Integrating tractor-tire-tool adjustable parameters and UAV-Derived Spectral Indices to Predict Fuel consumption and Crop Emergence in Spring Barley Sowing

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Abstract.

The optimization of energy use and agronomic performance in agricultural operations has become a central challenge in modern agriculture. To achieve this dual objective, farmers could adjust the machinery settings of a tractor-tire-tool system to ensure efficient resource utilization while maintaining optimal agronomic outcomes. This study was conducted as a part of the AgrEnOp project, which aims to predict fuel consumption (l/ha) and crop emergence (plant/m^2) based on operator-adjustable parameters of a tractor–tire–tool system during the sowing of spring barley (Hordeum vulgare). Field experiments were performed on 9 October 2025 in Saint-Quentin-des-Prés (Northern France) on a sandy soil. The experimental design included 29 treatments combining four adjustable factors: tractor speed Ts (8, 11, and 15 km/h), tire inflation pressure Tip (0.6, 1.1, and 1.6 bar), axle load distribution Ald (rear/front: 60/40 and 50/50), and soil working depth Swd (4, 6, and 8 cm) and 11 spectral indices derived from a UAV multispectral flight. The system consisted of a 150 HP four-wheel-drive tractor equipped with 480/70 R28 front tires and 580/70 R38 rear tires, and coupled with an air-seeder integrating tillage, consolidation, and sowing. Correlation analysis showed a strong negative relationship between fuel consumption and tractor speed ($r = -0.72$).The best polynomial model (P1), including Swd, Ts, and the interaction between Swd and Ald; achieved LOO-CV $R^2_{adj} = 0.583$ and RMSE = 0.310 L/ha (RPD = 1.64); when spectral indices were added, none reached $p < 0.05$. Machine learning models trained on the four adjustable factors and spectral indices showed that PLSR with bootstrap

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achieved competitive performance (LOO-CV RPD = 1.55; 5 K-Fold RPD = 1.60), demonstrating that UAV-derived spectral indices contribute latent predictive signal when handled through dimensionality-reduction methods. Conversely, prediction models for crop emergence remained weak, with adjusted R^2 values between −0.08 and −0.03, RMSE values ranging from 11.8 to 12 plants·m^{-2} and RPD < 1.0. The results indicate that fuel consumption during sowing can be reliable predicted using a limited set of operator-adjustable parameters (polynomial model) and combined with UAV spectral data (PLSR model with bootstrapping), on a sandy soil. In contrast, crop emergence appears to be weakly influenced by the mechanical and spectral variables considered in this study. This finding highlights the potential of integrating optimized machine setting with UAV derived indicators into decision support tools for more efficient sowing operations. Future research should focus on multi-year experiments, the inclusion of additional soil and climatic variables, the acquisition of more accurate soil and crop spectral data, and the development of advanced hybrid machine-learning. Such initiatives would help improve the prediction of crop emergence and generalize the proposed models across diverse soil types and cropping systems.

Keywords.
Precision agriculture, sowing optimization, fuel consumption, spectral indices, UAV, crop emergence, PLSR, bootstrap.

1. INTRODUCTION

The agricultural sector faces the challenge of ensuring a successful sowing operation from both agronomic and economic perspectives. Crop emergence and fuel consumption during sowing broadly represent this challenge. During tillage and sowing operations, fuel consumption depends on a complex combination of factors that the operator can adjust, such as tractor speed (Ts), tire inflation pressure (Tip), axle load distribution (Ald), and soil working depth (Swd) (Adewoyin and Ajav 2013; Damanauskas et al. 2015; Mohieddinne et al. 2023). The ability to predict energy consumption and crop emergence based on adjustable parameters constitutes a key tool for optimizing operational decisions, enabling a reduction in energy costs without compromising agronomic objectives.

In parallel, the rapid development of unmanned aerial vehicles (UAVs) has expanded the possibilities for characterizing field conditions at the plot scale, providing high-spatial-resolution information at relatively low operational cost (Yao et al. 2019). Multispectral images acquired from UAVs in the visible and near-infrared (NIR) regions enable the derivation of a set of spectral indices related to vegetation and soil, which have been widely applied in soil sciences and precision agriculture for biomass estimation, crop monitoring, and the inference of soil properties (Myneni et al. 1995; Bendig et al. 2015; Biney et al. 2021). However, their use as covariates in models predicting fuel consumption and crop emergence, in combination with TS, SWD, ALD, TIP in a tractor-tire-tool system, remains unexplored.

Fuel consumption and crop emergence prediction models have generally been based on multiple linear regressions (Almaliki et al. 2016; Mohieddinne et al. 2023) and, more recently, using convolutional neural networks (Jalilnezhad et al. 2023). However, no study has yet combined operator-adjustable tractor parameters with UAV-derived spectral indices as predictors a combination that introduces high inter-predictor correlation and potential interaction effects that challenge standard linear approaches. Machine learning methods such as Random Forest (RF), PLSR, and Cubist offer complementary strategies to address this, spanning the full spectrum from nonlinear ensemble learning to linear dimensionality reduction. Evaluating these approaches alongside classical polynomial regression allows identification of the most accurate and robust modeling framework for this novel predictor combination for predicting fuel consumption and crop emergence.

This study, conducted in the framework of the AgrEnOp project, has three objectives: (1) to evaluate the predictive capacity of operator-adjustable parameters, both individually and in combination with UAV-derived spectral indices, for fuel consumption and crop emergence during spring barley sowing; (2) to compare the performance of polynomial and machine learning models; and (3) to assess whether bootstrapping can improve model performance under small-sample conditions. We hypothesize that (H1) spectral indices provide complementary information on soil and crop conditions that cannot be fully explained by adjustable operational parameters alone; (H2) the ability to leverage this information depends on the modeling approach, differing between polynomial models and machine learning methods; and (H3) the use of bootstrapping improves model stability and performance under small-sample conditions.

2. MATERIALS AND METHODS

2.1. Study site and experimental design

The experiment was conducted on 9 October 2025 in a 3 ha agricultural field characterized by sandy soil located in Saint-Quentin-des-Prés, northern France (Figure 1). The spring barley variety sown was *LG ZORICA.*

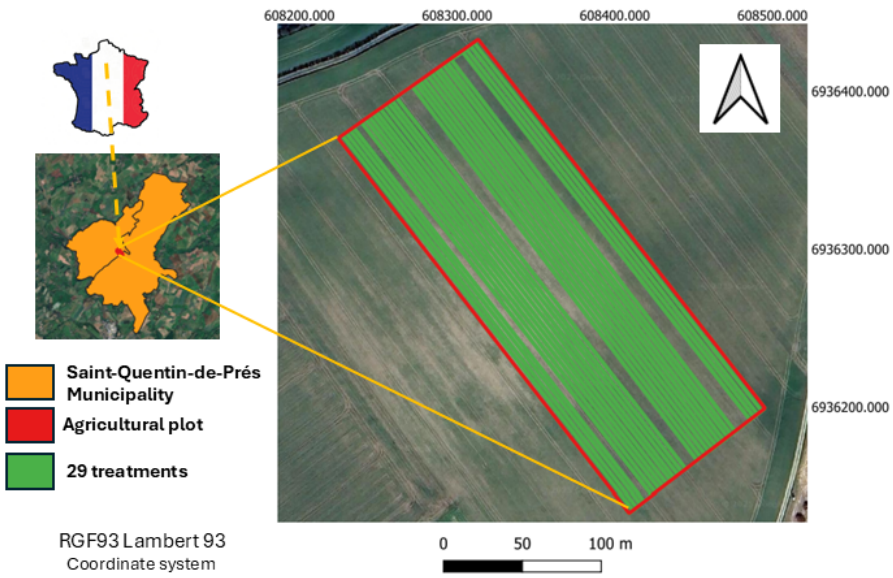

Figure 1. Study area location

The tractor-implement system consisted of a 150 HP four-wheel-drive tractor *(Massey-Ferguson 6S 155)* equipped with 480/70 R28 front tires and 580/70 R38 rear tires, coupled with an air-seeder *(Kuhn Espro 3000)* integrating minimum tillage section, press wheels, and a coulter bar.

The experiment was based on a Box-Behnken design (Box et al. 1960) with 29 treatments, which combined four adjustable parameters during the sowing process (Table 1). Each treatment was a strip of approximately 250 m length and 3 m of width. Specific fuel consumption (L/ha) data were collected with flowmeters RS- 511-3965 installed before motor fuel inlet and outlet. Data has been and recorded by a data logger (SIRIUSi 8xSTG+, DEWESoft) on the same time scale. Computing processing and conversions were made through the post-processing software (Devesoft X) provided by DEWESoft. Crop emergence (plants m^{-2}) was assessed manually at 30 days after sowing by using a 0.25 m^2 frame. Three sampling points, spaced 50 m apart, were established within each treatment, with three replicates per point, resulting in a total of nine counts per treatment.

Table 1. Operator-adjustable experimental factors and tested levels.

Factor	Symbol	Levels	Unit
Soil working depth (Swd)	X1	4, 6, 8	cm

Tractor speed (Ts)	X2	8, 11, 15	km/h
Axle load distribution (rear/front) (Ald)	X3	60/40 and 50/50	—
Tire inflation pressure (Tip)	X4	0.6, 1.1, 1.6	bar

2.2. UAV data acquisition and spectral index computation

A multispectral UAV flight was performed on 12 November 2025, using a DJI Phantom 4 Multispectral equipped with 1 RGB camera and 5 cameras covering five spectral bands: Blue 450 nm, Green 560 nm, Red 650 nm, Red-Edge 730 nm, NIR 840 nm. The flight was conducted at 36 m altitude with 80% forward and lateral overlap, yielding a ground sampling distance of 2 cm pixel^{-1} of resolution. Images were processed in Agisoft Metashape to generate georeferenced orthomosaics. Eleven spectral indices were derived per experimental strip (mean value) and used as model covariates (Table 2). Although the UAV flight was conducted 34 days after sowing, soil surface properties (e.g., grain size and soil color) affecting traction are relatively stable over time and can be effectively captured by spectral indices. Therefore, these indices provide a reliable spatial proxy of soil conditions at sowing.

Since UAV images do not include short-wave infrared (SWIR) data, it was not possible to apply a conventional bare soil index (BSI; Wentzel, 2002). Instead, a proxy index (Sproxy) for soil exposure was developed using RGB and NIR bands to highlight the contrast between emerging vegetation and bare soil. The image acquisition date coincided with a phenological phase of low vegetation cover, so the signal was primarily dominated by bare soil, facilitating the discrimination of texture patterns and surface heterogeneity.

Table 2. Spectral indices derived from UAV multispectral imagery and used as model covariates.

Acronym	Full Name	Equation	Reference
NDVI	Normalized Difference Vegetation Index	*(NIR−Red)/(NIR+Red)*	Tucker (1979)
SAVI	Soil-Adjusted Vegetation Index	*(NIR−Red)/(NIR+Red+L)·(1+L), L=1*	Huete (1988)
CIp	Coloration Index	*(Red-Green/Red+Green)*	Pouget et al. 1990
CIe	Coloration Index	*(Red-Blue)/Red*	Escadafal et al. 1994
CRI	Crust Index	*1- (Red-Blue/Red+Blue)*	Karnieli (1997)
GSI	Grain Size Index	*(Red−Blue)/(Red+Green+Blue)*	Xiao et al. 2006
Sproxy	Soil Proxy Index	*(Red+Green)-(NIR+Blue)/ (Red+Green)+(NIR+Blue)*	This study
BI	Brightness Index	$\sqrt{((Red^2+ Green^2+Blue^2)/3)}$	Pouget et al. 1990
HI	Hue Index	*(2·Red−Green−Blue)/(Green−Blue)*	Kalambukattu et al. 2018
SI	Saturation Index	*(Red-Blue/Red+blue)*	Garosi et al. 2022
SOCI	Soil Organic Carbon Index	*Blue/Red*Green*	Minhoni et al. 2021

2.3. Statistical and modeling framework

All analyses were implemented in Python 3.11. Pearson correlation was computed for all variables. Multicollinearity among spectral indices was assessed through pairwise correlation analysis.

Second-order polynomial regression models were developed using the four operator-adjustable factors (X1, X2, X3, and X4). The models were evaluated by sequentially incorporating interaction terms (X1×X2, X1×X3, X1×X4, X2×X3, X2×X4, X3×X4) and quadratic terms ($X1^2$, $X2^2$, $X3^2$, and $X4^2$), as well the spectral indices (Table 2). Only variables and terms with statistical significance ($p < 0.05$) were retained in the final models. Additionally, models were validated by leave-one-out cross-validation (LOO-CV, n = 29 folds) and stratified 5-fold cross-validation (5-Fold CV). For machine learning models, variable selection was performed on RF importance thresholding (≥ 3%) applied to the combined set of base variables and spectral indices, excluding interaction terms and quadratic terms. RF, PLSR and Cubist were evaluated with both LOO-CV and 5-Fold CV. A bootstrap method was applied to PLSR: 200 synthetic observations were generated by resampling with replacement from the 29 real observations, yielding n = 229 for model training. LOO-CV was subsequently applied to this dataset, with predictive performance evaluated exclusively on the 29 original observations to ensure unbiased estimation of generalization error.

3. RESULTS

3.1. Correlation of fuel consumption and crop emergence with adjustable factors and Spectral Indices

Pearson correlation results are presented in Table 3. Among the four operator-adjustable factors, only Ts (X2) showed a significant correlation with fuel consumption ($r = -0.726$, p value < 0.001), confirming that higher forward speeds reduce per-hectare fuel use at constant engine power. No other base variable reached significance. Among spectral indices, all correlations with fuel consumption were non-significant (best: CIe, $r = -0.273$, $p = 0.152$), and the correlation structure among indices was characterized by severe multicollinearity: CRI and GSI were nearly perfectly inversely correlated ($r = -0.99$), and Sproxy, BI, CIp, SI, and SOCI formed a cluster with pairwise $r > 0.92$. No variable of adjustable factors or spectral index showed a significant correlation with crop emergence ($-0.17 < |r| < 0.14$, all p value > 0.37).

Table 3. Pearson correlation coefficients (r) between all predictors and the two response variables.

Variable	r (Fuel consumption (L/ha))	p-value	r (Crop emergence (plants/m²))	p-value
Tractor speed (X2)	−0.726	<0.001 *	0.137	0.478
Soil working depth (X1)	0.218	0.256	−0.172	0.374
Axle load dist. (X3)	0.006	0.975	0.038	0.843
Tire inflation pressure (X4)	0.107	0.582	−0.068	0.725
NDVI	−0.010	0.957	−0.085	0.660
SAVI	0.182	0.346	−0.099	0.611
CIp (Coloration Index)	−0.237	0.216	0.018	0.926
CIe (Coloration Index)	−0.273	0.152	−0.068	0.726
CRI (Crust Index)	0.250	0.192	0.127	0.513
GSI (Grain Size Index)	−0.245	0.201	−0.128	0.508
Sproxy (Soil Proxy Index)	−0.213	0.268	−0.036	0.852
SOCI (Soil Organic Carbon Index)	-0,098	0.611	-0,0083	0.965
SI (Saturation Index)	-0,249	0.192	-0,024	0.899

HI (Hue Index)	-0,181	0.346	-0,142	0.459
BI (Brightness Index)	-0,193	0.314	-0,001	0.992

*** = p < 0.05; n = 29**

3.2. Prediction models

3.2.1. Fuel consumption

The best polynomial model (P1) retained three significant predictors: Swd (X1, p-value = 0.032), Ts (X2, p-value < 0.001), and their interaction with axle load distribution (X1×X3, p-value = 0.003). Achieving LOO-CV R^2_{adj} = 0.583 and RMSE = 0.310 L/ha (RPD = 1.64) (Table 4). The fitted equation was:

$$\hat{y} = 6.1549 + 0.1698 \cdot X1 - 0.4914 \cdot X2 - 0.2504 \cdot X1 \times X3 \quad (1)$$

When spectral indices were added individually to P1, none achieved p-value < 0.05 (best: CIp, p-value = 0.405; CIe, p-value = 0.474), and LOO-CV performance remained identical, confirming that spectral indices provide no additional explanatory power over the polynomial interaction terms under these experimental conditions.

RF variable importance analysis identified 11 variables above the 3% threshold (Figure 2). Ts (X2) dominated with 43.3% importance, followed by spectral indices: CIe (7.6%), SAVI (6.9%), and CRI (5.8%), indicating that spectral indices carry secondary predictive signal detectable by non-linear ensemble methods even when individually non-significant in linear models.

Among the machine learning models evaluated (Table 4), PLSR with bootstrap data achieved the best performance, with LOO-CV R^2 = 0.584, RMSE = 0.328 L/ha, and RPD = 1.55, and 5-Fold CV R^2 = 0.607, RMSE = 0.318 L/ha, and RPD = 1.60. Standard PLSR and Cubist showed comparable cross-validated performance, with RPD values ranging from 1.24 to 1.42 across both validation schemes, while Random Forest exhibited the weakest performance, achieving LOO-CV RPD = 1.01 and 5-Fold RPD = 1.28, indicating poor predictive capacity.

Table 4. Cross-validation performance of all models for fuel consumption

Model	Variables	n	Eval.	R^2	R^2adj	RMSE	RPD
P1	X1, X2, X1×X3	3	LOO-CV	0.627	0.583	0.310	**1.64**
			5-Fold	0.626	0.582	0.311	**1.64**
Random Forest	11 vars (imp ≥ 3%)	11	LOO-CV	0.021	-0.61	0.503	1.01
			5-Fold	0.388	-0.01	0.397	1.28
Cubist	11 vars (imp ≥ 3%)	11	LOO-CV	0.371	-0.03	0.403	1.26
			5-Fold	0.488	0.157	0.363	1.40
PLSR	11 vars (imp ≥ 3%)	11	LOO-CV	0.353	-0.06	0.409	1.24
			5-Fold	0.501	0.179	0.359	1.42
PLSR+Bootstrap	11 vars (imp ≥ 3%)	11	LOO-CV	0.584	0.315	0.328	**1.55**
			5-Fold	0.607	0.353	0.318	**1.60**

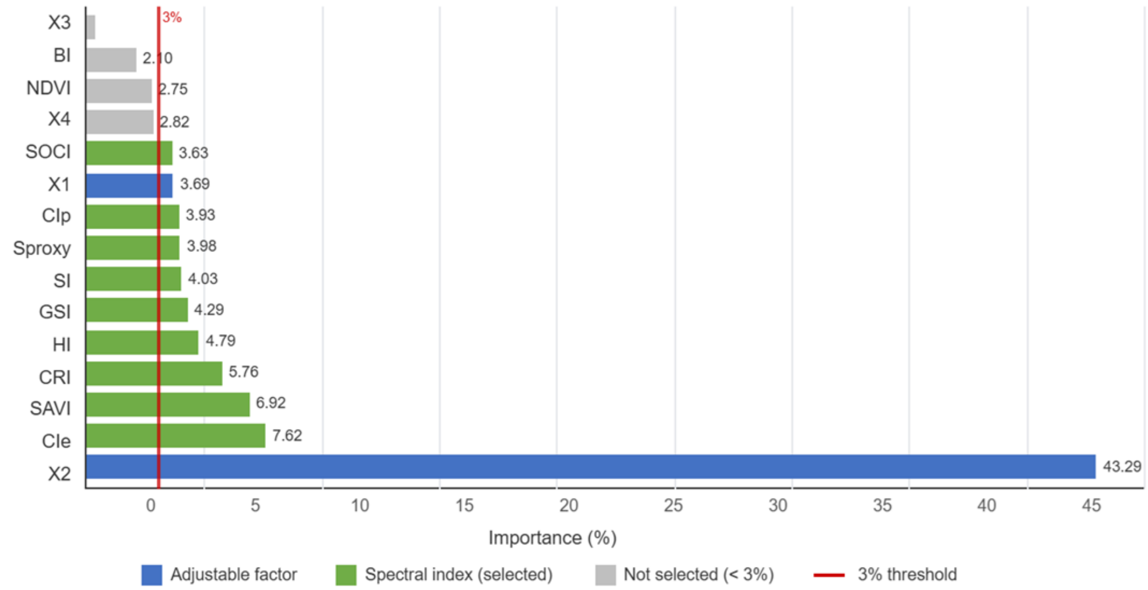

Figure 2. Random forest variable importance

3.2.2. Crop Emergence

Crop emergence proved unpredictable across all modeling approaches and validation schemes. LOO-CV RPD values remained below 1.0 for all models, with Cubist yielding the least unfavorable result (RPD = 0.97; RMSE = 12.92 plants m^{-2}). PLSR with bootstrap produced a marginal improvement in LOO-CV RPD (0.90 to 1.16); however, this value remained substantially below the minimum threshold for acceptable quantitative prediction (RPD ≥ 1.4; Chang et al. 2001).

4. DISCUSSION

4.1. Predominant Influence of Tractor Speed and Axle load distribution

In general, higher Ts is associated with increased fuel consumption. However, this does not necessarily imply that operating at lower speeds will always result in fuel efficiency. In practice, an appropriate match between tractor size and the implements used ensures operation within an optimal speed range that promotes efficient fuel consumption (Mamkagh 2018). The negative correlation observed between Ts and fuel consumption might be attributed to: (1) a higher forward speed, which potentially distributes energy over a larger area per unit of time, thereby reducing area-specific fuel consumption; or (2) the combined effect of Ts, Swd, and Ald (Mohieddinne et al. 2023). The significant interaction between Swd (X1) and Ald (X3) identified in the polynomial model (P1) supports the second reason. Increasing Swd raises the draft force requirements, which induces a dynamic load transfer toward the rear axle and increases both wheel slip and rolling resistance. Consequently, fuel consumption depends on an appropriate balance of Ald and Swd. Future studies should focus on identifying the optimal balance of this interaction across different soil types.

4.2. Contribution and limits of UAV spectral indices

In the polynomial framework, no spectral index improved model fit when added to P1. This result might be attributed to two factors. First, the multicollinearity present within the spectral index space (e.g., CRI vs. GSI: r = −0.999; Sproxy vs. SI: r = 0.994; Sproxy vs. BI: r = 0.980) prevents individual indices from expressing independent linear contributions beyond that already captured by the model through independent terms or interactions. Second, the weak independent correlation between spectral indices and fuel consumption.

In contrast, spectral indices provided additional predictive information within the PLSR bootstrapping framework. By combining the strengths of principal component analysis and multiple linear regression, PLSR projects both predictor variables and response variables into a reduced latent-variable space that maximizes their correlation. This approach is particularly effective in the presence of multicollinearity, as it reduces dimensionality while mitigating redundancy among highly correlated predictors (Wold et al. 2001). The Random Forest variable importance analysis revealed that indices such as CIe, HI, CRI, SI, GSI, and Sproxy, which are associated with soil texture and color, play a significant role in fuel consumption prediction within our approach. This finding is consistent with the physical relationship between soil conditions and tractor-tire-tool system performance, as soil color, moisture, and structure may provide information about soil surface conditions that affect traction.

A more comprehensive investigation of the influence of these soil properties and their relationship with traction, assessed through these indices under different pedoclimatic conditions, would help validate and further support our findings.

4.3. Limitations of spectral indices for crop emergence prediction

The poor performance of crop emergence models (LOO-CV RPD < 1.0 across all approaches) highlights fundamental limitations of the UAV-based methodology used in this study. One of the main limitations was the temporal mismatch between image acquisition and the emergence process. The UAV flight was conducted 34 days after sowing, when field observations indicated sparse and heterogeneous emergence, with bare soil still dominating the surface. Under these conditions, vegetation indices derived from imagery have limited sensitivity to emergence variability because soil reflectance largely controls the spectral signal. This is reflected in the absence of correlation between NDVI and crop emergence ($r = -0.010$), consistent with previous studies showing reduced index performance under low fractional vegetation cover (Huete. 1988).

Although SAVI was the most influential spectral predictor in the Random Forest analysis (15.0% importance), its contribution was insufficient to achieve acceptable predictive performance (LOO-CV RPD = 0.97). While SAVI reduces soil background effects relative to NDVI (Huete, 1988), the spectral variability associated with emergence remained smaller than the variability introduced by soil heterogeneity. Future studies could benefit from a multi-temporal UAV acquisition strategy covering key barley growth stages, which may help identify periods when spectral indices are more strongly associated with emergence variability.

Additionally, crop emergence is largely governed by seedbed properties operating at the micro-scale, including aggregate size distribution, bulk density, pore continuity, and soil seed contact quality. In this study, plant counts revealed substantial spatial variability (139 ± 18 plants m^{-2} on average) and an estimated emergence loss of 51% relative to the sowing density, suggesting that local variations in seedbed conditions, and climatic conditions played a major role in determining emergence. These processes occur at spatial and temporal scales that cannot be adequately detected by spectral indices derived from UAV imagery.

5. Conclusions

This study assessed the capacity of operator-adjustable tractor parameters and UAV-derived spectral indices to predict fuel consumption and crop emergence during spring barley sowing. Key results are summarized as follows:

- Tractor speed (X2) was the primary predictor of fuel consumption ($r = -0.726$; 43.3% RF importance). The interaction between soil working depth and axle load distribution

(X1×X3) provided additional mechanistic explanatory value, yielding a promising model performance (LOO-CV R^2adj = 0.583; RMSE = 0.310 L/ha; RPD = 1.64).

- UAV spectral indices contributed secondary predictive information only under latent-variable modeling (PLSR). No individual index improved the polynomial model, likely due to strong multicollinearity and limited statistical power.
- PLSR with bootstrap data improved cross-validated performance (LOO-CV RPD: 1.24 → 1.55), providing a robust small-sample framework for integrating high-dimensional spectral data in field experiments.
- Crop emergence was not predicted by any of the modeling approaches (RPD < 1.0), due to: (i) a temporal mismatch between UAV imagery acquisition and the crop's various growth stages; and (ii) the indirect relationship between the available spectral indices and the physical properties of the seedbed that control seedling establishment.

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