# The use of neural networks for non-linear spectral unmixing over urban areas

#### Zina Mitraka and Fabio Del Frate

Earth Observation Lab, University of Rome Tor Vergata, Rome, Italy contact: zinoviam@gmail.com

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### Abstract

The high spatial and spectral diversity of man-made structures and the 3D structure of the cities makes the mapping of urban surfaces using Earth Observation data one of the most challenging tasks of remote sensing field. Spectral unmixing techniques, although

spectral resolution data. The large spectral variability of urban structures imposes the use of multiple endmember spectral mixture analysis techniques, which are very demanding in terms of computation time. Moreover, the commonly used linear spectral contributes significantly to the measured by the satellites reflectances in the urban canyons. In this study, a method is proposed to overcome these limitations, using an artificial neural network trained with endmember and non-linearly mixed synthetic



designed for and mainly used with hyperspectral data, they can be proven useful for use with medium mixture analysis approaches do not account for the spectra to inverse the pixel spectral mixture in Landsat multiple scattering of light between surfaces, which imagery.

## Urban Spectral Mixture

Urban Surface										
Built-up			Vegetation		Non-urban bare surfaces		Water bodies			
Buildings/roofs	Transportation areas	Sport infrastructure	Green vegetation	Non-photosynthetic vegetation	Bare soil	Rocks	Natural water bodies	Swimming pools		

#### Linear Mixing Model

 $\rho_i = \sum_{j=1}^M a_j(i) \cdot \rho_j$ 

where  $\rho_i$  is the observed spectrum of pixel i,  $\rho_j$  is the representative spectrum of endmember j, M is the number of endmembers and  $a_j(i)$  is the contribution of endmember j to the observed spectrum.



#### Quadratic Mixing Model

$$\rho_{i} = \sum_{j=1}^{M} a_{j}(i) \cdot \rho_{j} + \sum_{j=1}^{M} \sum_{l=j}^{M} a_{j,l}(i) \cdot \rho_{j} \rho_{l}$$

The first term accounts for linear mixing, while the second one accounts for multiple reflections of light







between urban surfaces (Meganem et al., 2014).

central wavelength (µm)

## Study Area and Data Results



Urban Atlas Polygons of the study area of Rome, Italy. Dotted lined represent the validation area.

#### Data

- Six cloud-free Landsat 7 Surface Reflectance Climate Data Record for 2011
- High resolution (0.3 m) Land Cover information for
   2011



Pseudo color composition of the fraction images, RGB: Nonurban bare, vegetation, built-up; water is background.





#### Water Surfaces Laghetto Villa Ada

## Validation

Derived fraction image were compared to fractions from higher resolution land cover info



	Built-up	Vegetation	Non-urban bare	Water
slope	1.074	0.974	0.622	1.208
intersect	0.043	-0.007	0.027	-0.028
R <sup>2</sup>	0.686	0.777	0.105	0.812
MAE	0.152	0.097	0.073	0.053
RMSE	0.192	0.130	0.122	0.081



## Conclusions

 This study presents a spectral unmixing approach using endmember and non-linearly mixed synthetic spectra to estimate urban surface cover fraction from Landsat imagery;

 The 3D structure of cities imposes the use of nonlinear spectral mixture models to account for multiple reflections in the urban canyons; The estimated fractions were compared to higher resolution land cover information and a good agreement was observed, especially for the built-up surface cover fraction;

 Neural networks' quick and accurate performance makes them ideal to use for operational applications with the Copernicus Sentinels.

## References

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