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Assessment of the Relationship between NDVI and EVI and Leaf Area Index in Commercial Wheat Fields Using Sentinel-2

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ABSTRACT

Objective: To evaluate the relationship between the Normalized Difference Vegetation Index (NDVI) and the Enhanced Vegetation Index (EVI), derived from satellite imagery, and the Leaf Area Index (LAI) in wheat crops, in order to develop an LAI estimation model and validate its performance.

Design/methodology/approach: The study was conducted in 16 commercial wheat fields in the Yaqui Valley, Sonora, using an observational, non-experimental, multilevel design. Eight fields were sown with the durum wheat variety CIRNO C2008, and eight with the bread wheat variety Borlaug 100. LAI was measured during the booting and grain-filling stages using an AccuPAR LP-80 ceptometer. NDVI and EVI were obtained from Sentinel-2 imagery using the VICAL tool. Measurements were matched using a ±5-day time window. Data were analyzed through linear regression, Random Forest models, and linear mixed models, with performance assessed by cross-validation, R^2, and RMSE (Root Mean Square Error).

Results: NDVI and EVI exhibited positive relationships with LAI, with moderate predictive capacity (R^2=0.33-0.41; RMSE=1.18-1.35), and comparable accuracy between linear and machine learning models. The linear mixed models revealed that EVI explained LAI variability more consistently at the population level. Phenological stage had a significant effect, whereas variety did not exert a relevant influence.

Limitations on study/implications: The study was constrained by the limited number of LAI observations per field and by heterogeneity in planting dates, agronomic management, and environmental conditions.

Findings/conclusions: According to the linear mixed modeling approach, EVI showed greater consistency in explaining LAI variability at the average population level.

Keywords: Leaf area index; NDVI; EVI; remote sensing; mixed models.

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INTRODUCTION

Wheat (*Triticum* spp.) is one of the most important cereal crops due to its substantial contribution to caloric intake, protein supply, and micronutrient provision (Poudel and Bhatta, 2017). Its productivity and quality are determined by the genetic characteristics of the variety, which may in turn be influenced by agronomic practices and climatic conditions throughout the crop cycle (Peña-Bautista *et al.*, 2008). One of the main constraints affecting this crop is the reduction in leaf area, which may lead to yield losses by diminishing the interception of photosynthetically active radiation (Herranz *et al.*, 2017). Leaf Area Index (LAI) is defined as the cumulative one-sided leaf surface area per unit ground surface area (Fang *et al.*, 2019). LAI regulates radiation interception, canopy microclimate, and water and CO_2 exchange (Bréda, 2003). Moreover, it is an important input parameter for monitoring the development and progression of crop yield forecasting models, as well as hydrological and climate models (Hasan *et al.*, 2019). LAI can be determined through either direct or indirect methods.

Direct methods are costly and time-consuming because they require destructive biomass sampling (De França *et al.*, 2024), whereas indirect methods rely on field measurements using specific instruments and the application of complex mathematical models (Jonckheere *et al.*, 2004; De la Casa *et al.*, 2007; Casa *et al.*, 2019). Therefore, although indirect methods are more practical, direct LAI measurements for long-term monitoring remain challenging (Saitoh *et al.*, 2012). At present, remote sensing technology has advanced considerably in the estimation of physiological and ecological crop parameters, enabling more rapid assessment of variables such as biomass and LAI (Apolo-Apolo *et al.*, 2020; Hama *et al.*, 2020; Oliveira *et al.*, 2022). A key advantage of remote sensing is that it allows large-scale acquisition of canopy information without disturbing the normal growth of plants (Jiao *et al.*, 2014; Tan *et al.*, 2018).

The assessment of canopy cover, vigor, and growth dynamics based on local variability can be achieved through Vegetation Indices (VIs) derived from remote sensors (Mashonganyika *et al.*, 2021). The Enhanced Vegetation Index (EVI) and the Normalized Difference Vegetation Index (NDVI) are two indices commonly used to describe vegetation condition and performance (Liu *et al.*, 2020; Belmahi *et al.*, 2023). NDVI is based on the absorption properties of the red band (≈660 nm) and the near-infrared (NIR) band (≈860 nm); EVI, in turn, incorporates the blue band (≈450 nm), in addition to the red and NIR bands, in order to minimize bias in dense canopies (Shammi and Meng, 2021). Accordingly, VIs has become efficient tools for estimating the spatial variability of LAI through statistical relationships calibrated with experimental data or radiative transfer simulations (Viña *et al.*, 2011; Wu *et al.*, 2022). In contrast, the validation of LAI-VI models under real commercial conditions remains limited, despite the pronounced spatial and agronomic heterogeneity that characterizes such settings, where factors such as management, phenology, and inter-field differences may significantly influence the observed spectral relationship, thereby hindering the extrapolation of models calibrated under experimental conditions to operational scenarios (Fang *et al.*, 2019; Liu *et al.*, 2025). In this context, it is essential to evaluate methodological approaches that explicitly integrate such variability in order to obtain more robust LAI estimates at the population level. Therefore, the relationship between NDVI and EVI, derived from Sentinel-2 satellite imagery, and LAI in wheat was evaluated with the aim of developing and validating predictive models for estimating LAI from spectral indices under real field conditions.

MATERIALS AND METHODS

Study area

This study was conducted in the Yaqui Valley region, located in southern Sonora, between the Gulf of California and the Sierra Madre Occidental (27°10’ and 27° 50’ N, and 109° 55’ and 110° 36’ W). According to the Köppen classification, as modified by García (2004), the regional climate is classified as hot desert [BW(h)] and very hot semi-arid [BS(h)]. Precipitation is variable, with an annual average of 317 mm, while mean temperature is 21 °C during the autumn-winter cycle and 30 °C during the spring-summer cycle (Luers *et al.*, 2003).

Study design and evaluated variables

The study was conducted under an observational, non-experimental, multilevel design, considering a hierarchical structure in which measurements were nested within commercial fields, in order to evaluate the relationship between field-based and remotely sensed measurements. The response variable was the Leaf Area Index (LAI), defined as the total leaf area per unit ground surface area. The predictor variables were the Normalized Difference Vegetation Index (NDVI) and the Enhanced Vegetation Index (EVI), both derived from satellite imagery and used to characterize vegetation condition and performance.

Sowing and experimental design

Sixteen commercial wheat fields were selected, eight sown with the durum wheat variety (*Triticum durum* Desf.) CIRNO C2008 (Figueroa-López *et al.*, 2010) and eight with the bread wheat variety (*Triticum aestivum* L.) Borlaug 100 (Chávez-Villalba *et al.*, 2021) (Table 1). Sowing dates across the different fields ranged from November 16 to December 19, 2024. Agronomic crop management followed each producer’s standard practices, which included traditional regional methods such as row sowing, furrow irrigation, and conventional nitrogen fertilization management.

Each field was considered an independent experimental unit, whereas the LAI measurements within each field were treated as nested sampling units, thereby generating a hierarchical data structure. For each LAI measurement, the satellite image closest in time was identified in order to match each phenological observation with a corresponding NDVI and EVI value.

Given the variability in sowing dates and crop management, the design was classified as non-experimental and unbalanced. This between-field variability was incorporated into the statistical analysis, thereby allowing the relationship between the spectral indices and LAI to be evaluated under real field conditions.

Measurement of Leaf Area Index (LAI) in the Field

LAI was measured using an AccuPAR LP-80 ceptometer, which consists of an 87-cm bar equipped with 80 photosynthetically active radiation (PAR) sensors and an independent radiation sensor. The instrument estimates LAI as a function of the photosynthetically

Table 1. Geographic Location and Agronomic Characteristics of the Commercial Fields.

Field	Sowing Date	Latitude (N)	Longitude (W)	Variety	Area (ha)
B-1201	Nov 16	27° 17' 59.6"	110° 01' 22.5"	Borlaug 100	24
B-1512	Nov 16	27° 15' 45.7"	109° 55' 16.8"	Borlaug 100	7
B-2020	Nov 17	27° 10' 16.3"	109° 49' 20.0"	CIRNO C2008	20
B-1706	Nov 20	27° 13' 34.2"	109° 57' 12.9"	CIRNO C2008	23
B-817	Nov 24	27° 23' 27.2"	110° 11' 01.5"	Borlaug 100	6
B-207	Nov 25	27° 28' 58.4"	110 °04' 34.4"	CIRNO C2008	25
B-1716	Nov 25	27° 13' 34.3"	109° 51' 24.9"	Borlaug 100	40
B-1816	Nov 28	27° 12' 04.2"	109° 51' 04.7"	CIRNO C2008	30
B-812	Nov 30	27° 23' 17.5"	109° 54' 44.1"	CIRNO C2008	20
B-912	Dec 1	27° 21' 16.9"	109° 53' 45.9"	Borlaug 100	25
B-2008	Dec 4	27° 09' 43.9"	109° 56' 14.3"	CIRNO C2008	36
B-1115	Dec 4	27° 20' 08.9"	110° 09' 59.0"	Borlaug 100	40
B-1506	Dec 13	27° 15' 45.8"	109° 58' 25.1"	CIRNO C2008	40
B-808	Dec 13	27° 22' 35.9"	109° 56' 01.1"	CIRNO C2008	10
B-511	Dec 18	27° 26' 12.2"	110° 08' 13.9"	Borlaug 100	50
B-213	Dec 19	27° 29' 46.4"	110° 08' 33.9"	Borlaug 100	10

active radiation measured above (PARa) and below the crop canopy (PARd), according to Equation 1 proposed by Campbell and Norman (1998):

$$LAI = \frac{\left[\left(1-\frac{1}{2K}\right)f_b - 1\right]\ln\left(\frac{PARa}{PARd}\right)}{A\left(1-0.47f_h\right)} \quad (1)$$

Measurements were taken during the booting (Z45-Z49) and grain-filling (Z71-Z83) phenological stages, according to the scale proposed by Zadoks *et al.* (1974). In each field, an average of four readings was obtained along 50-m longitudinal transects, placing the ceptometer bar perpendicular to and beneath the crop canopy in order to capture the spatial variability of the canopy. Readings were conducted under clear-sky conditions between 10:00 and 13:00 h, so that the direct radiation fraction factor (f_b) corresponded to high values, thereby allowing more homogeneous data to be obtained.

Spectral Indices

The spectral indices NDVI and EVI were selected because of their widespread use, operational availability, and sensitivity to canopy structure. The values of both indices throughout the wheat growing cycle were obtained automatically using the VICAL tool (Jiménez-Jiménez *et al.*, 2022), which is supported by the Google Earth Engine (GEE) platform. Within VICAL, the polygons corresponding to each commercial field were digitized and, from the 23 available Vegetation Indices (VIs), NDVI (Equation 2) and EVI (Equation 3) were selected, both calculated from Sentinel-2 imagery with a spatial resolution of 10 m. The data were extracted from the earliest sowing date (November 16, 2024) through physiological maturity (May 30, 2025).

$$NDVI = \frac{NIR - R}{NIR + R} \tag{2}$$

$$EVI = 2.5\left(\frac{NIR - R}{NIR + C_1 R - C_2 B + L}\right) \tag{3}$$

where: $C_1=6.0$; $C_2=7.5$ and $L=1.0$ (Huete *et al.*, 2002).

Temporal Matching of LAI and Spectral Index Data

Because the dates of the spectral indices and the field measurement dates did not always coincide exactly, a temporal matching procedure was performed based on the smallest absolute difference in days. For each LAI measurement, the NDVI or EVI value corresponding to the nearest available date was selected, provided that the temporal difference was within ± 5 days, in order to ensure phenological synchrony between crop conditions and the spectral signal. This threshold was established on the basis that, within short temporal windows, crop phenological changes remain relatively stable, thereby enabling an appropriate correspondence between canopy status and spectral response, as has been adopted in similar studies based on satellite sensors with comparable temporal resolution (Claverie *et al.*, 2013; Fang *et al.*, 2019).

Statistical Analyses

The predictive capacity of the Vegetation Indices (VIs) for estimating LAI was assessed using simple linear regression models (LAI~NDVI; LAI~EVI), considering each index independently. Model predictive performance was evaluated through k-fold cross-validation (k=5), with grouped partitioning by field to avoid spatial dependence between the training and validation datasets. The metrics used were the coefficient of determination (R^2) and the Root Mean Square Error (RMSE). In addition, machine learning models based on Random Forest were included as a complementary approach to explore potential nonlinear relationships and to evaluate the robustness of the results obtained from the linear models.

Additionally, Linear Mixed Models (LMMs) were fitted in order to incorporate between-field variation as a random effect. In these models, LAI was considered the response variable, whereas the spectral index (NDVI or EVI), phenological stage, and variety were included as fixed effects, with the aim of capturing unexplained variability associated with spatial differences and agronomic factors, as well as unobserved heterogeneity at the field level. The model structure was as follows:

$$LAI = Index + Stage + Variety + (1 \mid Field) \tag{4}$$

The models were fitted using maximum likelihood estimation, and the basic assumptions of linear models, namely normality and homoscedasticity, were assessed through graphical inspection of the residuals, with no relevant deviations detected. Model performance was evaluated using the marginal coefficient of determination (R^2m), which represents the variance explained by the fixed effects, and the conditional coefficient of determination (R^2c), which includes both fixed and random effects. Model fit error was quantified using RMSE.

Statistical Software

The statistical analysis was conducted in RStudio software (version 4.5.2) (Posit Team, 2025), using the following packages: tidyverse, lubridate, performance, lme4, caret, randomForest, and patchwork. All scatterplots and fitted regression graphs were generated using the ggplot2 package.

RESULTS AND DISCUSSION

The combined analysis of field data and Vegetation Indices (VIs) derived from satellite imagery described a vigorous crop, characterized by high leaf density and strong photosynthetic activity (Table 2). LAI exhibited a wide range of values, with measurements spanning from 3.13 to 8.84 m^2/m^2 and a mean of 5.79±1.33, which is consistent with advanced canopy development. In wheat, canopy development is strongly associated with agronomic management, resource availability (nitrogen and water), and climatic conditions (Feng *et al.*, 2019); therefore, high LAI values generally reflect well-managed production systems under favorable growing conditions. The VIs exhibited high values and low variability. EVI ranged from 0.61 to 0.91, reflecting elevated photosynthetic activity and greater sensitivity to variations in canopy structure compared with NDVI. Measurements were collected between 68 and 120 days after sowing (DAS), encompassing the booting and grain-filling stages. The temporal difference between field measurements and satellite-derived data was minimal (2 days), thereby ensuring adequate correspondence between datasets.

The predictive capacity of the VIs (NDVI and EVI) to estimate LAI was evaluated using simple linear models with grouped cross-validation by field. The results showed moderate predictive performance for both indices when used independently, with R^2 values ranging from 0.33 to 0.41 and RMSE values ranging from 1.18 to 1.35 (Table 3).

Table 2. Descriptive Statistics (Minimum, Maximum, and Mean ± Standard Deviation) of the Variables Analyzed.

Variable	Unit	Minimum	Maximum	Mean±SD
LAI	m^2/m^2	3.13	8.84	5.79±1.33
NDVI	–	0.83	0.95	0.89±0.03
EVI	–	0.61	0.91	0.75±0.07
DAS	days	68	120	93±14.62
Date difference (LAI-VI)	days	0	2	1.06±0.72

LAI: Leaf Area Index; NDVI: Normalized Difference Vegetation Index; EVI: Enhanced Vegetation Index; DAS: Days After Sowing; VI: Vegetation Index; SD: standard deviation.

Table 3. Predictive Performance of the Linear Models for LAI Estimation Using Grouped Cross-Validation by Field.

Index	Model	R^2 (CV)	RMSE (CV)
NDVI	LM	0.41	1.26
NDVI	RF	0.35	1.31
EVI	LM	0.33	1.18
EVI	RF	0.38	1.35

NDVI: Normalized Difference Vegetation Index; EVI: Enhanced Vegetation Index; LM: Linear Model; RF: Random Forest; R^2: coefficient of determination; CV: cross-validation; RMSE: Root Mean Square Error.

Both indices captured similar information related to canopy development, as the simple models did not exhibit marked differences in predictive performance; likewise, the Random Forest models did not show substantial improvements over the linear models. This result suggests that, in commercial scenarios characterized by high spatial and agronomic heterogeneity, linear models provide an adequate representation of the relationship between VIs and LAI, with no clear evidence of substantial gains from the incorporation of more complex modeling approaches. Several studies have demonstrated the linearity of the relationship between EVI and LAI, regardless of vegetation type or geographic region (Potithep *et al.*, 2013; Alexandridis *et al.*, 2019), whereas other studies suggest that a more complex model fit may better explain this relationship (Son *et al.*, 2013). Although the results of the present study address the general objective, it is important to consider the inclusion of other VIs, as reported by He *et al.* (2019), who estimated LAI in rice (*Oryza sativa* L.) using a novel VI that combined near-infrared (NIR) and red-edge bands. The relationship between EVI and LAI showed a moderate positive trend, with lower data dispersion ($R=0.39$) (Figure 1A). In contrast, NDVI exhibited a limited linear response with respect to LAI, showing considerable data dispersion, particularly at high LAI values ($R=-0.05$) (Figure 1B). This finding is consistent with previous studies indicating that NDVI tends to saturate under high-biomass conditions, whereas EVI retains greater sensitivity in dense vegetation cover (Thenkabail *et al.*, 2000; Lin *et al.*, 2019; Sepúlveda, 2019; Jin *et al.*, 2021).

In order to interpret the influence of agronomic factors and the hierarchical structure of the data, Linear Mixed Models (LMMs) were fitted (Table 4). The EVI-based model showed a higher marginal coefficient of determination ($R^2m=0.60$), indicating a greater explanatory capacity for LAI once variability among phenological stages and varieties had been controlled for. In both models, the conditional coefficient of determination was high ($R^2c>0.70$), reflecting an important contribution of the random field effect.

The fitting error of the mixed models was moderate, with an RMSE of 0.60 for EVI and 0.42 for NDVI. The observed difference in marginal R^2 indicates that EVI describes LAI variability more consistently, regardless of field, whereas NDVI performance appears to be more strongly influenced by structural differences among fields. These results reinforce previous findings in both forest and agricultural systems. Crespo-Antia *et al.* (2024) found that EVI captures phenological changes in forest ecosystems more effectively. Similarly,

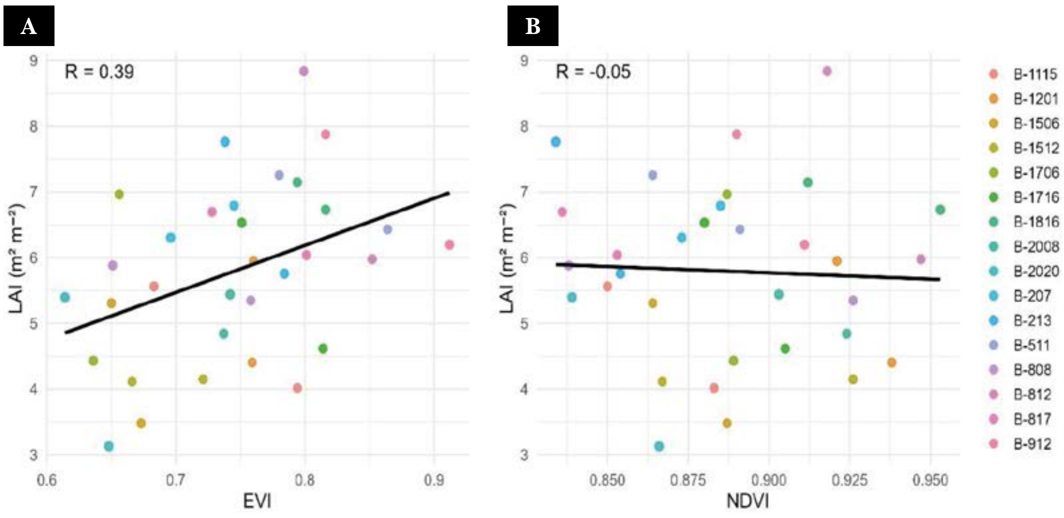

Figure 1. LAI-EVI (A) and LAI-NDVI (B) scatterplots with fitted linear regression lines.

Table 4. Performance Evaluation of the Linear Mixed Models.

Model	R^2m	R^2c	RMSE
LMM-NDVI	0.33	0.83	0.42
LMM-EVI	0.60	0.70	0.60

LMM: Linear Mixed Model; NDVI: Normalized Difference Vegetation Index; EVI: Enhanced Vegetation Index; R^2m: marginal coefficient of determination; R^2c: conditional coefficient of determination; RMSE: Root Mean Square Error.

Shi *et al.* (2024) demonstrated that EVI is also useful for predicting rice yield and detecting changes in vegetation greenness.

The EVI-based linear mixed model showed a positive and statistically significant effect on LAI (β=11.85±2.57; p<0.001; Table 5). Likewise, the grain-filling stage exhibited LAI values approximately 1.9 units greater than those observed during the booting stage. In contrast, no significant differences associated with variety were detected once the vegetation index and phenological stage were taken into account. Recent studies report that model precision may be subject to uncertainty and variation under different environmental conditions and among varieties, as these factors affect crop physiology, thereby regulating LAI, yield, and spectral responses across both spatial and temporal scales (Buthelezi *et al.*, 2023).

Table 5. Coefficients of the Enhanced Vegetation Index (EVI)-Based Linear Mixed Model (LMM).

Effect	Estimate	SE	p-value
Intercept	−4.26	2.06	0.05
EVI	11.85	2.57	0.001
Stage (Grain filling)	1.87	0.28	3.1×10^{-6}
Variety (CIRNO C2008)	0.59	0.37	0.13

EVI: Enhanced Vegetation Index; SE: standard error.

These results highlight the potential of remote sensing based on Vegetation Indices (VIs) as a practical and scalable tool to support agriculture, particularly EVI, given its lower sensitivity to atmospheric noise and background vegetation, which makes it a more reliable index for complex agricultural environments (Zhang *et al.*, 2023). In this context, the significant contribution of the random field effect underscores the need to explicitly account for spatial variability in regional-scale applications, where differences among production units may condition model performance. To improve the scalability and operational accuracy of these tools, future studies should integrate additional information on agronomic management and climatic conditions, as well as extend validation across a larger number of commercial fields.

CONCLUSIONS

The Normalized Difference Vegetation Index (NDVI) and the Enhanced Vegetation Index (EVI) showed a positive relationship with the Leaf Area Index (LAI), although their predictive capacity was moderate due to variability associated with agronomic management, phenology, and between-field discrepancies. Machine learning and linear models exhibited comparable performance. The analysis based on Linear Mixed Models showed that EVI was more consistent than NDVI in explaining the average variability of LAI, whereas between-field variability exerted a stronger influence on NDVI. LAI was significantly affected by phenological stage, whereas variety did not have a relevant impact.

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