



Evaluating Spectral Consistency of Fe-Related Wavelength Ranges between EO-1 Hyperion and Field Spectrometer Data in the Kulon Progo Iron Sand Deposit

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Received : August 05, 2026

Revised : September 09, 2026

Accepted : September 10, 2026

Online : October 07, 2026

Abstract

Iron sand deposits contain Fe-bearing oxide minerals with characteristic reflectance features, but field spectrometer and hyperspectral image measurements of these features do not always agree, owing to differences in sensor characteristics, observation scale, and surface conditions. This study evaluates the spectral consistency between ASD FieldSpec and EO-1 Hyperion reflectance over the Kulon Progo iron sand deposit, and examines how spectral processing and spatial representation affect that consistency. Fifteen Hyperion bands were selected on physical grounds, eight within 480-560 nm and seven within 850-950 nm, and compared with resampled ASD spectra at 35 points with paired laboratory total-Fe data, using Pearson correlation (r) and RMSE, under raw, Savitzky-Golay smoothed, and continuum-removed spectra, and across four spatial extraction windows (1x1 to 7x7 pixels). The 850-950 nm range showed markedly stronger agreement than 480-560 nm (raw mean $r = 0.573$ versus -0.037). Smoothing raised the 850-950 nm correlation to $r = 0.601$; the pattern suggests that high-frequency noise in the Hyperion spectra may contribute to part of the disagreement, though the improvement did not reach conventional statistical significance (Hotelling-Williams test, $p > 0.05$). Continuum removal did not improve cross-sensor agreement, and correlation in the 850-950 nm range increased with window size ($r = 0.614$ at 1x1 to $r = 0.693$ at 7x7) without a corresponding change in RMSE. These results show that physical relevance alone does not guarantee cross-sensor consistency, and that band selection for Fe detection with hyperspectral imagery should also consider sensor-related spectral variation and observation scale.

Keywords: *Iron Sand, Spectral Reflectance, EO-1 Hyperion, ASD FieldSpec, Cross-Sensor Consistency, Hyperspectral Remote Sensing.*

INTRODUCTION

Iron sand deposits contain Fe-bearing oxide and oxyhydroxide minerals, such as hematite and goethite, whose reflectance is governed by well-documented electronic transitions in the visible and near-infrared range (Sherman & Waite, 1985; Scheinost et al., 1998). This physical basis motivates the use of spectroscopy and hyperspectral remote sensing for Fe-bearing material, but reflectance is also modulated by grain size, mineral mixture, moisture, and surface condition, so a wavelength range being physically relevant to Fe does not by itself guarantee that two different sensors will record it consistently.

Hyperspectral imagery provides many contiguous bands, but not every band contributes equally to Fe analysis: regions near 1400 and 1900 nm, for instance, are strongly affected by water and hydroxyl absorption, making their interpretation less direct for the Fe-related spectral response examined here (Murphy, 2015), and a poorly justified band choice can introduce information that does not represent the material of interest. Even within bands that are physically relevant to Fe, agreement between a field spectrometer and a satellite sensor is not automatic, since the two instruments differ in spectral response, radiometric behaviour, and the spatial scale they

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sample (Chander et al., 2013; U.S. Geological Survey, 2023), a distinction that is frequently assumed rather than tested. As shown later in this study, the 480-560 nm range is physically relevant to Fe on exactly this basis (Scheinost et al., 1998), yet the empirical ASD-Hyperion correlation there was essentially absent (mean $r = -0.037$), while 850-950 nm, physically relevant on the same grounds, showed a substantially stronger correlation (mean $r = 0.573$). This gap between physical relevance and empirical cross-sensor consistency is the problem this study addresses, rather than assuming a physically justified band is automatically usable.

Prior Hyperion-based studies of iron ore and iron oxide deposits have used absorption-feature depth near 850-900 nm to estimate Fe content (Magendran & Sanjeevi, 2013, 2014; Shaik et al., 2021; Bouzidi et al., 2022), but generally do not report how closely the satellite spectrum agrees with concurrent field measurements at the same locations, nor how that agreement changes under common preprocessing or spatial aggregation choices. Kulon Progo's heterogeneous surface conditions, in mineral composition, grain size, moisture, and texture, make this question practically important whenever a field spectrum is used to validate or interpret an image pixel.

This raises four questions: (1) how consistent is ASD-Hyperion reflectance within Fe-related wavelength ranges at this site; (2) does this consistency differ between the 480-560 nm and 850-950 nm ranges; (3) how do Savitzky-Golay smoothing and continuum removal affect it; and (4) how does the spatial window used to extract Hyperion reflectance affect agreement with point-based field measurements?

To address these questions, this study evaluates the cross-sensor consistency of ASD and Hyperion reflectance within two physically justified Fe-related wavelength ranges, 480-560 nm and 850-950 nm, at 35 points with paired laboratory total-Fe data, and examines how Savitzky-Golay smoothing, continuum removal, and spatial extraction window affect that consistency. The results provide an empirical basis for selecting wavelength ranges for Fe detection with hyperspectral imagery, and clarify which processing and scale factors matter when field spectra are compared with image pixels.

LITERATURE REVIEW

Spectral response of Fe-bearing material

Fe-bearing oxide and oxyhydroxide minerals show reflectance features from electronic transitions in the mineral structure (Sherman & Waite, 1985). Feature position and strength vary by mineral: Scheinost et al. (1998), from diffuse reflectance spectroscopy of natural and synthetic iron oxide samples, reported hematite features near 521-565 nm and 848-906 nm, with other iron oxides at different positions. Reflectance is further modulated by grain size, mineral mixture, moisture, and surface condition; for instance, organic matter content has been shown to systematically alter the VIS-NIR spectral signature of iron oxides in controlled mixture experiments (Pearlshtien & Ben-Dor, 2020), which matters for heterogeneous material such as iron sand.

Fe-related spectral response in the visible and near-infrared

Several studies report Fe-related information in both ranges. In the near-infrared, Magendran and Sanjeevi (2014) found a strong absorption feature near 850-900 nm in Hyperion-derived iron ore spectra, with feature depth, width, and area related to oxide concentration; Magendran and Sanjeevi (2013) and Shaik et al. (2021) report comparable behaviour for hematite ore. In the visible range, 480-560 nm includes the hematite feature reported by Scheinost et al. (1998) near 521-565 nm, so Fe-related information is not confined to the near-infrared alone. This motivates comparing the two ranges empirically, rather than assuming both are equally usable.

Field spectroscopy and hyperspectral imagery for Fe detection

Field spectroscopy provides high spectral resolution over a small footprint and has been used to relate spectral features to Fe content or ore grade (Magendran & Sanjeevi, 2013). Hyperspectral imagery, by contrast, provides simultaneous spatial coverage: Hyperion pixels have distinguished ore grades and mapped Fe-bearing mineral abundance (Magendran & Sanjeevi, 2014), characterized hematite classes at a mining site (Shaik et al., 2021), and identified iron mineralization elsewhere (Bouzidi et al., 2022). More recent work has extended this toward automated, machine-learning-based iron ore and total-Fe estimation from hyperspectral data (Xu et al., 2023; Liu et al., 2023; Das et al., 2026), and toward coastal placer-deposit mapping using satellite spectral matching (Ng-Cutipa et al., 2025); like the earlier feature-based studies, these typically report within-sensor model or classification performance rather than field-to-image cross-sensor agreement, the gap this study addresses. Because a field measurement samples a small area while a satellite pixel integrates a much larger one, the two need not record the same composition, particularly over heterogeneous surfaces.

Factors affecting cross-sensor spectral agreement

Cross-sensor comparison depends on more than wavelength alone. Differences in spectral, radiometric, and spatial characteristics affect agreement between sensors (Chander et al., 2013), and EO-1 Hyperion itself combines two detector arrays, VNIR and SWIR, whose ranges overlap near 900-1000 nm (Pearlman et al., 2003), a region documented as more prone to calibration artefacts than surrounding bands. At the spatial scale, an intercomparison of transect-based field, drone, and satellite reflectance over heterogeneous rangeland found agreement between platforms to change systematically with the spatial support compared (Slade et al., 2023), consistent with a larger footprint averaging more surface heterogeneity than a field reading. Preprocessing also matters: Savitzky-Golay smoothing reduces high-frequency fluctuation while preserving spectral shape (Savitzky & Golay, 1964), and continuum removal renormalizes reflectance to a local continuum to emphasize absorption features (Kruse et al., 1993; Qi et al., 2024), but neither is guaranteed to improve cross-sensor agreement, since each operates on a single spectrum's noise and shape rather than the discrepancy between instruments. More direct approaches explicitly model and correct multi-sensor radiometric and spectral differences (Obata & Yoshioka, 2024), and terrain-aware uncertainty frameworks have likewise been proposed to quantify cross-sensor consistency of hyperspectral surface reflectance more generally (Zhao et al., 2026), offering routes beyond the band-position matching used here.

RESEARCH METHODOLOGY

Data

Three datasets were used: ASD FieldSpec reflectance (350-2500 nm, 1 nm sampling), EO-1 Hyperion surface reflectance, and laboratory total-Fe content. The supplied Hyperion dataset contained 160 valid bands from the sensor's original 242 bands and had already undergone good-band screening and masking as part of the upstream processing. Because this study used the processed cube directly, the 160 available bands were treated as the valid spectral dataset for subsequent analysis. The processed Hyperion cube represented surface reflectance at approximately 30 x 30 m spatial resolution (UTM Zone 49S, WGS84), and reflectance at each sample location was extracted as the pixel value at the corresponding coordinate. A total of 35 sampling points were randomly selected for analysis based on the availability of paired ASD, Hyperion, and laboratory total-Fe data, with total-Fe content ranging 0.02-0.13%; the field-measured population was larger overall, since laboratory Fe analysis was not obtained for every point. Laboratory total-Fe data were used as supporting data to evaluate whether the observed spectral responses showed

patterns associated with Fe variation, rather than as the primary target for quantitative modelling. One ASD sample with two available scans was represented by the mean of the two scans. Field reflectance measurements over granular sand surfaces are also known to be sensitive to viewing and illumination geometry (Wise & Mars, 2022), a factor not separately controlled for in the present field survey. Figure 1 shows the spatial distribution and Fe range of these 35 points.

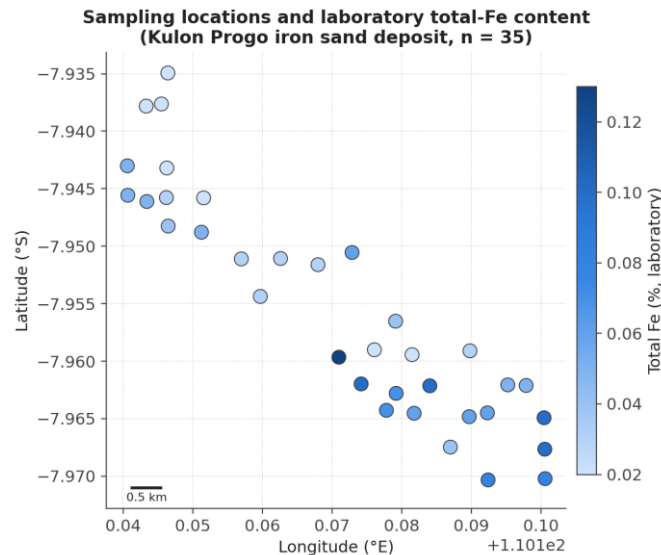


Figure 1. Sampling locations and laboratory total-Fe content (n = 35)

Wavelength resampling and band selection

ASD spectra were resampled to Hyperion band positions by nearest-wavelength matching, verified here to reproduce the resampled values to within rounding error, and hence treated as position-matching rather than full spectral-response-function harmonization. Two wavelength ranges reported as physically relevant to Fe, 480-560 nm and 850-950 nm (Section II), were selected before the comparison was run, corresponding to 15 of the 160 Hyperion bands, 8 within 480-560 nm and 7 within 850-950 nm (Table 1). Selecting both ranges from the literature, not from this dataset's own correlations, keeps the subsequent test of which range agrees better between sensors independent of the selection itself.

Table 1. Bands used

Wavelength range	Hyperion band (nm)
480-560 nm	487.87; 498.04; 508.22; 518.39; 528.57; 538.74; 548.92; 559.09
850-950 nm	854.18; 864.35; 874.53; 912.45; 922.54; 932.64; 942.73

Spectral processing

Two preprocessing variants were then tested. Savitzky-Golay smoothing (polynomial order 2; window lengths of 11, 21, 31, and 51 points) was applied to the 1 nm ASD spectra prior to resampling, and, exploratorily, to the Hyperion spectra using an 11-band window, to test whether reducing high-frequency fluctuation on either or both sides changes ASD-Hyperion agreement. Continuum removal (Kruse et al., 1993) isolated absorption-feature depth within 480-560, 650-700, and 850-950 nm, related both to laboratory Fe content and, separately, to the corresponding

depth on the other sensor; because continuum removal changes the reflectance scale, its output was treated as a feature-characterization measure rather than compared directly to absolute reflectance.

Cross-sensor agreement and spatial-window analysis

Using the raw and preprocessed spectra from Sections III.2-III.3, agreement between ASD and Hyperion was quantified with Pearson correlation (r) and RMSE at each of the 15 bands, summarized by wavelength range. In this study, RMSE values were considered comparable when they showed no material change across the compared processing or spatial conditions, rather than when they met a predefined absolute threshold. Because RMSE is reported in reflectance units, comparisons were made within the same dataset and analysis condition rather than against a universal RMSE benchmark. Here, a higher Pearson $|r|$ indicates a stronger linear association between the two spectra, while a lower RMSE indicates a smaller average discrepancy between the paired reflectance values; because these two measures capture different aspects, pattern versus magnitude, higher correlation need not mean lower RMSE, as shown in Section IV.5. No universal correlation threshold was imposed because the analysis was intended to compare the two physically selected wavelength ranges rather than classify agreement into fixed categories. RMSE was calculated as the square root of the mean squared difference between paired ASD and Hyperion reflectance values at each corresponding wavelength. To evaluate spatial support, the mean Hyperion reflectance within 3x3, 5x5, and 7x7 pixel windows was additionally extracted and compared against the same ASD spectra, using the single-pixel 1x1 extraction as the baseline; the 7x7 window covers approximately 210 x 210 m, much larger than the ASD footprint, so this test evidences how spatial support affects agreement rather than identifying an equivalent field footprint. Hyperion's spectral bandwidth was tested separately by integrating the 1 nm ASD spectrum using each band's full width at half maximum (FWHM) under Gaussian and boxcar weighting and comparing this to the unweighted nearest-wavelength value; using FWHM alone does not constitute full sensor harmonization, which would additionally require each band's complete spectral response function.

FINDINGS AND DISCUSSION

Comparison across the 15 selected bands

Pearson correlation between ASD and Hyperion differed sharply between the two ranges (Figure 2). Within 480-560 nm, r ranged from -0.170 to 0.137 (mean r = -0.037); within 850-950 nm, r ranged from 0.537 to 0.637 (mean r = 0.573), with the strongest agreement at 932.6 nm. Physical relevance to Fe is therefore not, by itself, a sufficient basis for band selection: 480-560 nm is physically relevant to Fe on the same grounds as 850-950 nm (Section II) yet performed far worse empirically. Because the physical basis for both ranges is comparable, the difference may partly reflect differences in signal-to-noise conditions, since visible-range reflectance over this dark iron sand surface is markedly lower in absolute terms than in the near-infrared, so a similar level of instrument noise represents a much larger relative error at 480-560 nm. The stronger agreement in the 850-950 nm range is consistent with, though weaker than, the strong near-infrared absorption reported for Hyperion-derived iron ore spectra elsewhere ([Magendran & Sanjeevi, 2014](#); [Shaik et al., 2021](#)), which characterize within-sensor spectral features rather than the cross-sensor agreement tested here.

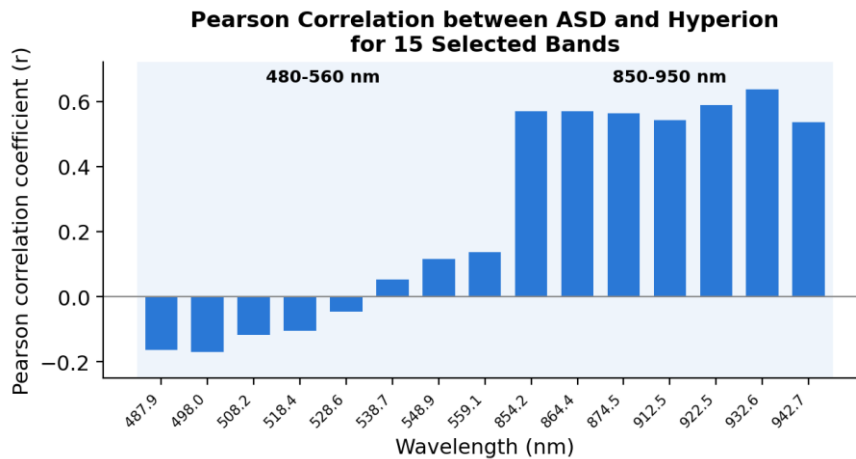


Figure 2. Pearson correlation (r) between ASD and Hyperion for each of the 15 selected bands

Effect of Savitzky-Golay smoothing

Smoothing raised the 850-950 nm mean correlation from $r = 0.573$ to $r = 0.601$, a small but informative change. Decomposing which side of the comparison drove this improvement shows that smoothing the ASD spectrum alone left the correlation effectively unchanged ($r = 0.573$), whereas smoothing the Hyperion spectrum alone reproduced the full improvement ($r = 0.601$) (Figure 3); the two spectrometers therefore did not contribute equally to the pre-smoothing discrepancy. This pattern suggests that high-frequency noise in the Hyperion spectra may contribute to part of the observed disagreement, consistent with a spaceborne sensor operating at a lower signal-to-noise ratio than a field spectroradiometer, though the comparison here is indicative rather than a controlled test of the noise source. Even at the single band showing the largest gain (912.5 nm, $r = 0.542$ to 0.638), a Hotelling-Williams test for dependent, overlapping correlations did not reach conventional significance ($t(32) = -1.82$, $p = 0.079$, $n = 35$), so the smoothing effect is best interpreted as a modest trend that may be related to high-frequency spectral fluctuation rather than as a confirmed improvement. The remaining gap after smoothing therefore reflects factors that smoothing cannot address, such as spectral response differences, spatial-scale mismatch, and the acquisition-time gap discussed in the Conclusion.

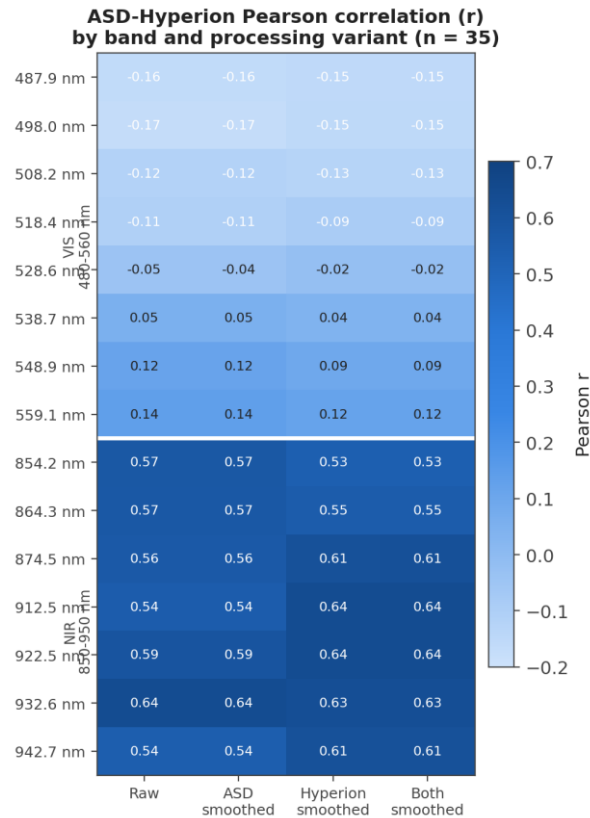
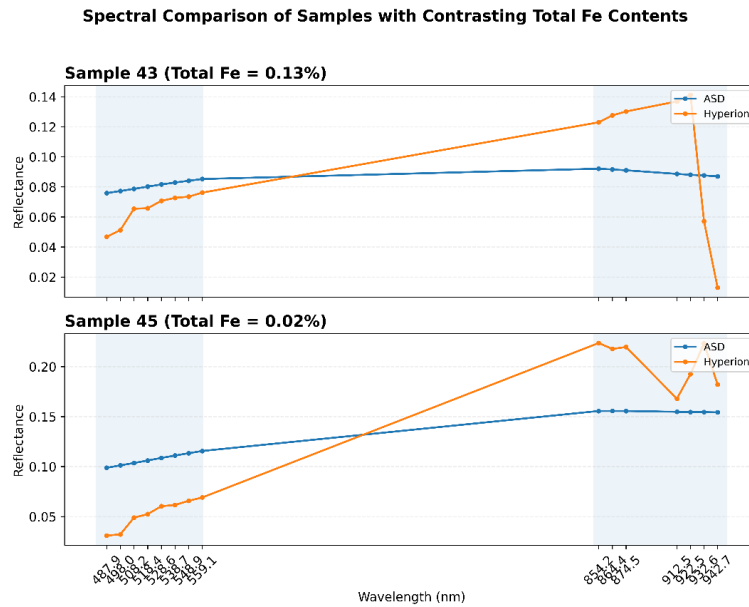


Figure 3. ASD-Hyperion Pearson correlation (r) by band and processing variant (raw, ASD-smoothed only, Hyperion-smoothed only, both smoothed)

Contrasting samples and a Hyperion-specific anomaly

Comparing samples with contrasting laboratory Fe (sample 43, Fe = 0.13%; sample 45, Fe = 0.02%) shows that higher total Fe did not correspond to a consistently lower or higher ASD reflectance, so total Fe alone does not predict the direction of reflectance change; mineral type, grain size, and material mixture plausibly also matter (Section II.1). Figure 4 compares the full ASD and Hyperion spectra at these two points. On Hyperion, both samples show a sharp reflectance drop near 932-943 nm with no counterpart on the ASD spectrum at the same wavelengths. This pattern is therefore unlikely to be a Fe absorption feature. This range sits close to the boundary between Hyperion's VNIR and SWIR detector arrays, which overlap near 900-1000 nm (Pearlman et al., 2003); a sensor-related calibration effect at this overlap is therefore a plausible explanation, though this dataset cannot rule out other causes and the interpretation should be read as indicative rather than confirmed.



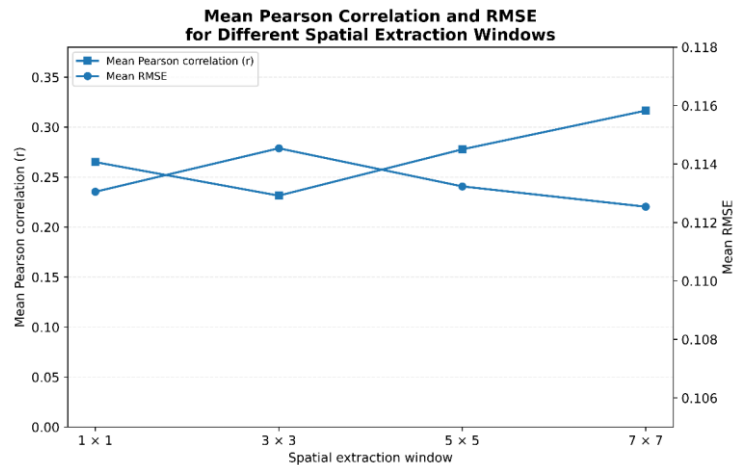


Figure 5. Correlation (r) and RMSE between ASD and Hyperion across spatial extraction windows (1x1 to 7x7 pixels), 850-950 nm. Note that the RMSE axis is scaled to the observed range rather than starting at zero, so apparent changes in the RMSE line should be read against its stated axis limits, not assumed to be zero-based.

To examine whether this window-size effect held consistently across individual points rather than being driven by a few outliers, Figure 6 plots the per-point ASD-Hyperion relationship separately for each window size; the near-parallel, upward-shifting fit lines indicate the correlation gain is a broad pattern across the sample rather than an artefact of a few points.

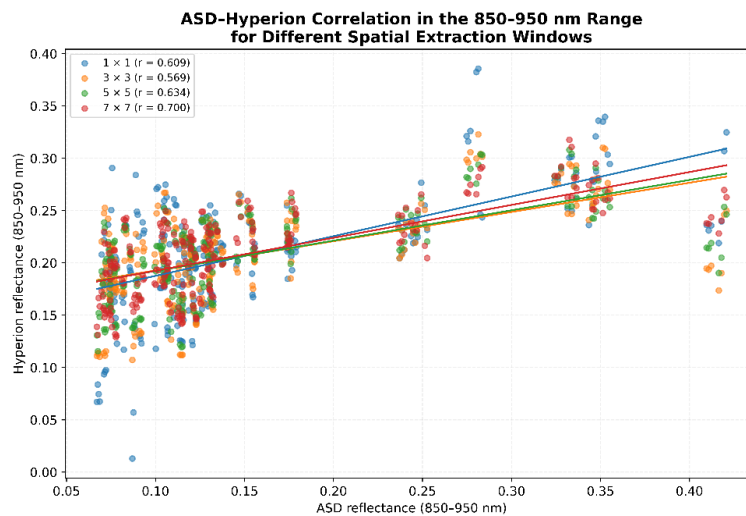


Figure 6. Per-point ASD-Hyperion reflectance relationship across spatial extraction window sizes, 850-950 nm

Because RMSE stayed essentially constant while correlation rose, the larger window improved how consistently the spectral pattern varied between sensors, rather than how closely the absolute reflectance values matched. A possible explanation is that averaging a larger area reduces local variation in surface reflectance. This makes the spatial support of the Hyperion data more comparable with the heterogeneous surface represented by the field measurements. This matches an independent intercomparison of field, drone, and satellite reflectance over heterogeneous rangeland, which likewise found agreement to depend systematically on the spatial support compared, not on wavelength alone (Slade et al., 2023). Because the 7x7 window (approximately 210 x 210 m) is far larger than the ASD footprint, this result shows that spatial

support affects cross-sensor agreement here, not that 7x7 is a corrected equivalent of the field measurement; for field-validation design, it suggests that differences between a single point measurement and a single satellite pixel may reflect spatial support in addition to sensor characteristics, and that multiple, spatially distributed field readings or an intermediate aggregation footprint may provide better validation of image-derived Fe indices at this site.

Effect of Hyperion bandwidth (FWHM)

Adjusting the ASD spectrum for each band's FWHM, under both Gaussian and boxcar weighting, left correlation and RMSE for the 15 bands essentially unchanged from the unweighted comparison ($r = 0.248$ unweighted; mean reflectance shift of about 6.5×10^{-5} after Gaussian integration). Because this test represents each band only by its FWHM, it cannot capture asymmetry or secondary lobes in the band's true spectral response function (SRF); bandwidth alone is therefore unlikely to be a major factor, though an effect from the complete SRF, unavailable here, cannot be excluded.

Implications for Fe detection with hyperspectral imagery

These findings indicate that wavelength selection for Fe analysis should weigh both physical relevance and empirical cross-sensor consistency rather than either alone. Section V translates these results into specific band, preprocessing, and spatial-scale guidance for practitioners comparing field and image spectra.

CONCLUSION AND FURTHER RESEARCH

This study evaluated the cross-sensor consistency of ASD and Hyperion reflectance within two Fe-related wavelength ranges over the Kulon Progo iron sand deposit. The 850-950 nm range showed substantially stronger and more consistent agreement than 480-560 nm despite comparable physical justification for both, with raw mean Pearson correlation of $r = 0.573$ versus $r = -0.037$ across 35 points. Savitzky-Golay smoothing raised the 850-950 nm correlation to $r = 0.601$, though the improvement was not statistically significant at the single band tested. Continuum removal did not improve, and for 850-950 nm worsened, cross-sensor agreement. Spatial window size affected correlation more than RMSE, with 850-950 nm correlation increasing from $r = 0.614$ at 1x1 to $r = 0.693$ at 7x7 pixels. The main contribution of this study is to show, quantitatively, that a wavelength range's physical relevance to Fe does not guarantee its empirical reliability across sensors. The results indicate that sensor-related spectral variation and spatial representation may be more influential than the tested bandwidth adjustment in explaining the differences between the two datasets.

These results support specific guidance for practitioners comparing ASD field spectra with Hyperion reflectance for Fe-bearing material. The 850-950 nm range (the seven bands near 854-943 nm used here) is recommended for cross-sensor Fe-related comparison at this site; 480-560 nm showed essentially no linear association (mean $r = -0.037$) and should not be relied on alone. Savitzky-Golay smoothing of the Hyperion spectrum gave a modest, non-significant improvement within 850-950 nm ($r = 0.573$ to 0.601) and may be applied but is not required, whereas continuum removal is not recommended for cross-sensor comparison, since it worsened agreement in both ranges. Extracting Hyperion reflectance over a larger spatial window, up to 7x7 pixels (approximately 210 x 210 m) here, improved correlation with point-based ASD measurements without reducing RMSE; practitioners should therefore expect closer pattern-level, not necessarily closer magnitude-level, agreement as the aggregation window grows, though this study does not establish 7x7 as an optimal or universally applicable window size.

Several limitations qualify these conclusions. First, Hyperion preprocessing (good-band screening and masking) was inherited from the data provider rather than performed independently, so band-level artefacts specific to that processing cannot be fully separated from genuine sensor behaviour. Second, the FWHM-based bandwidth test does not represent each band's complete spectral response function, so a residual bandwidth effect beyond FWHM cannot be excluded. Third, the analysis set ($n = 35$) is modest for band-level correlation testing, and the significance test in Section IV.2 should be read with this sample size in mind. Fourth, the approximately 20-year gap between the Hyperion acquisition (2006) and the ASD field survey (2026) means surface changes over that interval cannot be separated from sensor- and scale-related effects, so the ASD-Hyperion differences reported here should not be attributed to sensor characteristics alone. Further research should evaluate the temporal stability of the sampling locations using multi temporal imagery spanning this interval, apply the same comparison to more recent hyperspectral acquisitions where available, and extend the analysis to a larger, purpose-sampled dataset with full sensor spectral-response-function harmonization, for example following unmixing-based multi-sensor harmonization approaches (Obata & Yoshioka, 2024), to support quantitative Fe estimation models building on the 850-950 nm range identified here.

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