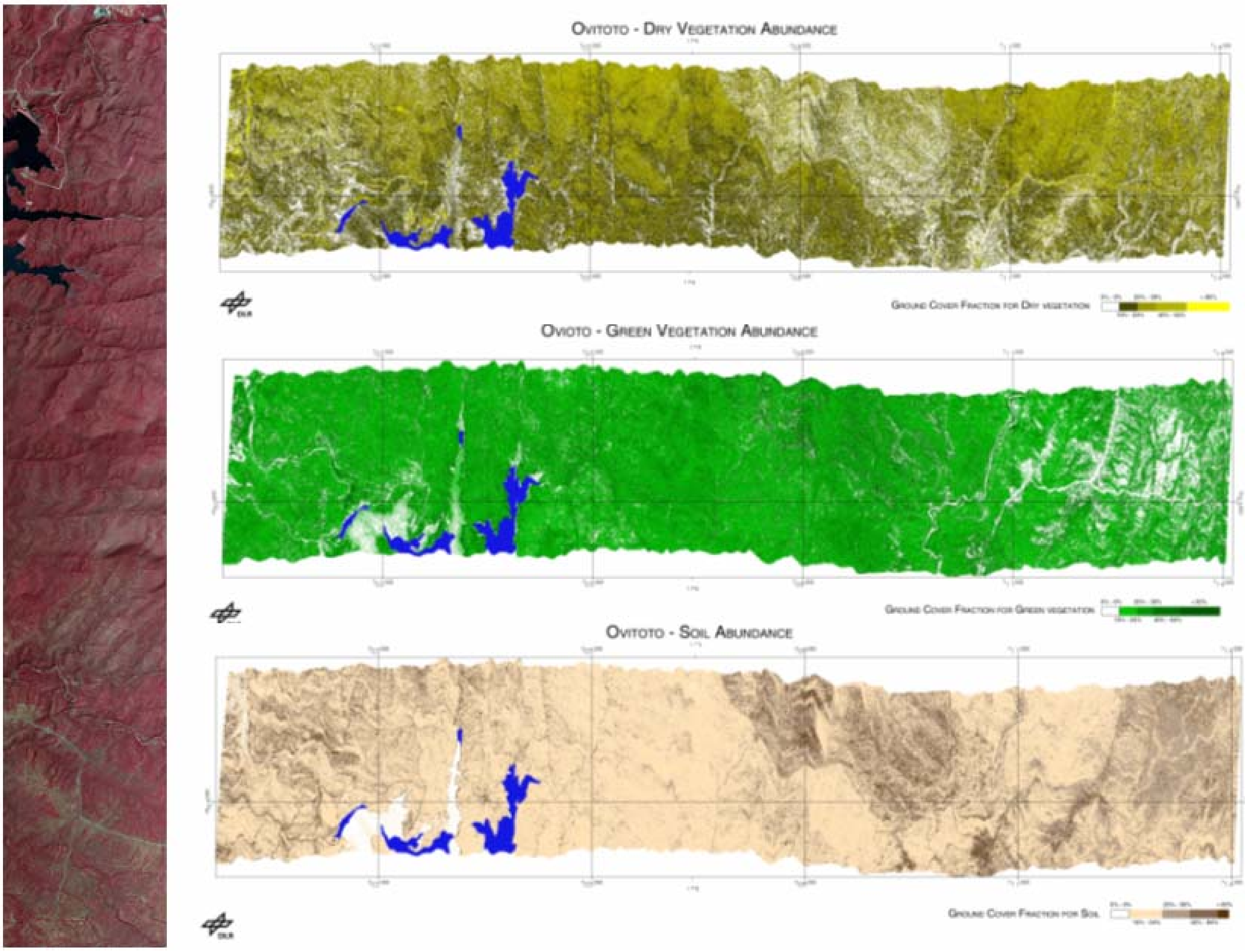

Figure 8: Abundance maps for the BIOTA Ovitoto test site in Namibia. Original HyMap data depicted on left.

ACKNOWLEDGEMENTS

The authors are grateful to S. Chabrillat (GFZ Potsdam) for ASD FieldSpec measurements, to C. Oyonarte Gutierrez and P. Escribano (both University of Almeria), and A. Palacios-Orueta (Polytechnic University of Madrid) for plant species discrimination, insights in the ecosystem and assistance during the field campaigns in Cabo de Gata 2003 and '04. Field spectroscopic measurements of Namibian plants and soils were provided by C. Schulz and M. Vogel, BIOTA south project at DLR-DFD and University of Würzburg. The authors would also like to thank HyVista, in particular T. Cocks and P. Hausknecht, for the excellent cooperation during many flight campaigns in the previous years.

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