# DOWN-SCALING OF SATELLITE HYPERSPECTRAL IMAGES FOR MONITORING CROPLANDS

*Eunyoung Choe[1*], SukYoung Hong[1], and YiHyun Kim[1],*

[1]Soil and Fertilizer Management Division, National Academy of Agricultural Science (NAAS), Rural Development Administration, Suwon441-707, Korea
* E-mail: eychoe726@korea.kr

## 1. INTRODUCTION

The analysis and estimate of the distribution and dynamics of soil properties such as soil carbon is an essential requirement for sustainable cropland management. Remote sensing has potential to provide a cost-efficient and fast tool to map soil properties across large areas. Recently, visible/near-infrared reflectance spectroscopy (VNIRS) has proven to be a promising technique for the investigation of various soil properties [1] and there is growing interest in the use of hyperspectral remote sensing technologies including the similar spectral resolution to the VNIRS to assist the identification and delineation of spatial variation in soils. Especially, hyperspectral image can potentially discriminate between crop residues and soils as well as vegetation [2]. Satellite hyperspectral image, EO-1 HYPERION, has very narrow spectral bands but a coarse spatial resolution (30 m) to detect soil properties and vegetation in small parcels of croplands. Many algorithms for down-scaling (from coarse to fine resolution) are being developed to fuse the spectral characteristic of the coarse-resolution image with the spatial information of the fine-resolution image [3]. Image fusion methods include spectral component substitution techniques such as hue-intensity-saturation (HIS), PCA, and regression methods and spatial domain techniques such as highpass filtration, wavelet decomposition, and Fourier decomposition. Because of surface heterogeneity, there are always some pixels at any spatial resolutions that contain multiple cover types. Determining the subpixel information like a spectral linear unmixing is considered a downscaling process [4].

This study focused on improving spatial resolution of the satellite hyperspectral image preserving fine- spectral resolution through the integrated down-scaling algorithms such as classification-based multiresolution data fusion method and spectral linear unmixing method for monitoring croplands.

## 2. METHODOLOGY

**DATA & PRE-PROCESSING:** In this study we established a test area, lying a latitude of 36° 51′ 19.3″ N and a longitude of 126° 49′ 1.5″ E, in Dangjin-gun, midwest of South Korea. The test satellite hyperspectral image, Hyperion, were acquired by the EO-1 satellite on 12 November 2009 (Fig. 1(a)). Hyperion image were used with level 1Gst which is terrain corrected and provided in 16-bit radiance values. QuickBird image were used for a fine-resolution dataset (Fig. 1(b). The speciation of each sensor was described in Table 1. Hyperion image was atmospherically corrected to create reflectance data using FLAASH which is MODTRAN4-based atmospheric correction software package (in ENVI, ITT co., USA). Geocoding was implemented between Hyperion and QuickBird image before the classification steps.

Table 1. Speciation of satellite image sensors used in this study.

| Speciations | Hyperion | QuickBird | |
|---|---|---|---|
| Imaging mode | Hyperspectral | Multispectral | Panchromatic |
| Spatial resolution | 30 m | 2.44 - 2.88 m | 0.61-0.72 m |
| Swatch width | 7.7 km | 16.5 km | 16.5 km |
| Channel | 242 (356-2577nm) | R/G/B/Nir | 1 (450-900 nm) |

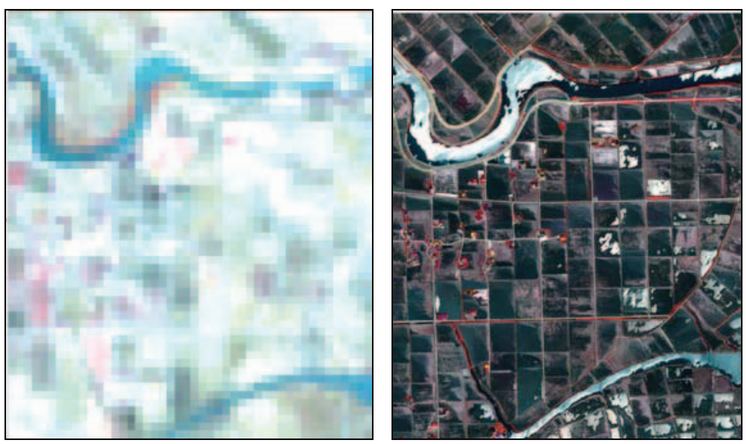

Fig. 1. Color composite of test images, Hyperion (RGB 46/32/21) (a) and QuickBird (RGB 4/3/2).

## DOWN-SCALING ALGORITHMS

**Classification-based multiresolution data fusion step:** Fine-resolution imagery by QuickBird was classified into a finite number of classes through object-based image segmentation and Fuzzy theory. This classification creates image objects defined as individual area with shape and spectral homogeneity [4], which one could recognize as segments or patches in the landscape literature. Then each class spectra were determined. Within a coarse-resolution pixel, there are many different classes

**Spectral linear unmixing step**: The linear unmixing model assumes that surface signals of all components that are called endmembers to estimate their reflectance and fractional abundances from a group of pixels at multiple wavebands [5]. The endmembers and fractions are determined by the results of classification-based fusion step, class spectra and individual area of objects.

## 3. CONCLUSIONS

In this paper, spatial down scaling of satellite hyperspectral image with 30 m resolution was investigated to improve the analysis and mapping performance of soil and vegetation characteristics in croplands. Coarse pixels which could include various components with their own reflectance, fractional abundances, and errors were decomposed by the linear unmixing model. Endmember and fraction in the unmixing step were determined from classes and individual object areas by classification-based multiresolution data fusion and enhanced performances of the linear unmixing decomposition for coarse pixels. This down-scaled hyperspectral image could show better analysis results of soil properties, crop residues, and vegetation types and enhance their mapping accuracy without loss of spectral information.

## REFERENCES


[1] G.M. Vasques, S. Grunwald, and J.O. Sickman, Comparison of multivariate methods for inferential modeling of soil carbon using visible/near-infrared spectra, *Geoderma*, 146 (1-2), pp. 14-25, 2008.

[2] G. Serbin, C.S.T. Daughtry, E.R. Hunt Jr, J.B. Reeves III, and D.J. Brown, Effects of soil composition and mineralogy on remote sensing of crop residue cover, *Remote Sensing of Environment,* 113 (1), pp. 224-238, 2008.

[3] M. Cetin and N. Musaoglu, Merging hyperspectral and panchromatic image data: Qualitative and quantitative analysis, *International Journal of Remote Sensing*, 30 (7), pp. 1779-1804, 2009.

[4] Liang, S., *Quantitative remote sensing of land surfaces*, John Wiley & Sons, Inc., Hoboken, 2004.

[5] Jensen, J.R., *Introductory digital image processing: A remote sensing perspective*, Pearson Education, Inc., Upper Saddle River, 2005.