



Introduction

As discussed in R.L. Nielsen's 1993 "Stand Establishment Variability in Corn," uneven corn emergence has negative impacts throughout the entire season. Scouting for these variabilities is important for finding and fixing the assorted problems which impact emergence, but physical scouting of corn is incredibly time and labor intensive and dependent on heavy extrapolation based on whatever the scout can see.

Use of Unmanned Aerial Systems (UAS) in agriculture has been on the rise for years thanks to the increased scouting potential among other possible uses. Multiple avenues for using this new technology exist to explore, as has been highlighted by Sebastian Varela et. al. in the 2018 study "Early-Season Stand Count Determination in Corn via Integration of Imagery from Unmanned Aerial Systems (UAS) and Supervised Learning Techniques"

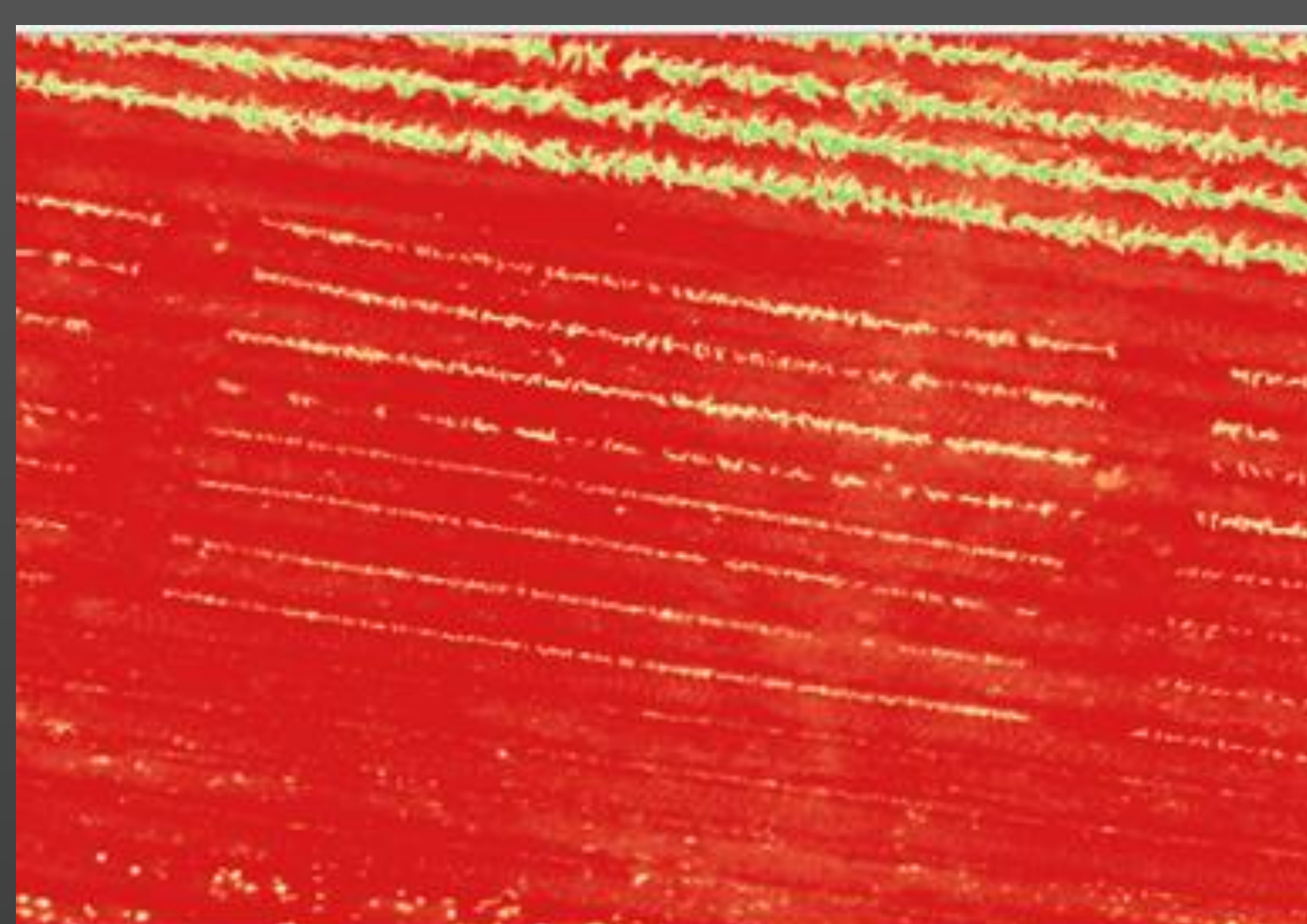
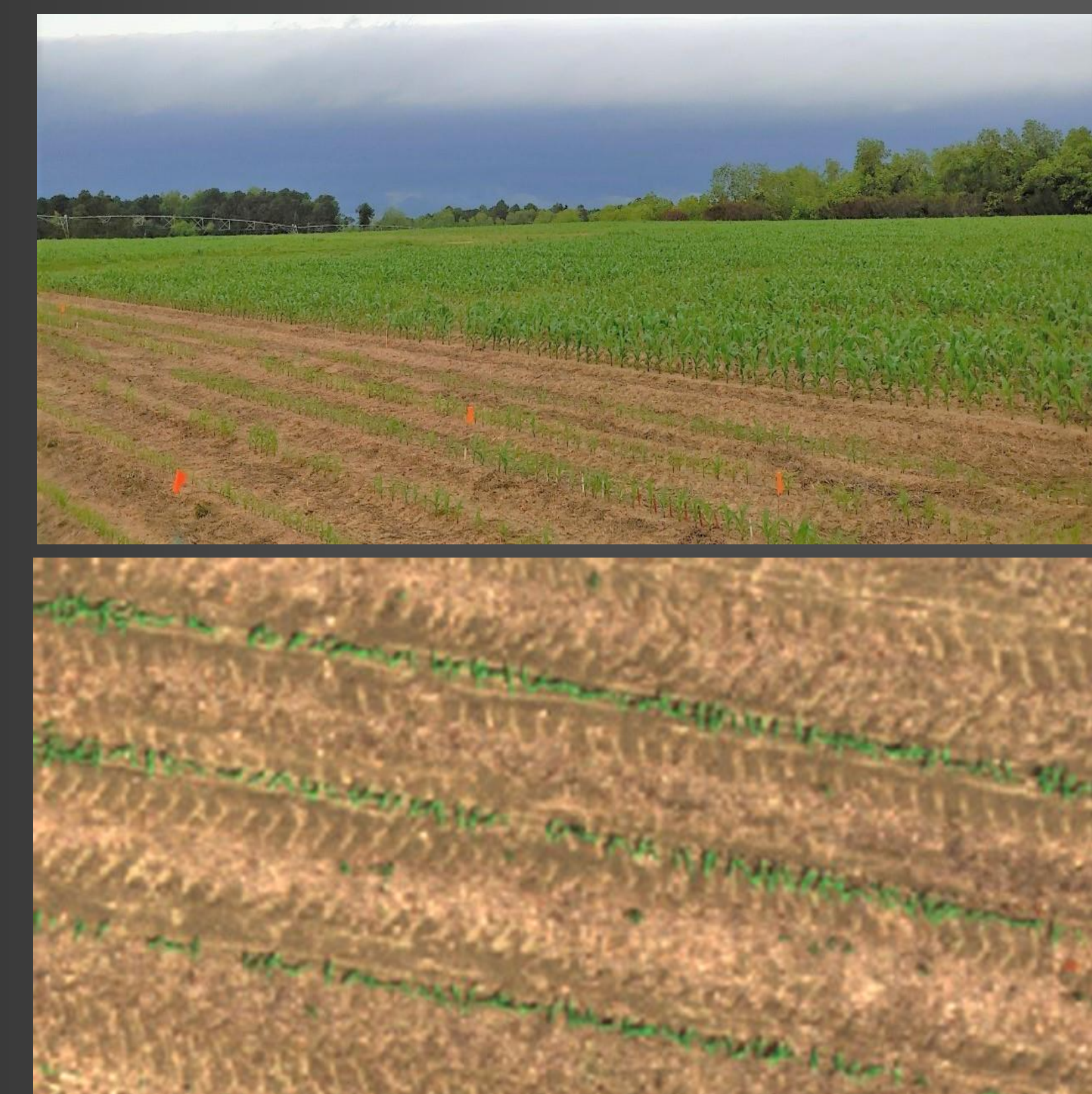
Research Objectives

The purpose of this experiment was to establish a relationship between early Normalized Difference Vegetative Index (NDVI) and final yield components in corn as well as develop a model to count corn plant emergence.



Materials & Methods

- One-year study (2020) conducted at J.G. Woodruff Farm at Abraham Baldwin Agricultural College
- Pioneer variety corn planted throughout April; plots were randomized blocks of different population goals (24K, 32K, 40K, and 48K Plants Per Acre)
- Remote imagery was collected beginning at 10 Days After Planting following the first planting date in 7-day intervals using an Unmanned Aerial System (UAS) outfitted with a multispectral camera.
- Used Agisoft to stitch imagery into an orthomosaic
- Exported orthomosaics into QGIS to process into an NDVI raster map
- Use a manual thresholding method in QGIS to show that it's possible to count pixels above a certain NDVI value
- Write a program in Python to use Otsu's automatic thresholding method to count the pixels above threshold
- This proof-of-concept model uses the cropped and exported NDVI imagery to correlate pixels above threshold to the number of plants physically counted in that section



NDVI Image of a plot

Results

```
fig, ax = plt.subplots(figsize=(15, 10))
ax.imshow(img_org)
plt.subplot(121)
plt.imshow(img_org)
plt.subplot(122)
plt.imshow(binary)
plt.show()
```

threshold value = 0.13594957

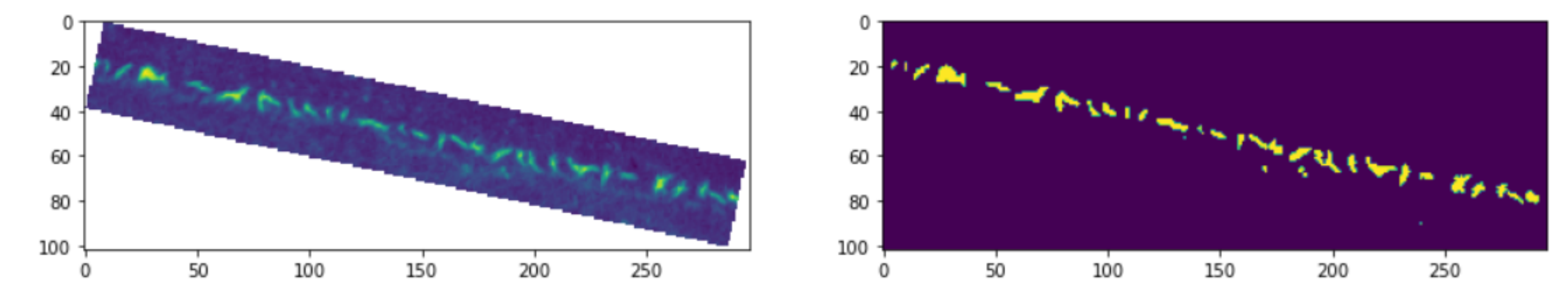


Fig. 1: Automated threshold for the 2nd planting, 17 DAP, with a goal of 32K PPA

```
#histBinary = plt.hist(img_int, bins="auto", fc="k", ec="k")
print(np.count_nonzero(binary))
#print(np.sum(img_int))
```

748

Fig. 2: Number of pixels above threshold for the processed imagery

Number of Pixels Above Threshold - Plant Population(17 DAP)

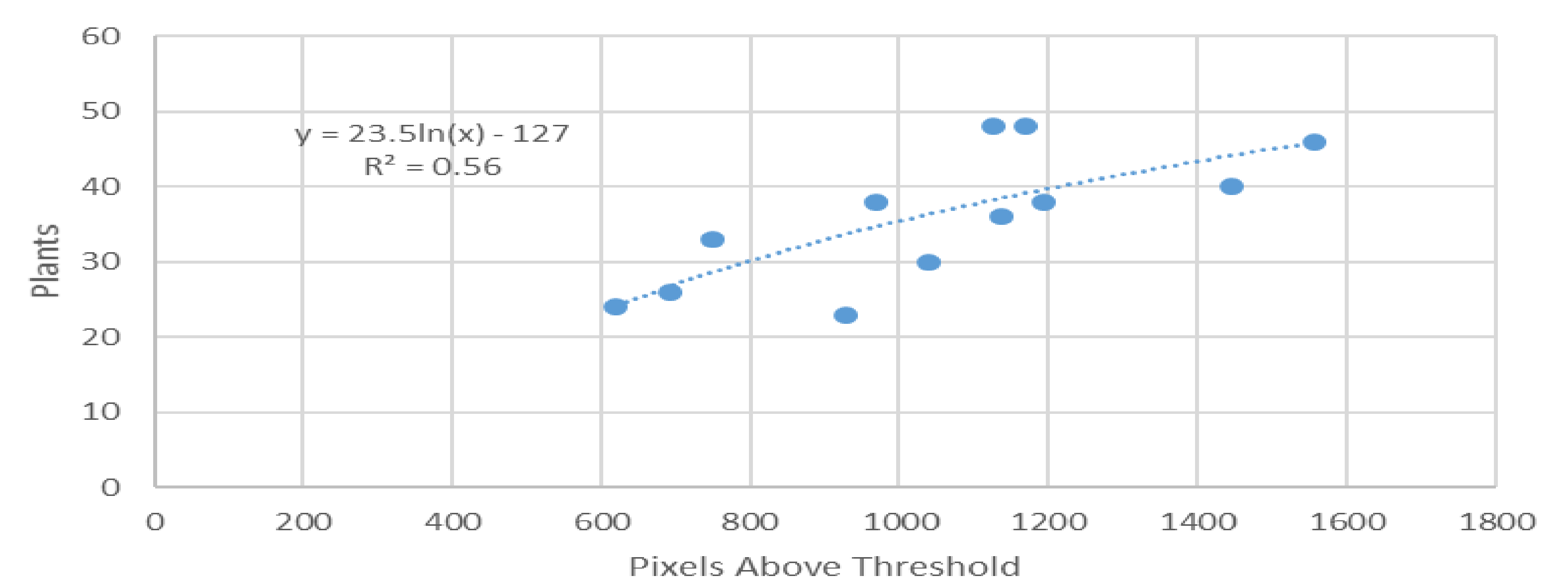


Fig. 3: Relationship between number of pixels above threshold and counted plants at 17 DAP

Number of Pixels Above Threshold - Plant Population(24DAP)

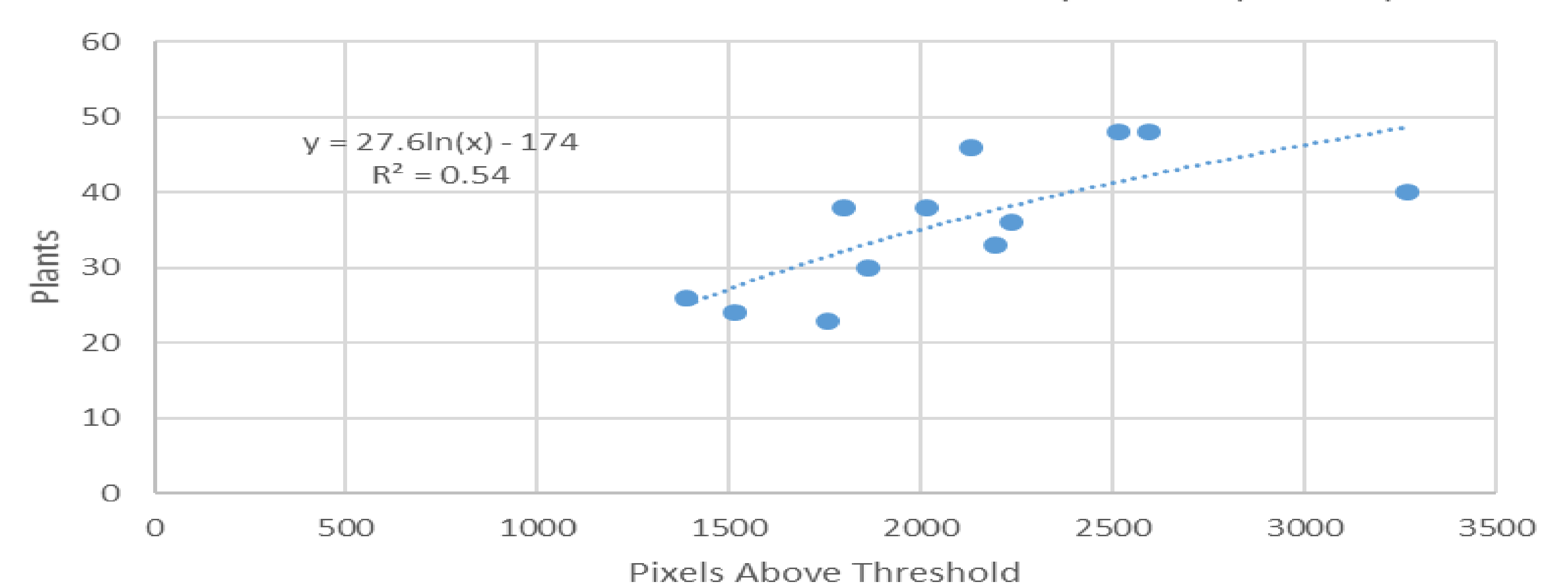


Fig. 4: Relationship between number of pixels above threshold and counted plants at 24 DAP

Conclusions

Using NDVI as a means of determining plant population shows promise when pixels above an automatically set threshold are counted and compared to the number of plant physically counted within that area.

Early NDVI data was also correlated with final yield, though results were scattered and did not show high predictive value.

Future tests would benefit from more frequent flights and closer monitoring of physical plant populations and health within the same frame as the exported images.