Spectral unmixing results for Airborne Visible/Infrared Imaging Spectrometer (AVIRIS) data acquired September 20, 2006 of the Cuprite Mining District, Nevada, USA.
SPECIAL ISSUE ON SPECTRAL UNMIXING OF REMOTELY SENSED DATA

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About the Cover: Spectral unmixing results for Airborne Visible/Infrared Imaging Spectrometer (AVIRIS) data acquired September 20, 2006 of the Cuprite Mining District, Nevada, USA. Visible true-color (0.65, 0.55, 0.45 μm as RGB) and shortwave infrared (SWIR) color (2.1, 2.2, 2.34 μm as RGB) images are shown at left for reference. Spectral endmembers extracted from the SWIR data (2.0–2.5 μm) are shown in the spectral plot. The color-coded images with color bars show the Matched Filter (MF) estimated abundances for each endmember. The lower left image is a Mixture-Tuned-Matched-Filter (MTMF) classification result that takes mixing feasibility into account, using 2-D scatterplotting of high MF abundance versus low infeasibility score to show the spectrally predominant surface mineralogy in the same colors as the plot spectral endmembers. This “Feasibility Constraint” insures that minerals incorporated in the final mineral map are feasible mixtures of the background and the target mineral spectrum. Cuprite is a well-known geologic site often used for testing sensor and algorithm performance. Several of the papers in this issue show analysis results for these data. For more information, please see “Analysis of Imaging Spectrometer Data Using N-Dimensional Geometry and a Mixture-Tuned Matched Filtering Approach,” by Boardman and Kruse, which begins on page 4138.