An investigation on spectral noise in the Hyperspectral Thermal Emission Spectrometer (HyTES)

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Data

- HyTES is a long wave spectrometer covering the range 7.5 – 12 um.
- Lakes are ideal sites for noise estimation, as they are large and homogeneous
- JPL has established aquatic validation sites at Lake Tahoe, CA/NV and Salton Sea CA.
- Lake Tahoe CA/NV is at a high elevation (small atmospheric correction), whereas Salton Sea is at a low elevation (large atmospheric correction).
- HyTES data was acquired over Salton Sea on 2013/04/29, 2014/07/06, and 2015/02/15, and over Lake Tahoe on 2013/04/25 and 2014/07/12.
- In each case, a subset (512 x 512 pixels) of the image was used, encompassing water only (see Figure 1).
- For further testing, a non-water scene was acquired in Cuprite, Nevada, on 2015/05/03. This is a well characterized site for mineral mapping, due to its heterogeneity and unchanging landscape.

Figure 1: A flightline of HyTES data acquired over Salton Sea in 2015.

Noise estimation

The objective of this study was to characterize the spectral noise in HyTES. In this case, "noise" refers to all deviations from the desired observable, in this case the surface radiance, and includes contributions from instrument noise, errors introduced by calibration and atmospheric correction, and any offset occurring as a result of non-linear spectral interactions. The full understanding of the scene-specific noise is vital for almost all higher-level processing, including temperature/emissivity separation, target gas detection, image whitening, the estimation of the intrinsic dimension of the image, spectral unmixing, image compression, target detection, and many other applications.

- Meer's **Spatially Based noise estimation method**, uses the spatial information in the image to approximate the noise. For each band, the image is divided into non-overlapping spatial blocks and the variance is calculated per block, for a pyramid of block sizes. Given that five of the test images contain water only, this method is particularly well suited to our test datasets.
- **Multiple regression** theory expresses each band in terms of all other bands. The error in this regression is used to approximate the noise per pixel in the band. This method is computationally complex; however, it accounts for spatially variable or substance-dependent noise.

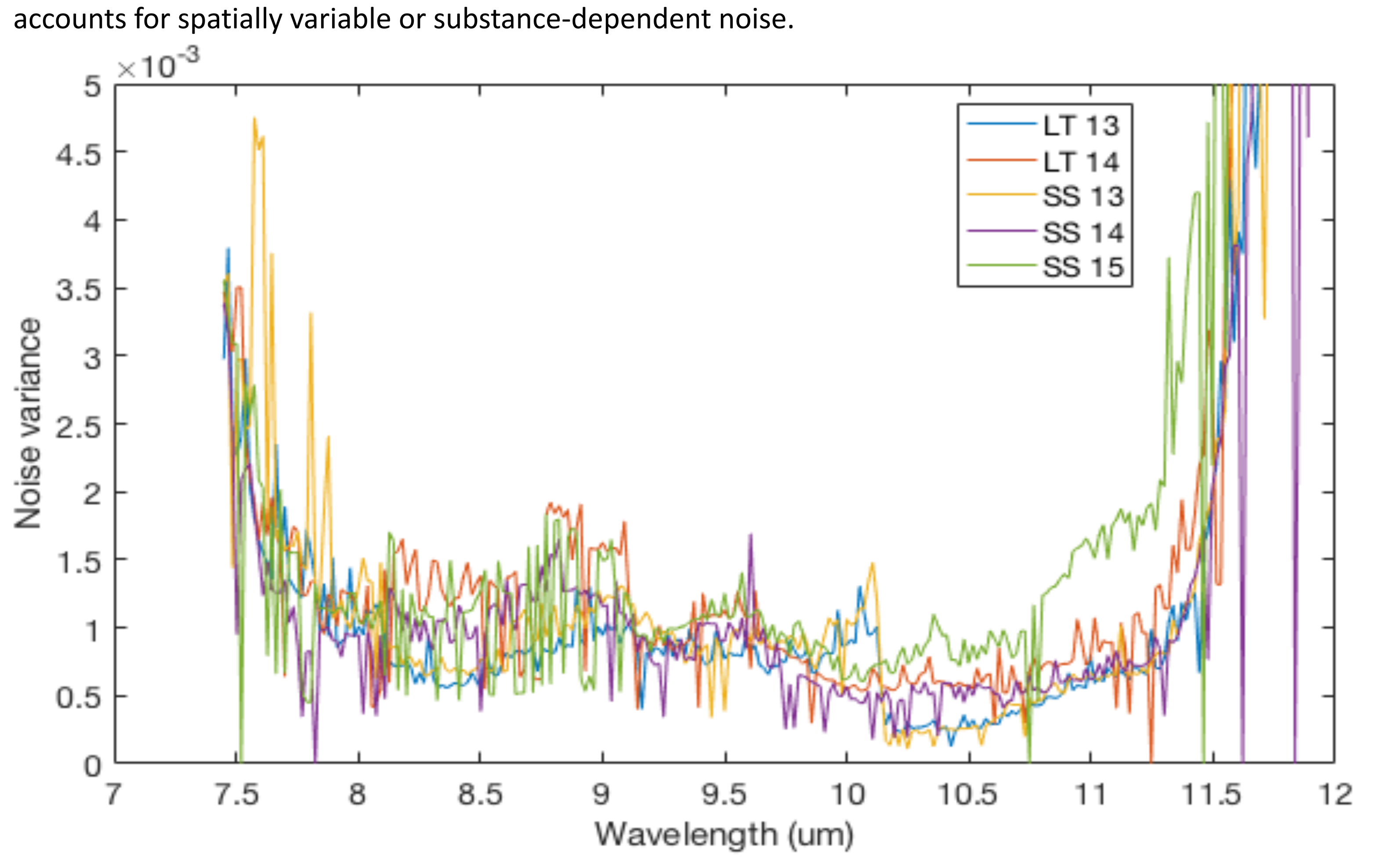

Figure 2: Noise variance per band as estimated by Meer's method for Lake Tahoe (LT) and Salton Sea (SS). The noise increases at the beginning and end of the spectrum, which is typical of many sensors. Here the noise increase is also due to large water absorption lines from 7.4-8.2 µm and low signal at wavelengths above 11.5 µm.

Correlated noise

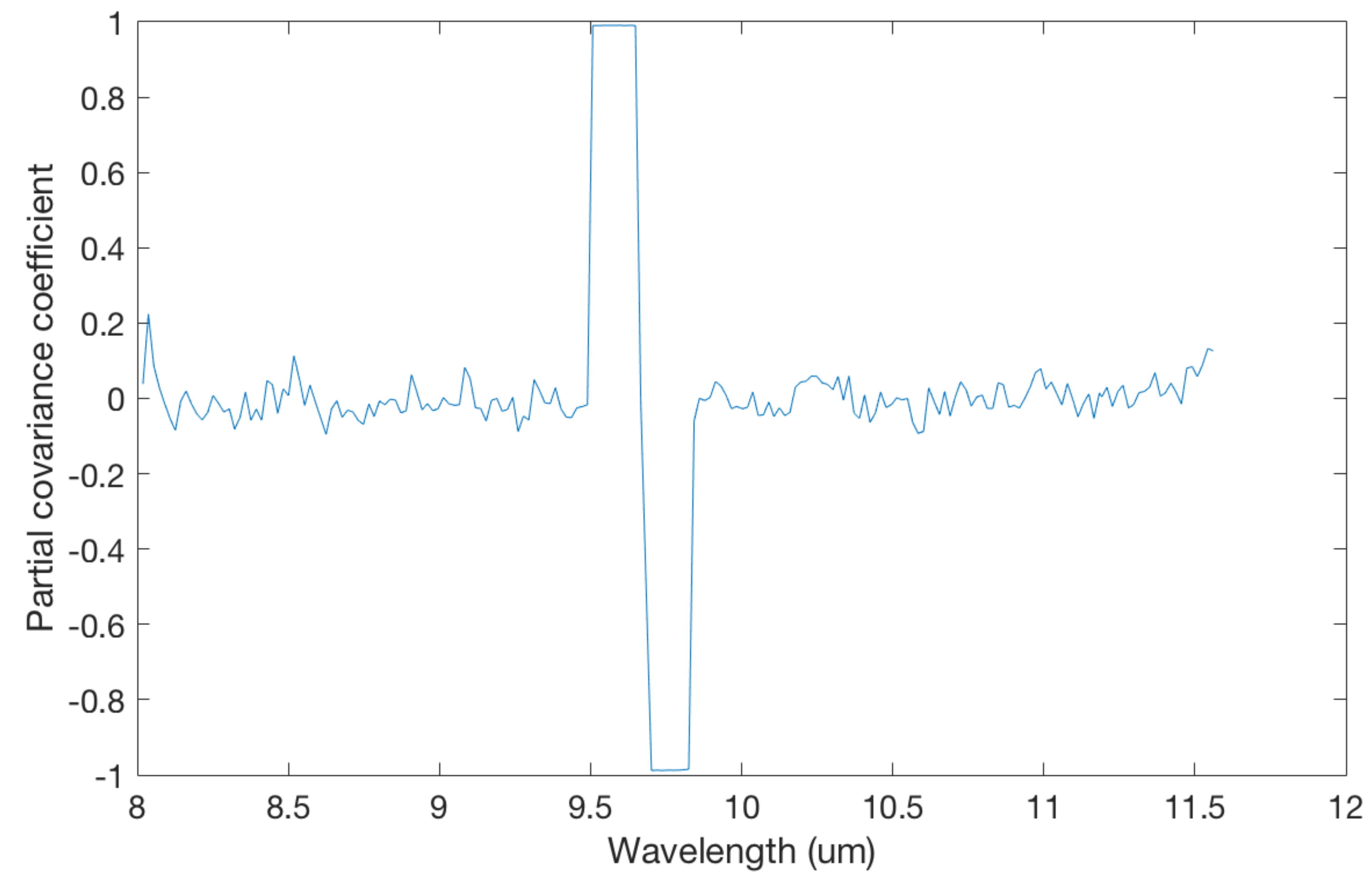

Figure 3: The band centered at 9.6839 µm has a very high positive correlation with the 9 bands preceding it, and a very high negative correlation with the 8 bands following it.

- Statistical noise estimations significantly underestimate noise when the noise is spectrally correlated.
- Spatial methods such as Meer's determine the noise variance band by band, but they do not capture the off-diagonal elements of the noise covariance matrix, which are needed for noise whitening.
- However, those methods that determine the correlations of noise are also adversely affected by correlated noise, creating a circular problem.
- Figure 3 shows that there is a high level of correlation in the range 9.5075 – 9.8251 µm. This region represents the overlap between the two detector bands within HyTES.
- Figure 4 shows that when alternate bands are removed, the statistical noise estimation appears to be continuous, when compared to the noise estimate from the original image, which shows step discontinuities when the bands become correlated.
- We propose a new method to estimate the full noise covariance matrix in cases of correlated noise as follows:

1. Split the bands into uncorrelated sets. For instance, in the datasets evaluated here, bands 1,3,…,201 are uncorrelated with 2,4,…,202.
2. Build up the uncorrelated sets so that all off-center noise covariance elements are covered. For instance, in the two separate sets listed above, it is impossible to know the noise covariance between bands 1 and 2 (etc.). In this case, it was possible to build a complete set using six band combinations.
3. Calculate the noise covariance matrix of each band subset listed above. Where multiple values are available for a particular band combination, the largest value is chosen, since correlation reduces the noise estimate, as seen in Figure 4.

Once the noise covariance has been accurately estimated, it can be used in many applications, including temperature/emissivity separation, target gas detection, noise whitening, target detection, the estimation of intrinsic dimensionality, etc.

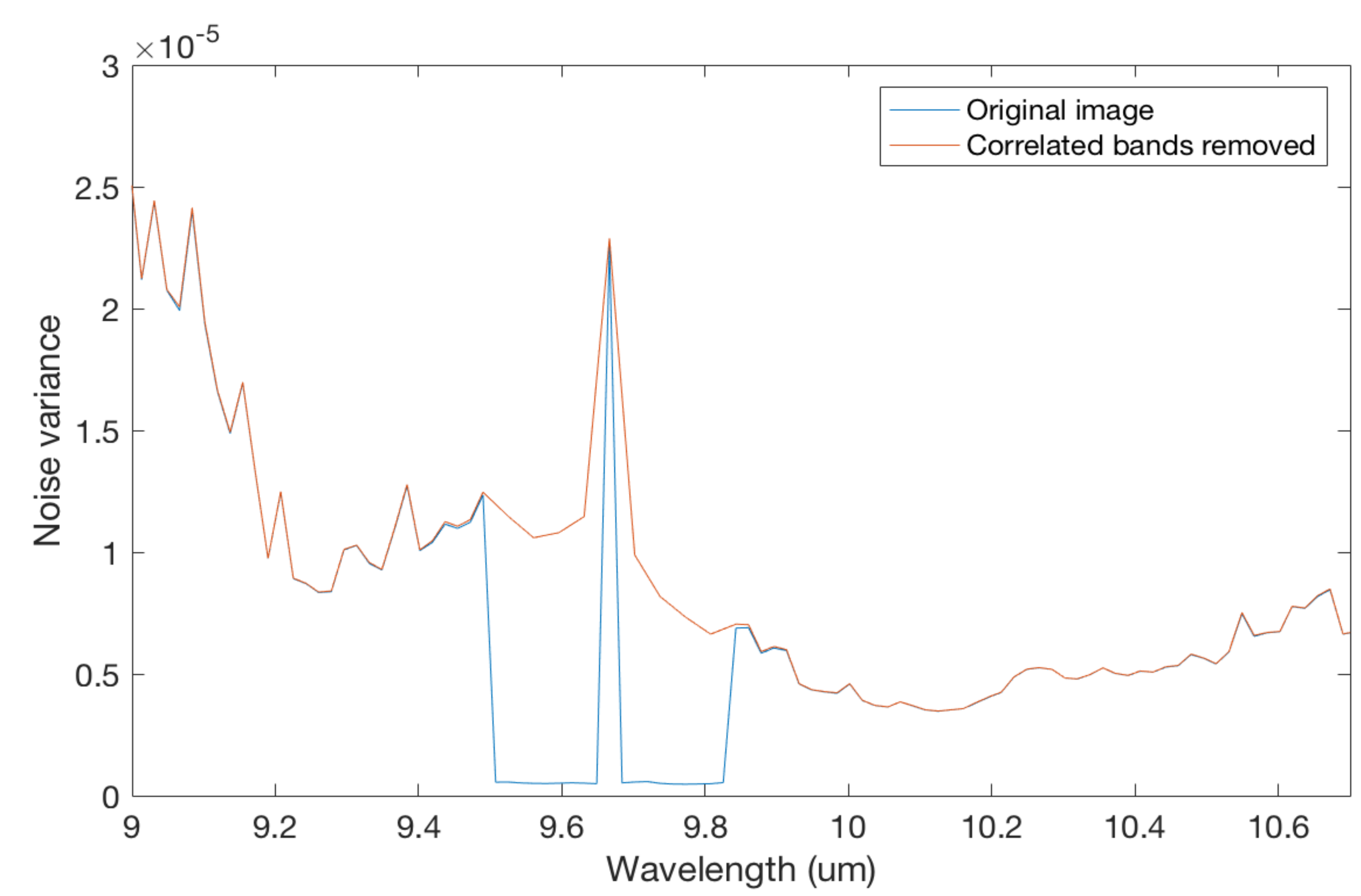

Figure 3: Statistical noise estimations show a step where bands become correlated. Removing correlation creates a smoother noise estimation.

Applications

To illustrate the utility of accurate noise estimation, we present an adaptive noise filtering technique, which takes the noise variance as input. The Savitzky-Golay filter uses a moving window to fit polynomials of order *n*, to each pixel subset (window). Each pixel is initially smoothed with a polynomial order of 3, and a window size of 11 bands (MATLAB default values). When comparing the original pixel to the smoothed spectrum, those channels that differ by more than twice the standard deviation of the noise are recomputed using iteratively smaller window sizes and polynomial orders. This ensures that the correction never exceeds the noise levels. Figure 3 shows the correction of a mineral spectrum taken from the Cuprite scene. The small features have been preserved, but the spurious noise has been smoothed.

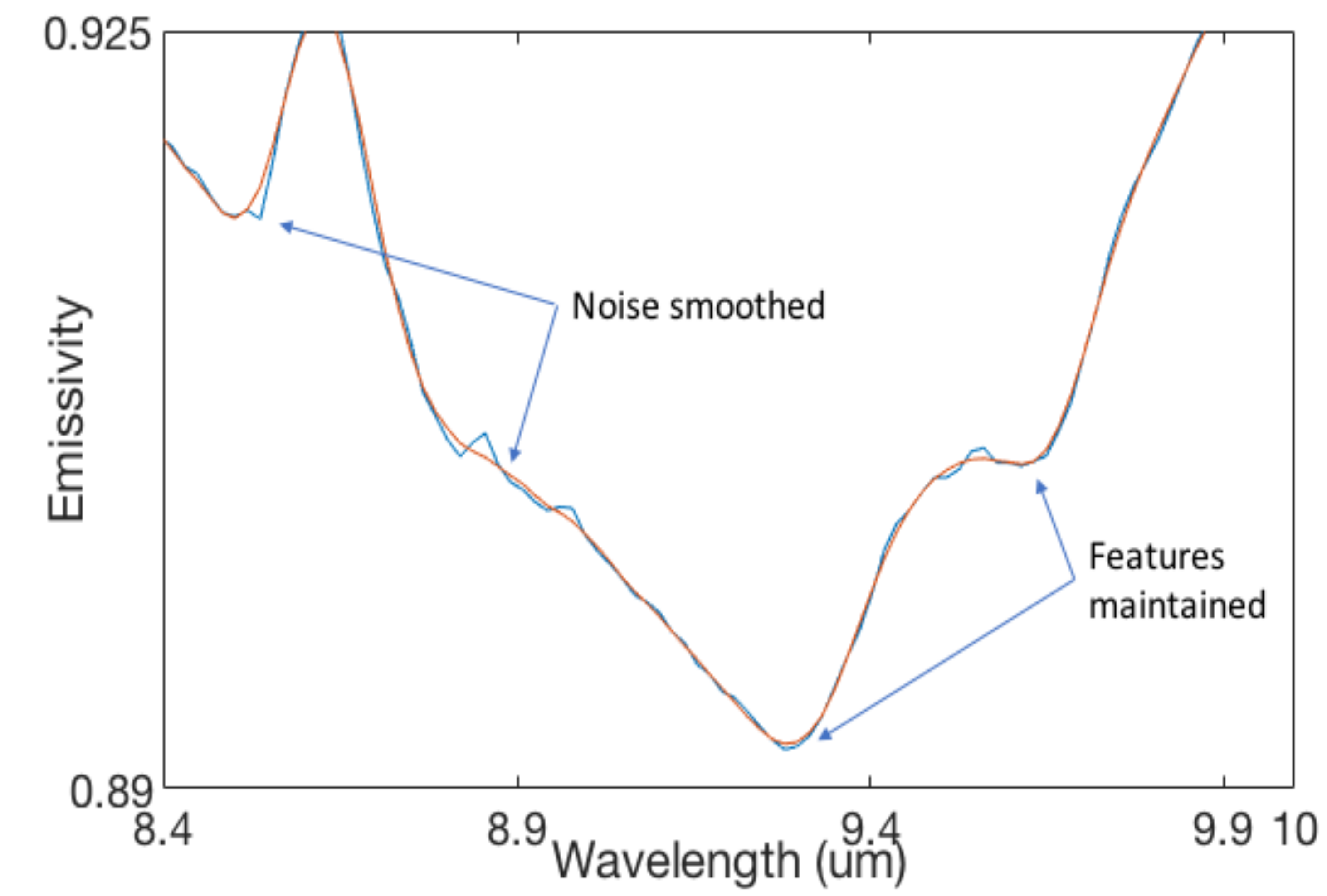

Figure 5: An illustration of an adaptive spectral smoothing technique, using the estimated noise covariance to ensure that signal features are not removed.

The correct estimation of noise is vital when determining the intrinsic dimensionality (ID) of a dataset. Using Random Matrix Theory (RMT), the original ID estimate for Cuprite is 178, which is much higher than anticipated for the area. RMT is known to be sensitive to correlated and underestimated noise, but the dimensionality overestimation is not unique to RMT – HySime returns an ID of 163. Using the corrected noise covariance matrix derived above, the RMT ID is determined to be 9.

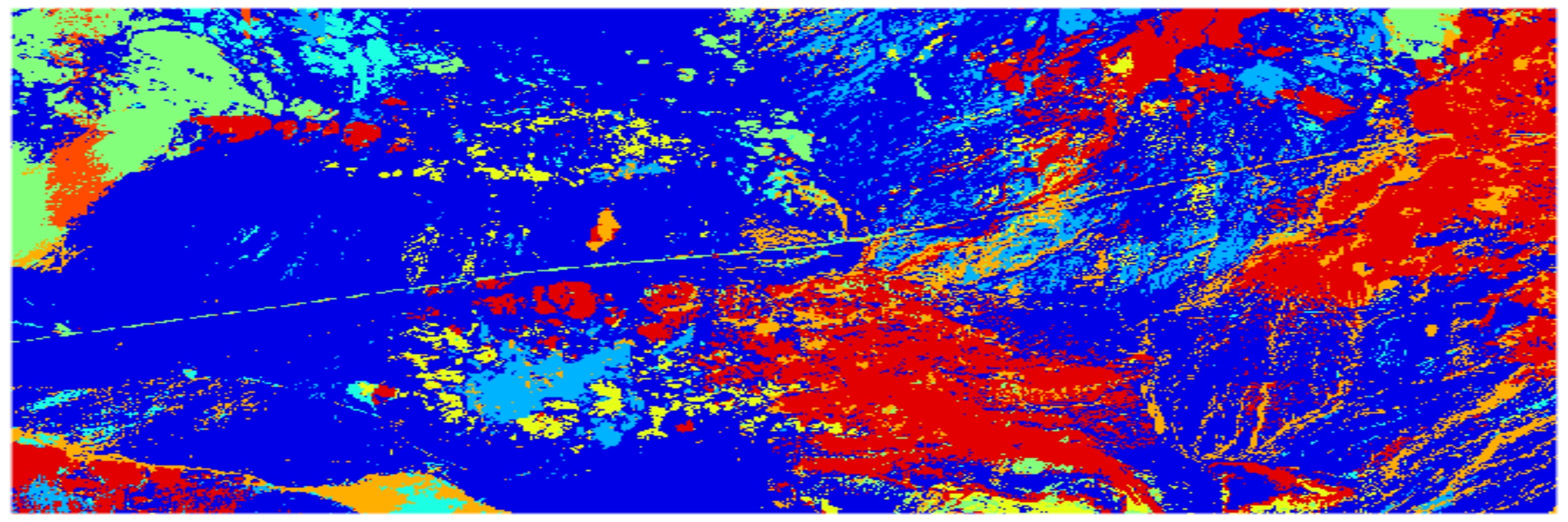

Figure 6: Unmixing the Cuprite scene using NFINDR with 9 endmembers, and non-negative least squares to determine abundances.

Discussion

- The estimation of the noise covariance matrix is necessary for many image processing applications.
- For example, in the determination of intrinsic dimensionality (ID), the noise covariance is necessary to separate the signal subspace from the noise subspace, and similarly, in image unmixing, and in the detection of small targets, the noise covariance is needed in order to separate the target from the background.
- However, the estimation of the noise covariance matrix is difficult, particularly in the case of correlated noise.
- In this project, we present the results of standard noise estimation algorithms, applied to images acquired by the airborne Hyperspectral Thermal Emission Spectrometer (HyTES), and modify them as needed to obtain an accurate estimation of the noise covariance matrix.
- Additionally, several applications are illustrated, including dimensionality estimation and noise removal.
- This technique will benefit the current HyTES data products by reducing noise in retrieval of spectral emissivity, reduce uncertainties in temperature estimation, and improve the sensitivity of trace gas detection (e.g. methane, ammonia).
- In addition, it will provide a framework for analyzing noise variances and correlations in future airborne and spaceborne hyperspectral missions.