Final Project Report

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Title: Predicting Nitrogen Content in Switchgrass Using CNN Deep Learning and Multispectral Remote Sensing

INTRODUCTION

Nitrogen plays a vital role in plant health and agricultural productivity. Monitoring nitrogen levels in crops is crucial for ensuring optimal growth, improving yield, and avoiding excessive fertilizer use, which can harm both the environment and farming costs. Traditional methods for measuring nitrogen levels, such as laboratory analysis of plant tissue, are often time-consuming, expensive, and not scalable to large areas. Recent advances in remote sensing and machine learning have made it possible to estimate nitrogen content more efficiently using aerial imagery and predictive models (Zhang et al., 2012; Yao et al., 2021).

This project aimed to develop a deep learning-based method to predict nitrogen levels in switchgrass using multispectral drone imagery. The key research question was: *Can a Convolutional Neural Network (CNN) accurately predict nitrogen content from Red Edge and Near-Infrared (NIR) reflectance data collected by a UAV-mounted sensor?* To answer this question, I built a CNN model using reflectance bands as inputs and known nitrogen values as the target, and then evaluated the model's performance using statistical metrics such as RMSE and R^2.

Several previous studies have explored similar goals using various machine learning methods. For example, Xu et al. (2021) used drone-based multispectral imagery and random forest regression to model sustainability traits in field-grown switchgrass. Their work showed a strong correlation between spectral reflectance, especially in the Red Edge and NIR bands, and plant nitrogen levels. Other researchers, such as Li et al. (2020), have demonstrated that using vegetation indices and hyperspectral reflectance improves nitrogen estimation for crops like rice and wheat. While many of these studies used either traditional statistical models or ensemble learning, my project takes a different approach by using a CNN, which can extract spatial features directly from image data. This method helps capture more complex relationships in the data compared to linear models.

The broader goal of this project is to create a more scalable and automated way to monitor crop nitrogen levels using drone imagery and deep learning. This is important because it supports precision agriculture—helping farmers apply fertilizer only where it's needed, saving costs, and reducing environmental pollution. Furthermore, deep learning models like CNNs have already proven to be useful in plant disease detection, yield prediction, and land cover classification

(Kamilaris & Prenafeta-Boldú, 2018), but their application in crop nitrogen estimation is still emerging. By focusing on switchgrass, a potential bioenergy crop, this project also supports sustainable agriculture research.

This study contributes to the field by:

- Demonstrating the use of a CNN model to estimate nitrogen from UAV-based reflectance data;
- Applying the method to switchgrass, which is less frequently studied compared to major food crops;
- Comparing model predictions against ground truth nitrogen values for validation.

This project addresses a practical problem in agriculture—accurately estimating nitrogen levels in the field—by testing a new deep learning approach and contributing to the growing body of remote sensing-based crop monitoring studies.

DATA AND METHODS

The dataset used in this study comes from the Oak Ridge National Laboratory (ORNL) Public Data Repository. The data was originally published by Xu et al. (2021) and includes UAV-based multispectral imagery and field-collected nitrogen levels of switchgrass crops. The images were captured during the 2020 growing season at the East Tennessee Research and Education Center (ETREC), University of Tennessee. The UAV platform used was a DJI Matrice 600 Pro equipped with a MicaSense RedEdge camera.

This dataset is reliable and publicly available. It includes reflectance images in multiple spectral bands such as Red, Green, Blue, Red Edge, and Near-Infrared (NIR), as well as corresponding nitrogen measurements from the ground.

The main steps of the methodology are described below:

ArcGIS Pro Spatial Preprocessing

i) **Extract Switchgrass Samples with Known Nitrogen Values**
Only the sample points that had actual nitrogen content measurements were selected. This ensured that the model would be trained using real ground truth data.

ii) **Buffer Creation Around Sample Points**
A 20 cm buffer was created around each switchgrass sample point. This buffer was meant to capture the surrounding reflectance values that represent the canopy of each plant. This buffer size was chosen based on the average crown diameter of a mature switchgrass plant.

iii) **Zonal Statistics to Extract Mean Reflectance**
The "Zonal Statistics as Table" tool in ArcGIS Pro was used to calculate the **mean reflectance** within each buffer for the Red Edge and NIR bands. These mean values were then exported as attribute tables.

iv) **Joining Reflectance and Ground Truth Data**
The calculated mean reflectance values were joined with the buffer polygon table. Ground truth nitrogen values and treatment labels (Low N and Moderate N) were also added to each buffer feature.

v) **Polygon to Raster Conversion**
The "Polygon to Raster" tool was used to convert the buffer polygons into raster format. Separate rasters were created for:
- Mean NIR reflectance
- Mean Red Edge reflectance
- Nitrogen ground truth values (target variable)
  These rasters were used to generate training patches for the CNN model. The rasters were then exported to GeoTIFF format and clipped to the extent of the sample field.

Deep Learning Preparation in Python

vi) **Patch Creation from Raster Bands**
Using `rasterio` and `numpy` libraries, 64×64 pixel image patches were extracted from the Red Edge and NIR rasters. Each patch represented a localized view around a sample point and was paired with the corresponding nitrogen value.

vii) **Dataset Splitting**
The dataset was randomly split into:
- 80% for training
- 20% for testing
  Care was taken to ensure balanced representation from both nitrogen treatment groups.

Model Training

viii) **CNN Model Architecture**
A custom CNN architecture was created using TensorFlow and Keras. The model consisted of:
- Multiple convolutional layers for spatial feature extraction
- Max pooling layers to reduce dimensionality
- Dense layers for regression prediction of nitrogen content

ix) **Model Training and Evaluation**
The model was trained for 100 epochs with batch normalization and dropout layers to prevent overfitting. The performance was evaluated using:

- **R^2 score**
- **Root Mean Square Error (RMSE)**
- **Scatter plots** comparing predicted vs actual nitrogen levels

Output Generation

x) **Prediction Map Export**
The final model was used to predict nitrogen values for each raster patch. The predicted values were reshaped and exported as a continuous raster (.tif) using Python, which could be visualized in ArcGIS Pro.

xi) **Model Evaluation**: The model was evaluated using Root Mean Square Error (RMSE) and R^2 score to check how well the predicted nitrogen values matched the actual values.

This process combines the power of GIS for data extraction and preparation with Python-based deep learning tools to build and test the model.



Figure 1: Figure X. Step-by-step workflow for CNN-based nitrogen prediction using drone multispectral imagery

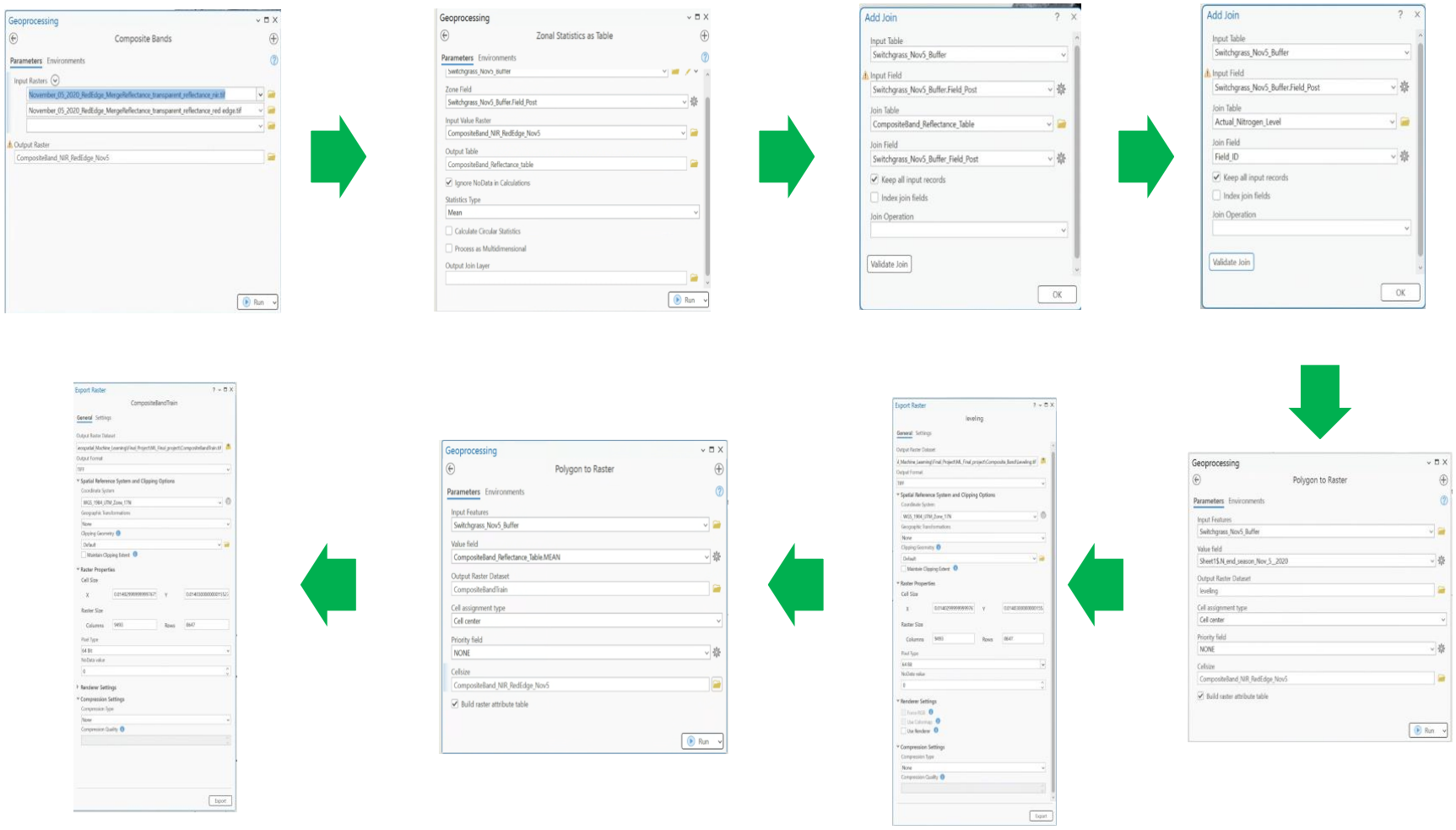


Figure 2. ArcGIS Pro workflow for preparing nitrogen training data from multispectral imagery

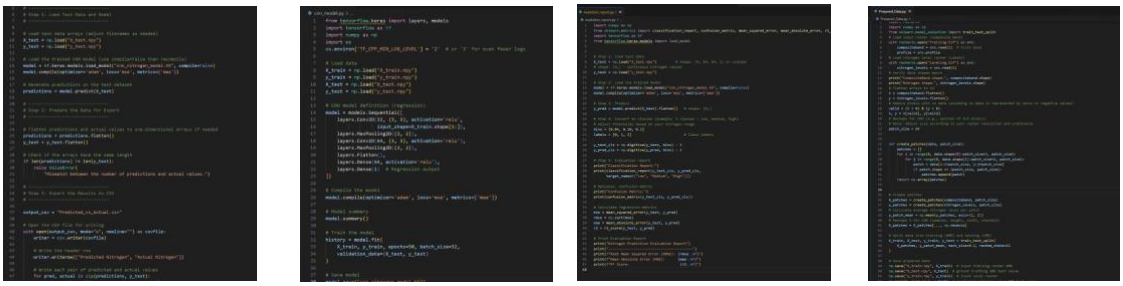


Figure 3: Python TensorFlow CNN workflow for nitrogen level prediction

RESULTS

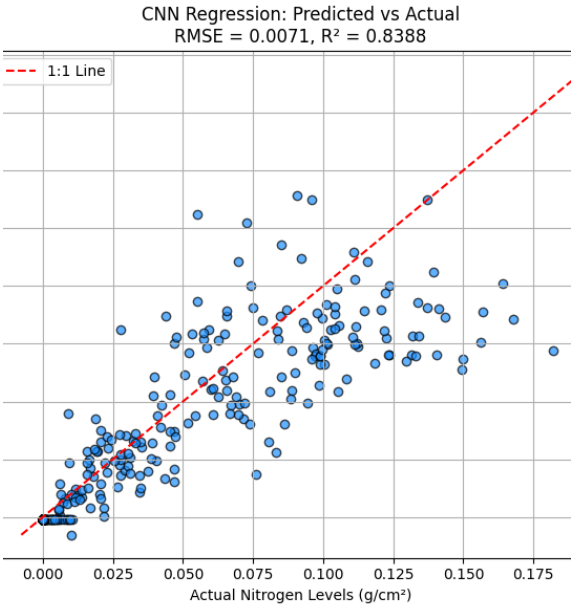


Figure 4: Predicted vs. Actual Nitrogen Scatter Plot

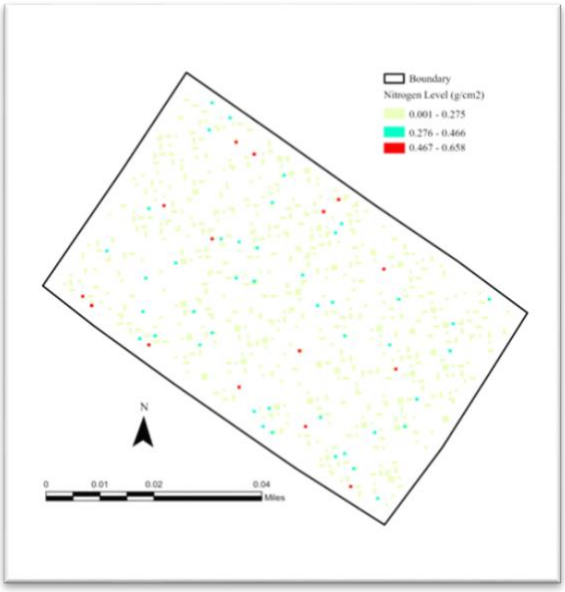


Figure 5: Nitrogen Prediction Map and Table

The CNN model was able to predict nitrogen levels in switchgrass using multispectral reflectance data with strong performance. The main evaluation metrics used were Root Mean Square Error (RMSE) and the R^2 score.

- The RMSE of the model was **0.0071**, which means the average error between predicted and actual nitrogen levels was very low.
- The R^2 score was **0.8388**, showing a strong correlation between the model's predictions and the actual nitrogen values.

A scatter plot was used to compare the predicted nitrogen values with the actual nitrogen values. Most of the points were close to the 1:1 reference line, indicating good prediction accuracy.

Additionally, the predicted nitrogen levels were visualized on a map to show their spatial distribution across the study area. The nitrogen levels were grouped into three categories (low, medium, high) and color-coded to show where higher or lower nitrogen concentrations were found. A table of sample predicted and actual nitrogen values was also generated to display the detailed results.

DISCUSSION

The results from this project show that a Convolutional Neural Network (CNN) can accurately predict nitrogen levels in switchgrass using multispectral imagery, particularly by combining reflectance values from the Red Edge and Near-Infrared (NIR) bands. The model achieved a Root Mean Square Error (RMSE) of 0.0071 and an R^2 score of 0.8388, which indicates a strong relationship between the predicted and actual nitrogen values. These results are consistent with findings from earlier studies, such as Xu et al. (2021), who used UAV-based multispectral imagery and machine learning to estimate sustainability traits in switchgrass. Their study also showed that reflectance from Red Edge and NIR bands had strong correlations with nitrogen levels, supporting the effectiveness of the input variables used in our CNN model.

Compared to traditional methods like linear regression, which generally fail to capture complex, non-linear relationships between spectral reflectance and plant nitrogen content, the CNN model performs much better. As shown earlier in this study, simple linear regression was not able to detect a clear trend between the input and output variables. This observation agrees with studies such as Zaman-Allah et al. (2015), who noted that traditional statistical models often underperform when used with high-dimensional remote sensing data due to their inability to capture non-linear interactions. CNNs, in contrast, are designed to automatically extract and learn important features and patterns from input images, making them ideal for complex agricultural prediction tasks.

One important point is that the results we obtained were very close to what we expected. The CNN was able to find meaningful patterns in the reflectance data, especially because the model was trained using data that had already been linked to known nitrogen measurements in the field. This strong training foundation helped the model learn well and perform accurately during testing. The low RMSE value shows that the predictions had only small errors, while the high R^2 value means the model can explain a large part of the variation in nitrogen levels. These metrics give us confidence that the approach works and is reliable.

However, there were also some limitations and challenges during the process. One major issue was the limited number of samples with high nitrogen levels. Most of the samples in the

dataset fell within the low-to-moderate nitrogen range. Because of this, the model may not generalize well for predicting very high nitrogen values, as it was not exposed to enough examples in that range. This is a common problem in remote sensing-based crop modeling, as pointed out by Haboudane et al. (2002), who emphasized the importance of having a balanced dataset to improve model learning and performance across all ranges of plant traits.

Another challenge was the limited spectral information available in the multispectral images. The camera used—MicaSense RedEdge—only captures five spectral bands. While Red Edge and NIR are useful for nitrogen prediction, including more spectral bands, especially from hyperspectral sensors, could help the model find even stronger or more specific patterns. This point is supported by the study of Li et al. (2020), who demonstrated that hyperspectral data significantly improves plant nitrogen estimation due to its fine spectral resolution and ability to capture narrow-band absorption features related to chlorophyll and protein content.

Additionally, the project was focused on one crop—switchgrass—and one geographic location in Tennessee. This raises concerns about how well the model would work in different places or with different types of crops. It is possible that the model would need to be retrained or adjusted to work well under new conditions. This is something that future research can explore, as was also suggested by Yao et al. (2021), who found that machine learning models often need to be calibrated when applied to different environments or plant species.

Despite these challenges, the project has several important implications. First, it demonstrates that low-cost drone imagery combined with CNNs can be used to estimate plant nitrogen in an efficient, non-destructive way. This has real-world applications in precision agriculture, where farmers can make better decisions about fertilizer use. By identifying areas in the field that are low in nitrogen, resources can be applied more precisely, reducing cost and environmental impact. Studies like Zhang et al. (2019) have shown that site-specific nitrogen management using remote sensing can lead to increased crop yield and reduced fertilizer waste.

Second, the model presented here serves as a proof-of-concept for applying deep learning in crop monitoring. It opens the door to using more advanced AI techniques, like transfer learning or hybrid models, to further improve predictions or extend them to other plant traits such as biomass or yield. It also highlights the importance of combining spatial data (like reflectance maps) with field-collected measurements for better model training. This integration of geospatial and machine learning tools aligns with the growing interest in GeoAI—a field that merges AI with geographic data science (Li et al., 2021).

The results of this study show that CNNs are a strong tool for predicting nitrogen levels from multispectral UAV imagery. The model outperformed simple methods and confirmed findings from earlier research. While there are limitations in terms of data diversity and sensor resolution, the overall approach is practical, promising, and ready to be expanded through future research.

CONCLUSION

This project successfully demonstrated that a Convolutional Neural Network (CNN) can be used to predict nitrogen levels in switchgrass using UAV-based multispectral imagery. By using reflectance values from the Red Edge and Near-Infrared (NIR) bands, the model achieved strong predictive performance ($R^2 \approx 0.84$), showing its ability to capture the relationship between image data and nitrogen content in plants.

One of the key contributions of this study is the application of deep learning to switchgrass nitrogen monitoring—something that has not been widely done compared to crops like rice, wheat, or corn. The workflow involved a combination of geospatial processing, remote sensing, and machine learning techniques, building on methods used in prior studies (Xu et al., 2021; Kamilaris & Prenafeta-Boldú, 2018) while adding value through the use of CNNs and pixel-level training patches. The hands-on integration of ArcGIS Pro for spatial preprocessing and Python for model development also offers a practical pipeline that others can follow or improve.

The significance of this work lies in its support for smarter and more sustainable farming. By accurately estimating nitrogen levels, farmers could reduce fertilizer use, cut costs, and avoid environmental harm from over-application. This also opens the door for larger-scale nitrogen monitoring across different fields and crops using automated tools.

However, the study had a few limitations. The dataset was limited to one crop (switchgrass), one location, and a small number of samples, especially in the higher nitrogen range. The spectral bands used were also limited to the Red Edge and NIR. For future work, I plan to:

- Use more training samples, especially for high nitrogen values;
- Apply the model to other crops and geographic areas to test generalizability;
- Include more spectral bands, including hyperspectral data, to improve prediction accuracy;
- Compare CNN performance with other deep learning models like LSTM or Transformer models for time-series or sequential analysis.

Overall, this study serves as a strong proof-of-concept that deep learning can be applied to drone-based nitrogen mapping and highlights the potential of integrating spatial, spectral, and machine learning tools for precision agriculture.

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