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Research article

Hyperspectral analysis of sugar beet (*Beta vulgaris* L.) response to different potassium fertilization levels for sustainable crop production

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S1. Reflectance signature variation among sugar beet samples during growth at 60 K

S1.1. Spectral Signature of Sugar beet samples

The spectral reflectance curves of twelve sugar beet samples collected during the growth stage exhibit distinct patterns across the 350–1100 nm wavelength range (Figure S1). All samples demonstrated the characteristic vegetation spectral signature, with a strong increase in reflectance around 700 nm corresponding to the red-edge region, indicating healthy chlorophyll content and active photosynthesis.

Among the samples, variation in reflectance intensity was observed, especially in the near-infrared (NIR) region (750–1050 nm), where differences in leaf structure, biomass, and internal cellular composition typically influence spectral response. Notably, Sugar Beet 6 exhibited the highest reflectance across most wavelengths, suggesting higher vigor or biomass compared to the other samples. In contrast, Sugar Beet 3 showed relatively lower reflectance, particularly in the NIR region, potentially indicating lower chlorophyll content or stress-related factors.

The visible spectrum (400–700 nm) revealed consistent absorption in the blue (450 nm) and red (680 nm) regions and a modest peak around 550 nm (green), which is typical for green vegetation. However, slight differences in the depth of absorption and slope of the red edge further emphasize physiological variation among samples.

Overall, the reflectance fingerprint analysis reveals intra-species diversity in physiological status among the sugar beet plants during active growth, providing a non-destructive tool for monitoring crop health and guiding precision nutrient or irrigation management.

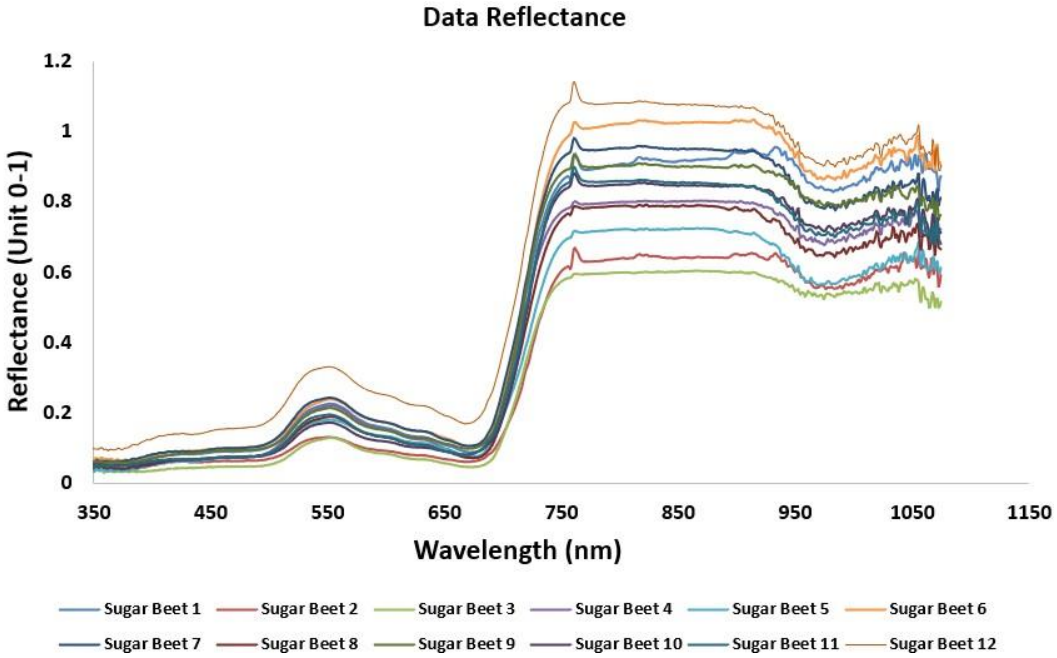


Figure S1. Reflectance signature variation among Sugar Beet samples.

S1.2. ANOVA of sugar beet spectral reflectance among Sugar Beet samples

The ANOVA results for spectral reflectance of sugar beet samples treated with 60 kg K_2O/fed revealed significant differences among individual samples across all spectral regions (Blue, Green, Red, and NIR) ($P < 0.05$) (Figure S2). Mean ± SE comparisons indicated that variation among sugar beet plants was most pronounced in the NIR band, where reflectance values ranged widely, reflecting differences in internal leaf structure and canopy density. In contrast, the blue and red regions displayed more consistent patterns, with clear troughs corresponding to pigment absorption zones.

In the green region, variability was observed among samples, consistent with differential chlorophyll absorption around 550 nm. The NIR region (700–1100 nm) exhibited the largest separation among plants, confirming its sensitivity to structural and physiological differences even within the same fertilization treatment. These findings highlight that, although potassium was applied at the same rate (60 K_2O), individual plant responses exhibited detectable spectral variability, emphasizing the potential of hyperspectral sensing in capturing within-treatment.

The spectral vegetation indices recorded for twelve sugar beet samples during the growth stage reveal notable physiological variability among individual plants. NDVI values ranged from 0.7033 in Sugar Beet 12 to 0.8541 in Sugar Beet 3, suggesting considerable differences in chlorophyll content and canopy vigor.

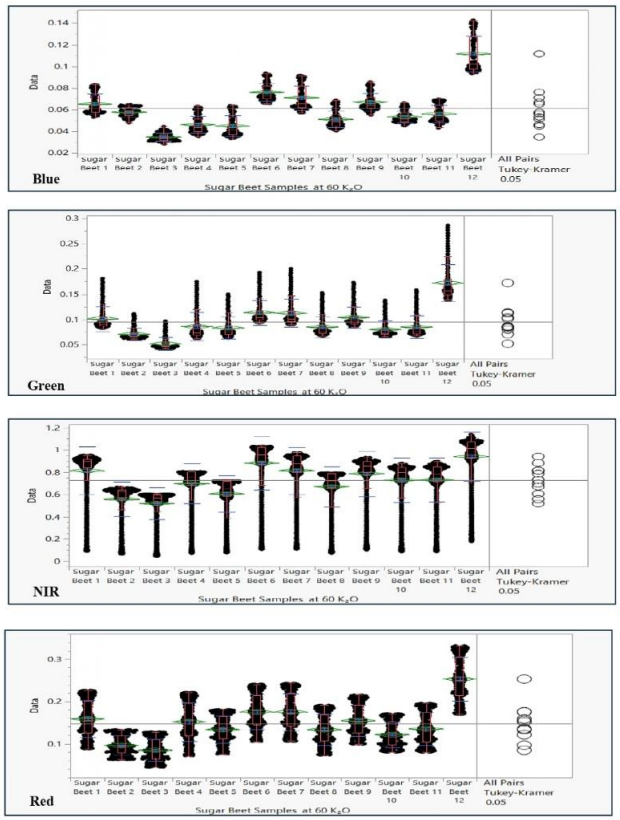


Figure S2. One-way ANOVA of sugar beet spectral reflectance among Sugar Beet samples.

LDA analysis was conducted on the hyperspectral dataset of plant and soil samples to identify discriminative wavelengths among individual samples within the potassium treatment framework. The results of this analysis are presented in Sections S1 and S2.

S1.3. LDA-based identification of discriminative wavelengths under potassium fertilization

A Linear Discriminant Analysis (LDA) was performed to detect discriminative wavebands among the twelve sugar beet samples. The analysis revealed that only *Sugar Beet 3* exhibited distinct spectral signatures that enabled its separation from the other samples, which were largely misclassified due to strong spectral overlap. The discriminatory wavelengths identified for *Sugar Beet 3* were concentrated in the visible to near-infrared region, specifically at (327, 339, 351, 363, 375, 387, 399, 411, 423, 435, 447, 459, 471, 483, 495, 507, 519, 531, 543, 555, 567, 579, 591, 603, 615, 627, 639, 651, 663, 675, 687, 699, 711, 723, 735, 747, 759, 771, 783, 795, 807, 819, 831, 843, 855, 867, 879, 891, 903, 915, 927, 939, 951, 963, 975, 987, 999, 1011, 1023, 1035, 1047, 1059, and 1071 nm). These results demonstrate that hyperspectral discrimination of potassium responses was subtle across most plants, but certain individuals, such as Sugar Beet *3*, showed waveband-specific sensitivity that could be leveraged for trait-based monitoring.

S1.4. Spectral signature indices of Sugar Beet Samples

Table S1 showed that the Carotenoid Reflectance Index (CRI1) exhibited the widest range, from 1.7258 (Sugar Beet 12) to a peak of 8.1588 (Sugar Beet 3), indicating high variability in carotenoid levels among the genotypes. Similarly, the Anthocyanin Reflectance Index (ARI1) varied markedly, with values such as 0.4758 in Sugar Beet 10 and 0.0325 in Sugar Beet 6, highlighting differences in pigment-related stress or metabolic status. The Plant Senescence Reflectance Index (PSRI) values were predominantly negative, with slight positive shifts in a few samples (e.g., Sugar Beet 10, 11, and 12), potentially indicating early onset of senescence or pigment imbalance. The Structure Insensitive Pigment Index (SIPI) showed relatively high and stable values across most samples, peaking at 0.8593 (Sugar Beet 3), reinforcing its strong physiological state.

Overall, this variation in spectral indices underscores the inherent biochemical and structural differences among individual sugar beet plants, even within the same field conditions, emphasizing the utility of hyperspectral indices for precise crop monitoring and selection.

Table S1. Spectral signature indices of Sugar Beet Samples.

Sample	NDVI	CRI1	ARI1	PSRI	SIPI
Sugar Beet 1	0.8164	3.6091	0.1961	-0.0138	0.8220
Sugar Beet 2	0.8093	4.8079	0.3278	-0.0071	0.8153
Sugar Beet 3	0.8541	8.1588	0.0742	-0.0075	0.8593
Sugar Beet 4	0.8301	4.2589	0.1192	-0.0186	0.8385
Sugar Beet 5	0.8012	3.8868	0.2246	-0.0109	0.8164
Sugar Beet 6	0.8081	3.1155	0.0325	-0.0071	0.8184
Sugar Beet 7	0.7882	3.0727	0.3672	-0.0028	0.8064
Sugar Beet 8	0.8247	4.2923	0.0641	-0.0145	0.8308
Sugar Beet 9	0.7897	3.4588	0.3187	0.0008	0.8056
Sugar Beet 10	0.8072	4.6492	0.4758	0.0122	0.8299
Sugar Beet 11	0.8044	4.3824	0.4193	0.0083	0.8283
Sugar Beet 12	0.7033	1.7258	0.3291	0.0093	0.7378

Spectral vegetation indices were calculated mathematically from reflectance measurements and are presented as descriptive indicators.

S2. Soil reflectance measurements across 12 Sugar Beet Cultivation Sites

S2.1. Spectral reflectance profiles of soil samples from Sugar Beet

The spectral reflectance data for soil samples (Figure S3) collected from 12 sugar beet cultivation sites exhibit notable variability across the visible to shortwave infrared spectrum (350–1150 nm) (figure 10). Most soil samples demonstrated a gradual increase in reflectance from the visible region (~350 nm) through the near-infrared (NIR) region (~900 nm), which is typical of bare soils. Specifically, *Sugar* Beet Soil 2 displayed the highest reflectance values across the entire spectrum, suggesting lower organic matter content and possibly drier conditions. Conversely, Sugar

Beet Soils 1, 6, and 12 exhibited lower overall reflectance, indicating higher moisture content or denser surface composition.

The red-edge region (~700–750 nm) showed a moderate reflectance plateau in all samples, with Soil 3, 7, and 8 reflecting slightly higher values in this range, potentially due to residual vegetation or slight differences in mineral composition. Overall, the spectral curves emphasize heterogeneity among soil properties across the sampling locations, which may influence sugar beet growth and spectral responses. These findings underscore the importance of accounting for soil variability in interpreting crop reflectance data.

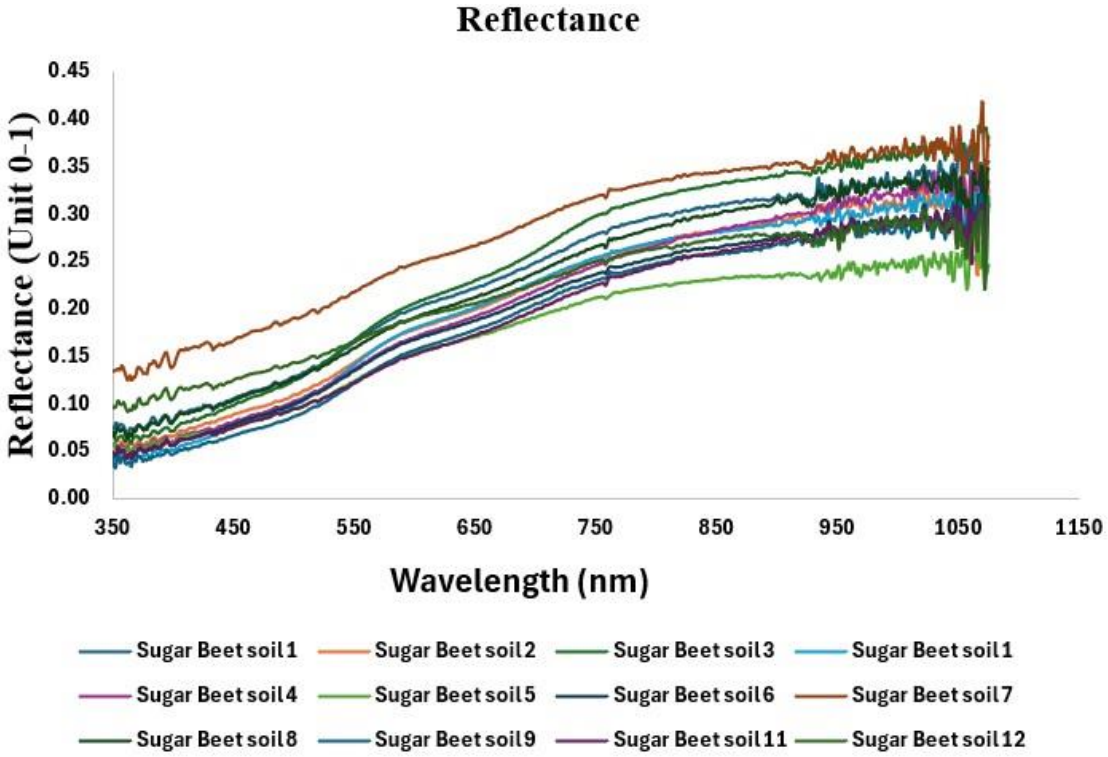


Figure S3. Spectral reflectance profiles of soil samples from Sugar Beet Experimental Plots at 60K_2O application.

S2.2. One-way ANOVA of sugar beet spectral reflectance among soil samples from Sugar Beet Samples

Figure S4 shows the variability in spectral reflectance of sugar beet across twelve soils in the blue, green, red, and NIR bands, together with the Tukey–Kramer HSD test results. In the blue band (~450 nm), reflectance values were generally low (0.02–0.15), yet significant differences were observed among soils, with Soil 6 and Soil 7 exhibiting higher reflectance compared to Soil 5 and Soil 9. In the green band (~550 nm), values ranged between 0.08 and 0.20, where Soils 6 and 7 displayed the highest mean reflectance, reflecting stronger chlorophyll-related responses, while Soils 4 and 5 were lower. In the red band (~670 nm), reflectance values clustered between 0.12 and 0.25, with less pronounced differences, although Soil 7 still showed elevated values that may indicate reduced chlorophyll absorption. As expected, NIR reflectance (~800 nm) was markedly higher than

in the visible spectrum, ranging between 0.20 and 0.40. Soils 3, 7, and 8 recorded the strongest NIR signals, consistent with healthier and denser canopy conditions. The Tukey–Kramer HSD test ($p < 0.05$) confirmed that several soils differed significantly in their spectral responses, particularly in the blue and NIR regions, which are sensitive indicators of crop vigor. These results highlight the influence of soil variability on sugar beet spectral signatures and demonstrate the potential of hyperspectral analysis for discriminating crop performance across different soil environments.

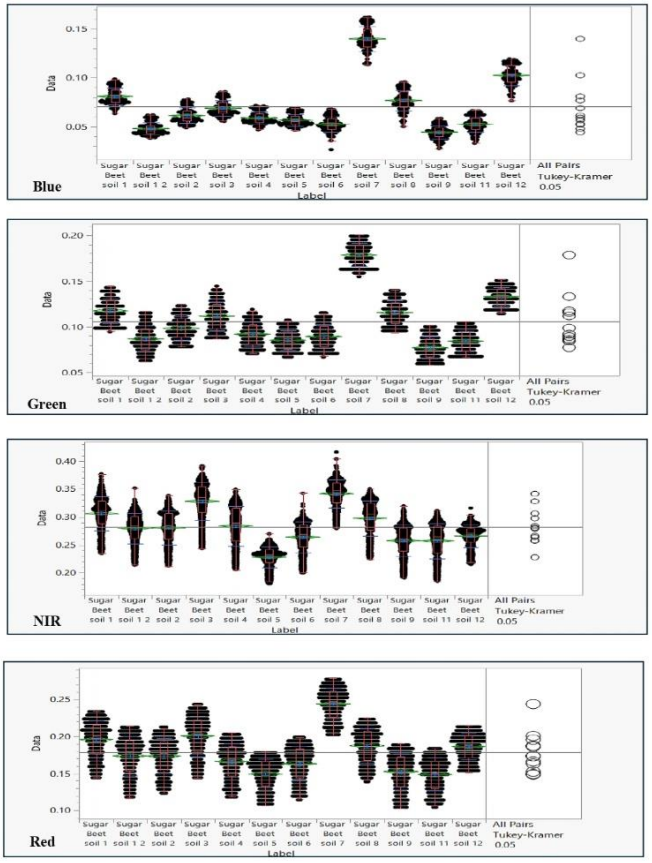


Figure S4. One-way ANOVA of sugar beet spectral reflectance among soil samples from Sugar Beet Experimental Plots at $60K_2O$ application.

S2.3. LDA-based discrimination of soil samples and identification of unique wavelengths

Linear Discriminant Analysis (LDA) was further applied to the spectral reflectance data of the twelve soil samples corresponding to the sugar beet plants. Interestingly, despite the standardized agronomic management and the uniform sandy soil conditions across all treatments, only Soil Sample 1 exhibited distinct discriminative wavelengths. The identified wavelengths after removal of redundancy were: (325, 337, 349, 361, 373, 385, 397, 409, 421, 433, 445, 457, 469, 481, 493, 505,

517, 529, 541, 553, 565, 577, 589, 601, 613, 625, 637, 649, 661, 673, 685, 697, 709, 721, 733, 745, 757, 769, 781, 793, 805, 817, 829, 841, 853, 865, 877, 889, 901, 913, 925, 937, 949, 961, 973, 985, 997, 1009, 1021, 1033, 1045, 1057, and 1069 nm).

This outcome suggests that while the majority of soil samples were spectrally similar and could not be discriminated by LDA (misclassified), soil sample 1 retained a unique spectral fingerprint. Such variation, even under homogenized soil preparation, may indicate subtle micro-scale heterogeneity in soil composition or nutrient availability that influenced spectral responses. These findings reinforce the sensitivity of hyperspectral techniques in detecting hidden variability not apparent through conventional soil analyses.



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