Integrating Pattern, Process, Scale and Hierarchy

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Estimating CAPLTER vegetation cover using remote sensing data

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ABSTRACT

The ultimate objective of our research is to quantify vegetation structure and investigate how urbanization affects ecosystem primary productivity in the Sonoran Desert where CAPLTER is located. The study combines field survey, remote sensing, GIS, and ecological modeling. As the first step towards our research goal, we used multi-spectral Landsat and airborne super-spectral MASTER data to derive vegetation indices (NDVI and SAVI) as well as sub-pixel vegetation fractions using the spectral linear unmixing technique. We then attempted to relate remote sensing-based measures to actual vegetation cover using regression analysis. The results were compared with the CAPLTER 200-survey estimates of green vegetation cover. Our results showed that the ability of remote sensing data to quantify vegetation parameters is the highest for agricultural plots, relatively high for urban plots, and poor for desert plots. The results also suggest that, although we originally hypothesized it would, spectral linear unmixing did not significantly improve the vegetation cover estimates relative to the results directly obtained using NDVI and SAVI.

METHODS

❑ Vegetation indices (band ratios)

$$NDVI = \frac{NIR - RED}{NIR + RED} \qquad SAVI = \frac{NIR - RED}{NIR + RED + L}(1 + L)$$

where NIR is Landsat band 4 (0.76-0.9 μm) and MASTER band 8 (0.78-0.82 μm), RED is Landsat band 3 (0.63-0.69 μm) and MASTER band 5 (0.63-0.69 μm) respectively. *L* is the correction factor which was set to 0.5 (intermediate vegetation cover).

❑ Spectral Linear Unmixing makes use of information at the subpixel level to estimate fractions of the so-called endmembers. To conduct the analysis I used ENVI software and followed the procedures shown in the diagram below

Minimum Noise Fraction (MNF) transformation (to determine dimensionality of image data and segregate noise)

↓

Pixel Purity Index (PPI) procedure (iterative reprojections of n-dimensional scatterplots onto a random unit vector to find the most spectrally "pure" pixels)

↓

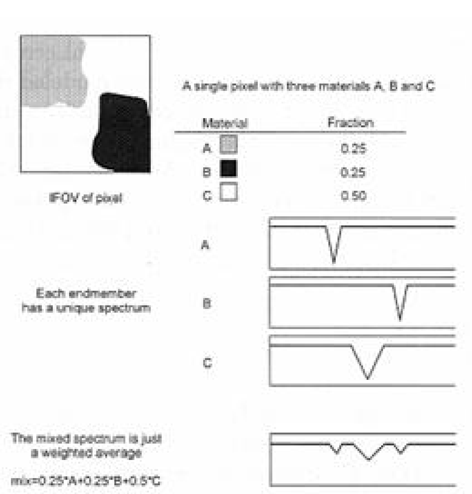
PPI values are plotted in **n-D Visualizer** and clusters of extreme spectral responses are identified. They are image **endmembers**

↓

Endmembers are transferred to **Linear Spectral Unmixing** algorithm to deconvolve the inversely transformed **MNF** image

↓

Series of grey-scale images, one for each **endmember**, plus a root mean square (RMS) error image → Green vegetation endmember image



❑ Correlation and regression analyses.

All resulting images are overlaid with the mask grid consisting of a total of 174 200-survey plots. MASTER vegetation images were resampled prior to this in order to match Ground Instantaneous Field of View (GIFOV) of Landsat.

OBJECTIVES

■ Relate multiple spatial and spectral resolution remote sensing imagery to vegetation cover estimates collected for 200-survey field plots and develop an appropriate model for extrapolating vegetation parameters such as biovolume and biomass across the entire CAP LTER study area

■ Compare traditional vegetation indexes with subpixel analysis (Spectral Linear Unmixing technique) applied to Landsat ETM imagery.

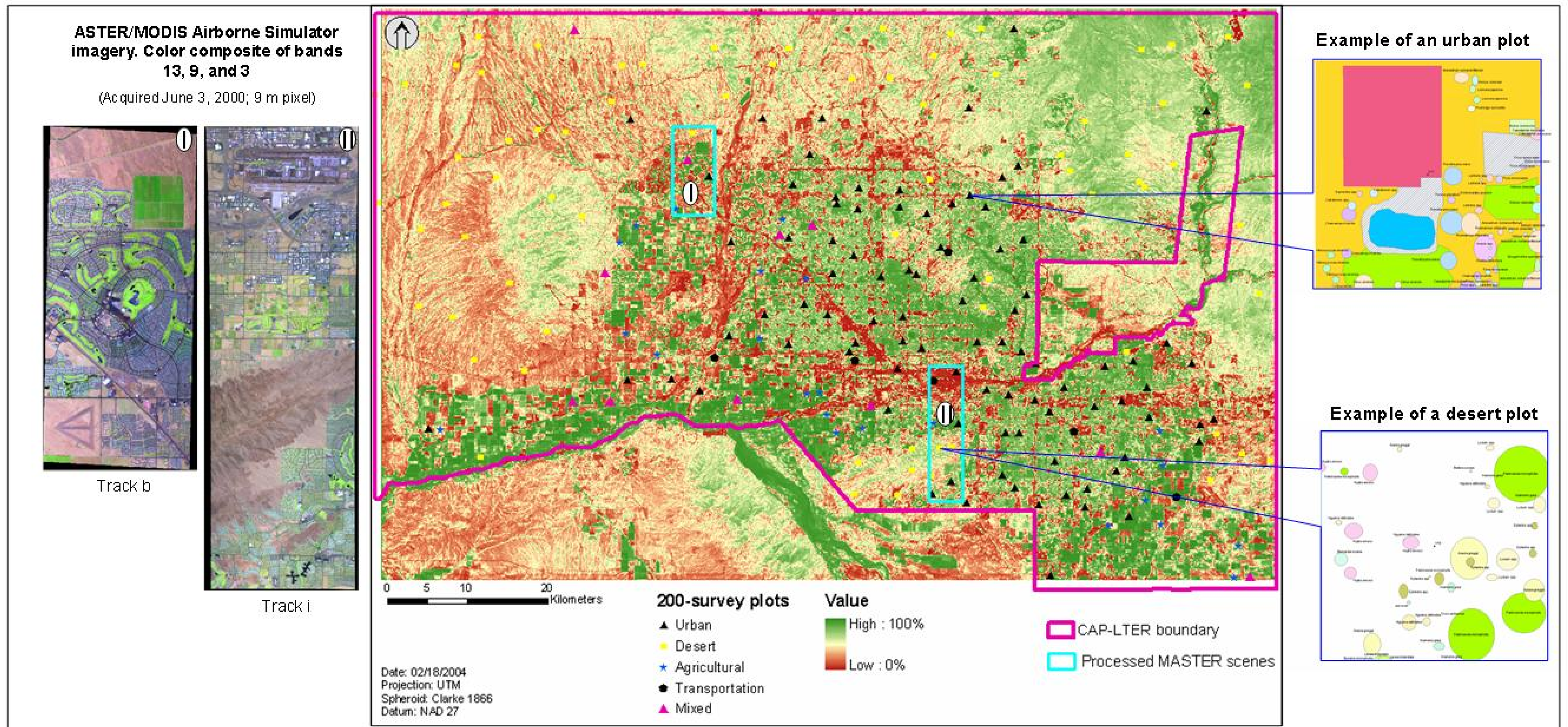


Figure 1. General pattern of actively photosynthesizing vegetation in CAPLTER in May 2000. Abundance measures derived from SAVI image of the 05/21/2000 Landsat ETM+ using the regression model *cover = 0.28 + 0.82*SAVI*.

RESULTS

⌗ Although SAVI had a wider range of values, which should probably be considered advantageous in some applications of remote sensing, it did not demonstrate any significant improvement over NDVI (Fig. 2.).

⌗ Capability of remote sensing approach to quantify vegetation abundance is the highest for agricultural plots, relatively high for urban plots, and poor for desert plots (Fig. 1, 2).

⌗ Compared to SAVI and NDVI, vegetation fraction estimates obtained by spectral linear unmixing were less correlated with field data (Fig. 2).

⌗ Vegetation images derived from spatially degraded MASTER imagery exhibited weaker relationship with ground measures.

CONCLUSIONS

⌗ Spatial, spectral, and temporal resolution of Landsat ETM is clearly adequate for studying regional to local urban vegetation in Sonoran Desert. On the other hand, data with finer spatial and spectral resolution, such as MASTER, should be further explored in terms of their ability to distinguish between major plant communities in the area.

⌗ Relating remotely sensed vegetation parameters to ground measures in CAPLTER should be done separately for different land use/land cover types. No single model can be developed for such a diverse area.

⌗ Agricultural land use is undoubtedly the easiest target for remote sensing classifications due to the largest number of spectrally pure pixels and spatially extensive homogeneous patches of vegetation.

⌗ Although R^2 values are considerably high for agricultural plots as well as in the MASTER vs Landsat example, it may be that low available sample size is not adequate for statistical analyses

⌗ Spectral linear unmixing, which utilizes all spectral bands of a particular remote sensor and provides physically based measure of vegetation abundance, was originally proposed to be a more meaningful approach than simple band ratios. Unfortunately we were unable to outperform SAVI and NDVI by applying this technique to Landsat imagery.

DATA

⌗200-survey plots (CAPLTER). GPS coordinates of individual perennial plants and their recorded size measurements (N-S and E-W extents of foliage) used to generate a coverage with elliptical plant canopies (Fig. 1). Single plants were dissolved in GIS with previously mapped vegetation patches (beds, hedges, lawns) and total cover was computed. Cover estimates for desert sites might be inaccurate because only 5 representatives per species were used. Seventeen non-green plant genera were excluded from the analysis.

⌗Remote sensing data

1) Landsat ETM+ acquired at three dates and corresponding to the 200-survey campaign (3/18/00, 4/19/00, and 5/21/00) were georeferenced to the NAD27 UTM zone 12 coordinate system with and estimated positional error of 0.5-1 pixel. We used Landiscor aerial photomosaic (3m pixel) of Phoenix metro area as reference image. Atmospheric correction - ATCOR 2.0 in ERDAS Imagine.

2) Two subsets of ASTER/MODIS Airborne Simulator (MASTER) data (9m pixel) acquired in June 2000 were rectified and georeferenced (Fig. 1).

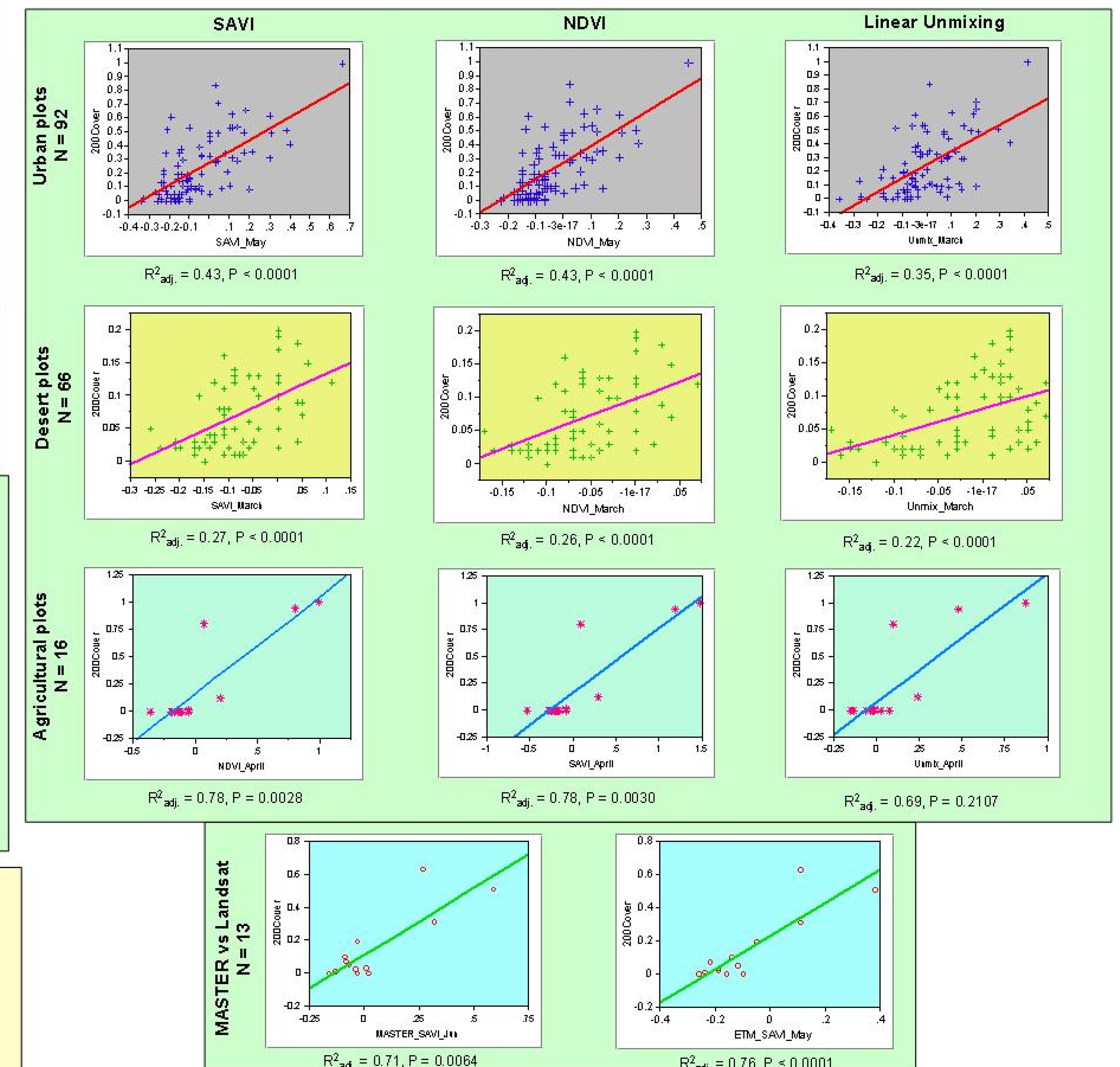


Figure 2. OLS linear fit and regression analysis performed on subsets of original 200-survey data by major land use type. 200Cover is actual vegetation cover estimated from field data (scaled 0 to 1). Linear unmixing is scaled 0 to 1, while NDVI and SAVI are scaled from –1 to 1. Negative values in unmixing results indicate errors and represent pixels devoid of vegetation endmember.

Acknowledgments

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