A case study of detecting nutrient deficiencies in corn using multispectral satellite imagery

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Abstract. We explore the feasibility of detecting nitrogen deficiencies in a cornfield using exclusively multispectral satellite imagery. Attempts to leverage Sentinel-1 and Sentinel-2 data demonstrate that while nutrient shortages are successfully identified through multi-sensor approaches—often incorporating UAV imagery, ground-based measurements, or advanced vegetation indices—reliably detecting these deficits from satellite imagery alone remains challenging. Data scarcity, uneven initial and structural soil conditions, noise introduced by atmospheric effects and cloud cover complicate the direct association of spectral signals with nutrient levels. Despite observed differences in key vegetation indices, such as NDVI, between fertilized and unfertilized plots at late growth stages, early-season detection proved unreliable. These findings illustrate the complexity of detecting nutrient deficiencies and highlight the need for improved data quality, supplementary ground truth measurements, or more sophisticated modeling approaches to enhance the accuracy and accessibility of satellite-only nutrient deficiency detection in precision agriculture.

Keywords: Nitrogen deficiency · Sentinel-2 · Vegetation Indices · NDVI · Precision agriculture · Precision fertilization.

1 Introduction

Detecting nutrient deficiencies, such as nitrogen (N) shortages, is crucial for precision agriculture. Remote sensing, particularly with multispectral and radar satellite imagery, offers a scalable solution for monitoring crop health. Vegetation indices like Normalized Difference Vegetation Index (NDVI) and Nitrogen Nutrition Index (NNI), as well as red-edge and shortwave infrared bands, have shown strong correlations with nutrient levels in crops.

Challenges such as cloud cover, data noise, and variability in soil conditions remain significant obstacles. Additionally, many methods depend on supplementary data, such as Unmanned Aerial Vehicle (UAV) imagery or ground measurements, which can reduce practicality and accessibility for widespread use.

In this study, we investigate the potential of using only Sentinel-1 and Sentinel-2 data to identify N deficiencies in corn fields. A successful approach could enhance fertilizer management, improve yields, and reduce environmental impact.

2 Related Work

Identifying nutrient deficiencies in crops using satellite imagery has been a widely studied topic. Much of this work has focused on the selection of appropriate spectral bands and indices, the integration of multiple data sources, and the application of advanced algorithms to enhance detection accuracy.

2.1 Spectral Bands and Vegetation Indices

Choosing the correct spectral bands is crucial for monitoring nutrient status. Red and ShortWave InfraRed (SWIR) bands, for example, have proven effective for detecting nitrogen deficiency in corn by capturing variations in chlorophyll content and leaf structure [12]. Similarly, studies have shown that combining different Sentinel-2 bands improves the estimation of the Nitrogen Nutrition Index (NNI) [15,10]. Red-edge bands, in particular, correlate strongly with nitrogen concentrations and have become a popular choice for deriving vegetation indices.

Traditional indices like NDVI and Enhanced Vegetation Index (EVI) remain important but have been complemented by newer, nutrient-focused indices [7,3]. Some studies propose indices that integrate multiple spectral bands or combine optical and radar data to improve reliability under changing conditions [9,13,7,4,3].

2.2 Data Sources and Preprocessing

Sentinel-2 is a commonly used satellite due to its spectral resolution and the availability of red-edge and SWIR bands. Other satellites, such as Landsat-8, PRISMA, and PlanetScope, provide complementary data, while radar information from Sentinel-1 can help address cloud issues and refine biomass estimates [8,1,6,14]. Sentinel-2 and Sentinel-1 spectral bands selected for this study are presented in Table 1.

Preprocessing steps, such as atmospheric corrections using tools like Sen2Cor and QGIS [9,7], are essential for ensuring data consistency. Downscaling Sentinel-2 bands for finer spatial resolution, applying cloud masks, and using smoothing filters like Whittaker can improve data quality [4]. Ground-based measurements of NNI, Plant Dry Matter (PDM), and Plant Nitrogen Accumulation (PNA) [7,9,5], as well as UAV imagery, often serve as reference points to validate satellite-based findings.

Table 1. Summary of Sentinel-1 and Sentinel-2 bands used, where "Res." is spatial resolution in meters.

Band	Res.	Description
Sentinel-2		
B1	60	Aerosols: 443.9nm / 442.3nm
B2	10	Blue: 496.6nm / 492.1nm
B3	10	Green: 560nm / 559nm
B4	10	Red: 664.5nm / 665nm
B5	20	Red Edge 1: 703.9nm / 703.8nm
B6	20	Red Edge 2: 740.2nm / 739.1nm
B7	20	Red Edge 3: 782.5nm / 779.7nm
B8	10	NIR: 835.1nm / 833nm
B8A	20	Red Edge 4: 864.8nm / 864nm
B9	60	Water vapor: 945nm / 943.2nm
B11	20	SWIR 1: 1613.7nm / 1610.4nm
B12	20	SWIR 2: 2202.4nm / 2185.7nm
MSK CLDPRB	20	Cloud Probability Map
SCL	20	Scene Classification Map (4 - Vegetation, 5 - Bare Soils)
Sentinel-1		
VV	10	Single co-polarization, vertical transmit/vertical receive
VH	10	Dual-band cross-polarization, vertical transmit/horizontal receive

2.3 Algorithms and Modeling Approaches

Vegetation indices remain a key tool for detecting nutrient deficiencies, and NDVI remains a frequently used index despite its sensitivity to certain emission-related factors [3]. More specialized indices, such as the Normalized Difference Red-Edge Index (NDRE), have shown strong relationships with nitrogen uptake and NNI [2]. Some of the indices considered are presented in Table 2.

Machine learning methods, including Partial Least Squares Regression (PLSR), Support Vector Regression (SVR), and Random Forest Regression (RFR), have been used to link foliar nutrient levels to spectral and textural features derived from satellite data [6]. Among these, Random Forest models have shown high accuracy for predicting parameters like PDM and PNA, benefitting from their ability to handle complex data and multiple variables [7]. Bootstrap resampling, atmospheric correction, and super-resolution techniques have further improved predictions.

2.4 Applications to Different Crops and Nutrients

Research on nutrient deficiency detection spans various crops. Nitrogen deficiency in corn has been a common focus [8], while others have predicted corn yields [1] or assessed nitrogen status in winter wheat [14], cranberries [6], and vineyards [11]. UAV and satellite imagery have been used together to successfully predict nitrogen uptake, achieving strong correlations with ground truth data for wheat and rice [7,9].

Table 2. Vegetation indices considered.

Index	Equation	Description
NDVI	$\frac{B8-B4}{B8+B4}$	Measures vegetation health. Higher values indicate healthy crops.
EVI	$2.5 \times \frac{B8-B4}{B8+6\times B4-7.5\times B2+1}$	Improves sensitivity in dense vegetation; compensates for atmospheric effects.
GNDVI	$\frac{B8-B3}{B8+B3}$	Focuses on chlorophyll content using green band (B3) for vegetation analysis.
CVI	$\frac{B8}{B4}$	Indicates chlorophyll levels, helpful for assessing photosynthetic activity.
MNDVI	$\frac{B8-B4}{B8+B4+0.16}$	A variant of NDVI with better performance in areas with dense vegetation.
MCARI	$\frac{(B5-B4)-0.2\times(B5-B3)}{B5}$	Sensitive to chlorophyll absorption, effective for early stress detection.
NDMI	$\frac{B8-B11}{B8+B11}$	Assesses moisture content in crops, useful for irrigation and drought management.
PRI	$\frac{B5-B4}{B5+B4}$	Reflects photosynthetic efficiency, useful for detecting stress conditions.

While progress is clear, relying solely on satellite images to detect nutrient deficiencies remains difficult. Most successful studies combine satellite data with ground-based measurements or UAV support. As research continues, improving methods for satellite-only assessments will be key to making precision agriculture more accessible and effective.

3 Methods

In this section, we describe the steps we take to find out whether it is possible to detect nitrogen (N) shortages in a specific corn field using satellite data. We explain how we collect and prepare the data, how we look for patterns, and how we build different models to predict areas with nutrient problems.

3.1 Data Collection and Preprocessing

Our data comes from a corn field and a winter wheat field where N fertilizers were intentionally not applied in certain spots. We call these areas “subplots” and present them in Figure 1. We track these fields through their growing season of 2024.

We collect two types of satellite data: Sentinel-1 (radar) and Sentinel-2 (spectral). Sentinel-1 data are not affected much by clouds, so we do not need heavy filtering. Sentinel-2 data, on the other hand, can be blocked or distorted by clouds and atmospheric conditions. To handle this, we remove any Sentinel-2 pixels with a cloud probability greater than zero or that do not represent vegetation or bare soil. The satellite bands are described in Table 1.

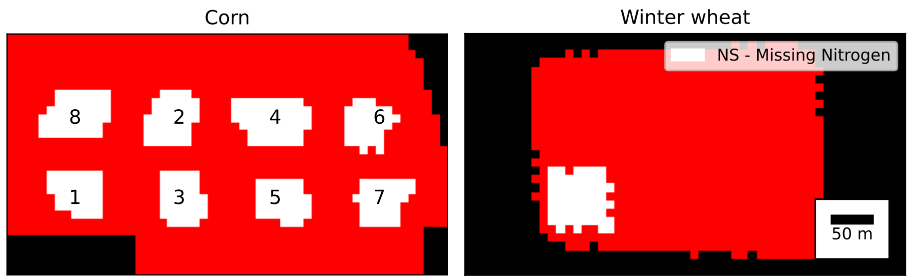

Fig. 1. Visual representation of the corn and winter wheat fields with fertilized (in red) and non-fertilized (in white) subplots.

After filtering, we have 14 Sentinel-2 images of the corn field for analysis (see Table 3). We project all satellite data (Sentinel-1 and Sentinel-2) to the same coordinate system (EPSG:3346) at a 10 m resolution per pixel. We then calculate several vegetation indices (such as NDVI) from these images to help assess plant health (see Table 2 for the list of indices).

Table 3. Satellite observations with varying cloud cover percentages from 2024-05-13 to 2024-10-01.

Satellite	Observations for cloud cover percentage				
	$\leq 0\%$	$\leq 1\%$	$\leq 10\%$	$\leq 50\%$	$\leq 100\%$
Sentinel-2	11	23	27	33	57
Sentinel-1					36

3.2 Data Analysis

To understand how the lack of N fertilizer affects the plants, we compare areas without fertilizer to areas with proper fertilization. We do this at two scales:

- **Whole-field comparison:** We examine the entire subplot area that lacks fertilizer against the rest of the field.
- **Local comparison:** We focus on a smaller area around each subplot (approximately a 70-meter radius). Looking at a more localized region, we aim to reduce the influence of varying initial soil conditions throughout the field.

We examine histograms to see if the distributions of vegetation indices and spectral values differ between fertilized and unfertilized areas.

3.3 Modeling Approaches

We try four types of machine learning models to identify nutrient deficiencies: Neural Network (NN), Random Forest (RF), Support Vector Machine (SVM), and Logistic Regression (LR).

We use the same inputs for all the models, which include the Sentinel-1 and Sentinel-2 bands in Table 1. We apply the models for each pixel separately.

First, we split our corn field data into a training set (subplots 8, 2, 5, 7) and a test set (subplots 1, 3, 4, 6). We also standardize all the input values. Each model is trained to classify whether a pixel belongs to an area lacking N fertilizer (deficient) or an area with normal fertilization (sufficient).

Since we only have one subplot in the winter wheat field, we only use it to test whether the models trained on corn are transferable to winter wheat.

Our NN model has four hidden layers with 16 ReLu-activated neurons each and a logistic-sigmoid-activated output neuron. It is trained minimizing binary cross-entropy loss using Adam optimizer and 30% dropout rate in the hidden layers. The RF has 100 trees, each with a maximum depth of four. The SVM uses Gaussian kernel and the regularization parameter set to 1.0.

4 Results

In this section, we present our findings after processing and analyzing the data. We look at how vegetation health changes over time, compare fertilized and unfertilized areas, and try different models to predict nutrient shortages.

4.1 NDVI Changes Over Time

Figure 2 shows how the NDVI changed from 2024-05-13 to 2024-09-17. As expected, the NDVI increased as the corn and winter wheat grew and then dropped when the plants matured and were close to harvest.

From these NDVI curves, we notice two key points:

– After August 28, fertilized areas generally have a slightly higher NDVI than unfertilized areas.
– Before August 28, the NDVI differences are not always clear. In some cases, unfertilized areas looked similar to fertilized ones. (see subplots 1, 3 and 7)

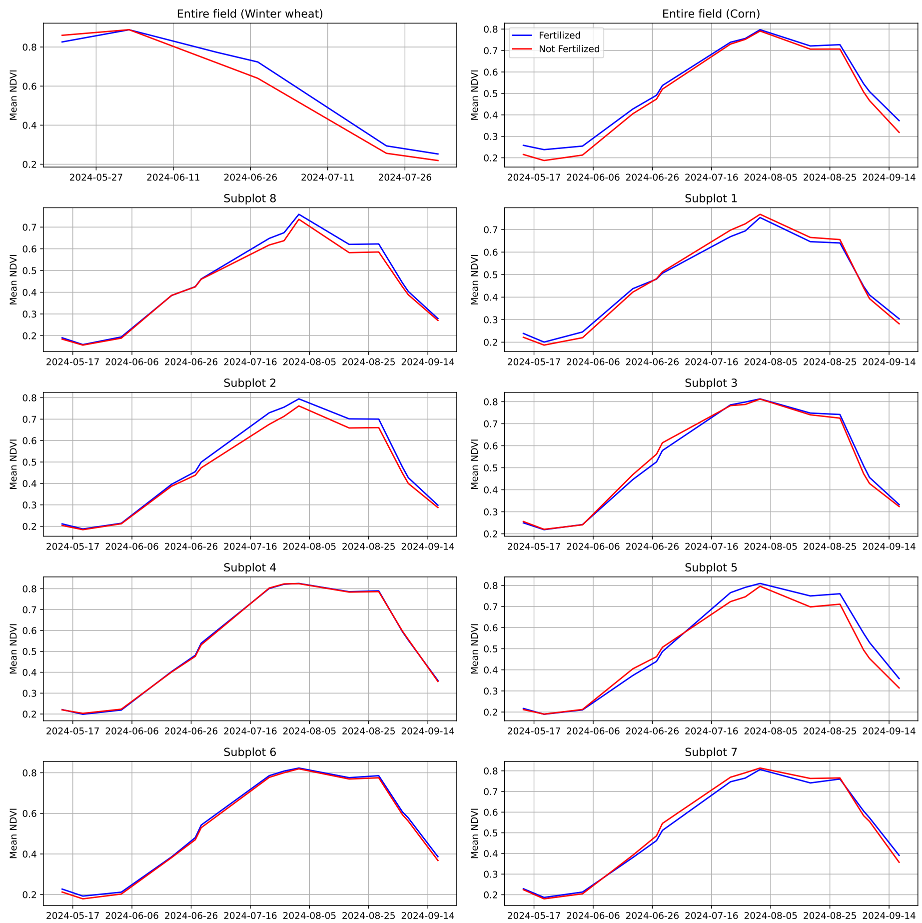

Fig. 2. Mean normalized difference vegetation index (NDVI) dynamics over the entire growth season for the fertilized (blue lines) and not fertilized (red lines) areas for the entire fields, and each subplot versus its surrounding area individually.

4.2 NDVI Distributions

To understand these differences better, we look at NDVI histograms on specific dates. For example, at 2024-09-17, the NDVI histograms (see Figure 3) show that fertilized plots have NDVI values slightly shifted toward higher numbers compared to the unfertilized plots. This suggests that by the end of the growing season, fertilized areas maintained a healthier state.

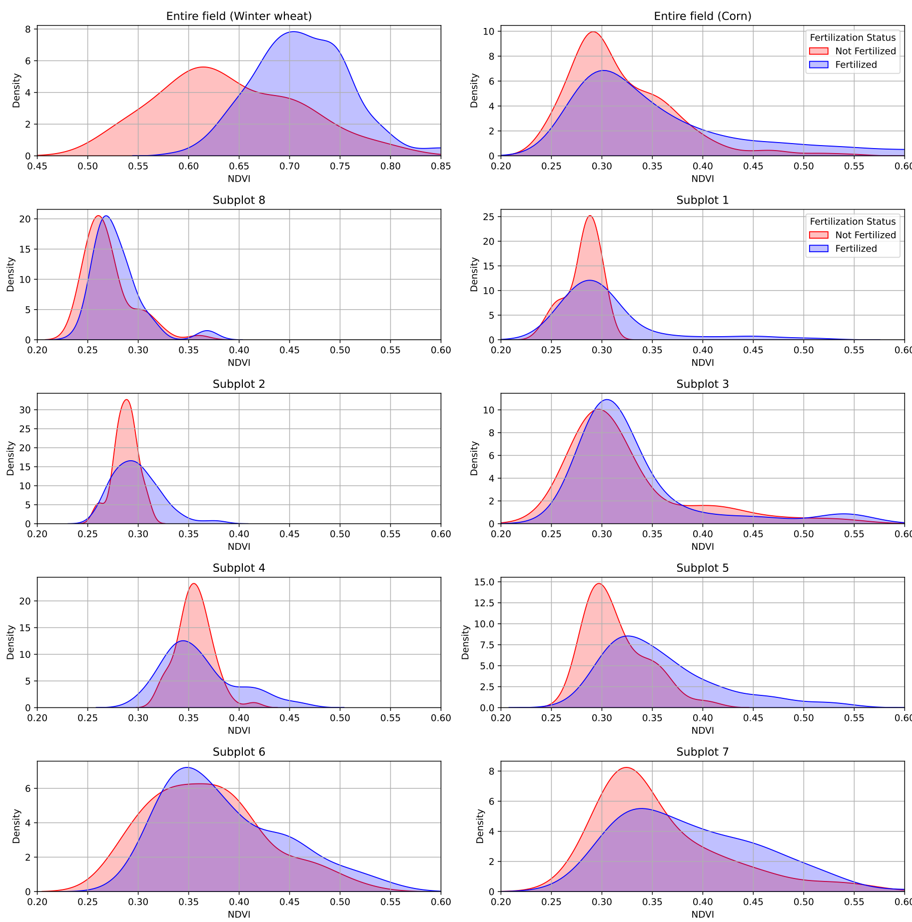

Fig. 3. Normalized difference vegetation index (NDVI) histograms for fertilized (blue lines) and not fertilized (red lines) areas at 2024-09-17

However, at earlier dates, such as 2024-07-27, this pattern was not consistent (see Figure 4). The NDVI distributions vary a lot from one subplot to another. This means that early in the season, it is harder to tell fertilized and unfertilized areas apart just by looking at NDVI.

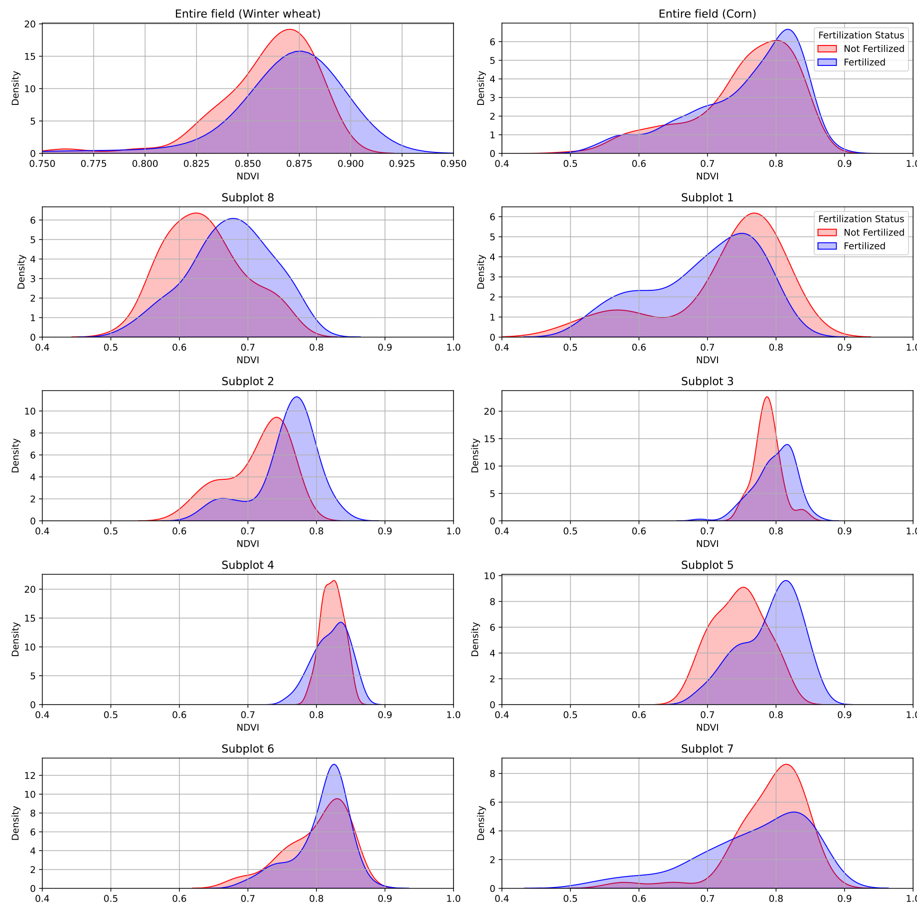

Fig. 4. Normalized difference vegetation index (NDVI) histograms for fertilized (blue lines) and not fertilized (red lines) areas at 2024-07-27 for the entire fields, and each subplot versus its surrounding area individually.

4.3 Modeling Attempts

We try using four different models—Neural Network, Random Forest, Support Vector Machine, and Logistic Regression—to detect unfertilized areas. These models are trained to classify pixels as either unfertilized or fertilized.

We use the corn field for training (subplots 8, 2, 3, 7) and validation (subplots 1, 3, 5, 7) and test the same models on winter wheat.

In Figures 5 and 6, we can see “probability maps” produced by the machine learning models for the corn and winter wheat fields respectively. Unfortunately, none of the models produce clear and reliable patterns that match the unfertilized areas in the corn field. We also notice that models tend to do a bit better on the training subplots but not so on the validation ones.

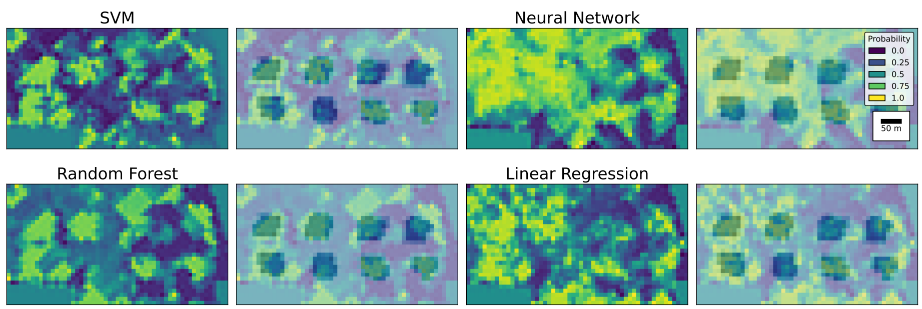

Fig. 5. Modeling results as probability heat maps for Support vector machine (SVM), Neural Network, Random Forest, and Linear Regression models for the corn field.

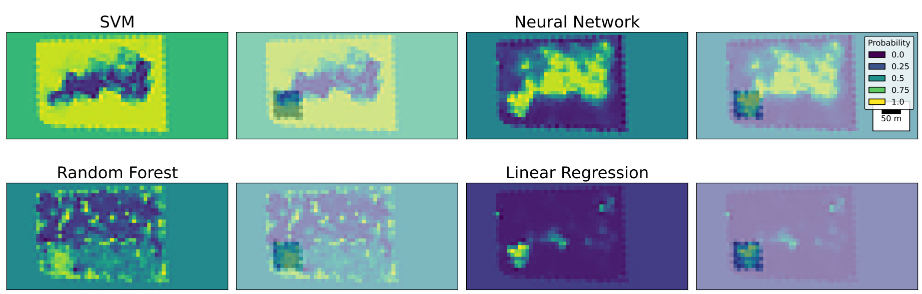

Fig. 6. Modeling results as probability heat maps for Support vector machine (SVM), Neural Network, Random Forest, and Linear Regression models for the winter wheat field.

Interestingly, we see in Figure 6 that the models trained on corn can to some extent capture deficiencies in winter wheat.

Trying different dates and adjusting model hyperparameters did not produce a noticeable improvement in the results. We suspect that other factors, such as variations in soil and weather conditions, might have made it difficult for the models to detect nutrient shortages from the satellite data alone.

5 Discussion

Our attempts to detect nutrient shortages using only satellite imagery faced several challenges. One major issue was the limited amount of data. We only had a few field areas where fertilizer was intentionally withheld, resulting in very few pixels representing unfertilized conditions. This small amount of training data makes it difficult for any model to learn reliable patterns.

Additionally, the initial soil conditions might have varied significantly across the field. Some unfertilized areas might have started with enough residual nitrogen to appear similar to fertilized areas. This variability adds noise to the data and makes it harder to separate the influence of missing fertilizer from natural soil differences. Human error while fertilizing is also not excluded.

Our NDVI and other vegetation indices showed some promise at the end of the season, with fertilized plots generally showing slightly higher values than unfertilized plots. However, such detection is too late to improve the yields, but early in the season, these differences were not consistent or strong enough to train a reliable classification model.

In summary, the limited data, lack of precise nutrient-level measurements, and varying initial soil conditions made it challenging to develop an accurate model for detecting N shortages using satellite images alone. In future research, having more ground-truth measurements, larger datasets, or additional data sources (such as soil tests or UAV images) could improve the model performance.

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